

UNIVERSITY OF OXFORD

DETECTING ARCHAEOLOGICAL SITES IN THE
EASTERN SAHARA USING SATELLITE REMOTE SENSING
AND DIGITAL IMAGE PROCESSING

A DISSERTATION SUBMITTED FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

BY
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THE QUEEN'S COLLEGE, OXFORD

OCTOBER 11, 2015

This dissertation
is dedicated
to my mother,
Ailsa Brigham,
who always
believed in me
and encouraged me
to follow my dreams...

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This research was funded through grants from The Queen's College, Oxford (Barns Scholarship) and The National Aeronautics and Space Administration (NASA / JPL Graduate Fellowship – JPLGF). In this regard I am extremely grateful to John Baines (Oxford) and Tom Farr (JPL/NASA) in securing funding that made this endeavour possible and for their recognition of the potential use of remote sensing in the field of archaeology.

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Abbreviations and acronyms

6S	Second Simulation of a Satellite Signal in the Solar Spectrum
A/D	Analog-to-Digital
ADEOS	Advanced Earth Observing Satellite (JAXA)
ALOS	Advanced Land Observing Satellite (JAXA)
ASAR	Advanced Synthetic Aperture Radar
ASI	Agenzia Spaziale Italiana (Italian Space Agency)
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AVIRIS	Airborne Visible / Infrared Imaging Spectrometer
AVNIR	Advanced Visible and Near Infrared Radiometer
AVHRR	Advanced Very High Resolution Radiometer
CAT	Computed Axial Tomography
CAVIS	Clouds, Aerosols, Vapours, Ice, and Snow (WorldView-3 sensor bands)
CID	Combined Image Data (SRTM amplitude)
CCD	Charge Coupled Device
CEOS	Committee on Earth Observing Satellites
CGIAR-CSI	The Consortium for Spatial Information
CNES	Centre National d'Etudes Spatiales (French space agency)
Cross-pol	Cross-polarization
CT	Computed Tomography
DEM	Digital Elevation Model
DIP	Digital Image Processing
DLR	Deutsches Zentrum für Luft- und Raumfahrt e.V. (German Aerospace Centre)
DN	Digital Number
DSM	Digital Surface Model
DSP	Digital Signals Processing
EO	Earth Observation
EM	Electromagnetic
EMR	Electromagnetic Radiation
ENVI	ENvironment for Visualizing Images
EROS	Earth Resources Observation Science (USGS)
ERS	European Remote Sensing Satellite
ERSDAC	Earth Remote Sensing Data Analysis Centre (Japan)
ESRI	Environmental Systems Research Institute
ESA	European Space Agency
ETM+	Enhanced Thematic Mapper Plus (Landsat)
EUMETSAT	European Organization for the Exploitation of Meteorological Satellites
FCC	False Colour Composite
FFT	Fast Fourier Transform
FOV	Field of View
FTIR	Fourier Transform Infrared Spectrometry
GCP	Ground Control Point
GeoTIFF	Geographic Tagged Image File Format
GDEM	Global Digital Elevation Model (ASTER)
GIS	Geographical Information System
GLCF	Global Land Cover Facility (The University of Maryland / NASA)

GOES	Geostationary Operational Environmental Satellite
GPR	Ground Penetrating Radar
GPS	Global Positioning System
DGPS	Differential Global Positioning System
GPS	Global Positioning System
GSFC	Goddard Space Flight Centre (NASA)
H-pol	Horizontal polarization
HDF	Hierarchical Data Format
HGT	Height (elevation) data raw file format for SRTM
HH	Horizontally transmitted and received (signal polarization), see VV
IDL	Interactive Data Language
IEEE	Institute of Electrical and Electronics Engineers
IFOV	Instantaneous Field of View
InSAR	Interferometric SAR
ISODATA	Iterative Self Organizing Data Analysis Technique
IVI	Improved Vegetation Index
IR	Infrared
JAMSTEC	Japan Agency for Marine Earth Science and Technology (Japan)
JAXA	Japan Aerospace and Exploration Agency
JPL	Jet Propulsion Laboratory (NASA)
LDCM	Landsat Data Continuity Mission
LIDAR	Light Detection And Ranging
LP DAAC	Land Processes Active Archive Centre (NASA / USGS)
LUT	LookUp Table
METSAT	Meteorological satellite
MODIS	Moderate Resolution Imaging Spectrometer
MODTRAN	MODerate resolution atmospheric TRANsmission
MSAVI	Modified Soil Adjusted Vegetation Index
MSS	Multispectral Scanner (Landsat)
NASA	National Aeronautics and Space Administration (USA)
NASDA	National Space Development Agency (Japan)
NDSI	Normalized Difference Soil Index, Normalized Difference Spectral Index
NDVI	Normalized Difference Vegetation Index
NGA	National Geospatial-Intelligence Agency (USA)
NIMA	National Imagery and Mapping Agency (USA)
NIR	Near InfraRed
NOAA	National Oceanic and Atmospheric Administration (USA)
OLI	Operational Land Imager
PC	Principal component
PCA	Principal Components Analysis
PCn	nth principal component
Quad-pol	Quad (full) polarization
LIDAR	Light Detection and Ranging
PALSAR	Phased Array L-Band Synthetic Aperture Radar
PFRS	Portable Field Reflectance Spectrometer
POES	Polar Operational Environmental Satellite
PolSAR	Polarimetric SAR

PRISM	Panchromatic Remote-sensing Instrument for Stereo Mapping
PSF	Point Spread Function
RADAR	Radio Detection and Ranging
RAR	Real Aperture Radar
RGB	Red, Green, Blue
RS	Remote sensing
SAVI	Soil Adjusted Vegetation Index
SAR	Synthetic Aperture Radar
SD	Standard Deviation
SIR-A/B/C	Shuttle Imaging Radar (3 separate missions)
SID	Swath Image Data (SRTM amplitude)
SLAR	Side Looking Airborne Radar
SLC	Single Look Complex
S/N	Signal to Noise ratio
SODAR	Sound Detection and Ranging
SONAR	Sound Navigation and Ranging
SPOT	System Pour l'Observation de la Terre (France)
SRTM	Shuttle Radar Topography Mission
STS	Space Transportation System (Shuttle - USA)
SWIR	Short Wave InfraRed
TADS	Trans-Africa Drainage System
TDRS	Tracking and Data Relay Satellite
TIFF	Tagged Image File Format
TIMS	Thermal Infrared Multispectral Scanner
TIN	Triangular Irregular Network
TIR	Thermal InfraRed
TM	Thematic Mapper (Landsat)
TRIC	Tokai University Research and Information Centre
UAV	Unmanned Aerial Vehicle
USGS	United States Geological Survey
UTM	Universal Transverse Mercator
UV	Ultraviolet
V-pol	Vertical polarization
VI	Vegetation Index
VIS	Visible
VNIR	Visible and Near InfraRed
VV	Vertically transmitted and received (signal polarization), see HH
WIST	Warehouse Inventory Search Tool (NASA)

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Acknowledgements

This dissertation represents the culmination of a 4-year commitment, but the process of getting there took the best part of a 15-year journey to complete. Finding an interesting and reasonably focused research topic was relatively easy. The challenging part was locating a program that provided the necessary expertise and resources to match.

The success in reaching the finishing line has to be due in large part to the people who you interact with on a daily basis and those who you can call upon at any time, for both personal and professional support. I have been extremely fortunate to have had two of the best supervisors I could have possibly asked for to help guide me through my time at Oxford: John Baines of the Oriental Institute and Gary Lock of the School of Archaeology. I would like to sincerely thank both of them for recognizing the potential in me during our initial interview that lead them to take me on as a postgraduate research student, and for their guidance and encouragement over the course of four and a half years leading me up to this point. If I ever had any problems or needed help in discussing research plans they were always more than happy to assist and always at short notice. They allowed me total freedom to follow my interests and at the same time provided me with helpful suggestions along the way. The match could not have been a better one. I would also like to thank John and The Queen's College for funding my D.Phil., in part, when my initial funding for the course had fallen through. Without financial support from the Barns Scholarship it would have made completing the D.Phil. next to impossible.

Keble College and The Queen's College became my second homes during my time at Oxford (I migrated from Keble to Queen's due to accepting a Queen's scholarship). I would like to thank both colleges for their academic, personal, and often their financial support. My college advisors, Angus Bowie (Queen's) and Lisa Bendall (Keble) also deserve mention for their support in many academic matters. I would also like to acknowledge my old master degree supervisor, Clive Oppenheimer of Cambridge University. He was always welcoming when I dropped by his office in Cambridge unannounced for an informal chat over a cup of tea.

Thanks are due to Elizabeth Frood and Sebastian Engelstaedter, both at Oxford, for their efforts as examiners during my Confirmation of D.Phil. Status. They gave generously of their

time and allowed the interview to take place over a Skype session while I was working at JPL in California. Thanks are also due to Rick Schulting and Penny Wilson of Oxford and Durham University respectively, for taking on the role as examiners for my Transfer of Status from Postgraduate Research Student to D.Phil. status.

I would like to thank the School of Archaeology, and in particular the department administrator, Lidia Lozano, who allowed me to keep a desk space in the attic of the institute. This working area proved invaluable especially when working at home or in the university libraries was not that appealing...

Tom Farr and Charles Elachi of the NASA Jet Propulsion Laboratory (JPL) deserve special mention. I was extremely fortunate in being chosen for a JPL Graduate Fellowship (JPLGF) over the course of my D.Phil., where I worked in the Solid Earth Science Working Group (SESWG) over the summer of 2013. Charles Elachi, the director of JPL, was very kind to push my application through during a time when budget cuts were a constant problem. Tom Farr was the perfect host and presented the perfect balance of always being around but without the constant supervision that can sometimes stifle creativity. He asked me what I wanted to work on, gave me access to as much data as I needed, and just let me get on with it. JPL was a very open and welcoming community and it was a privilege to be able to work there. I was given access to almost any building and research facility on the campus and the employees were actively encouraged to attend any lectures, talks, and presentations that were of interest to them during normal working hours. I was truly amazed by the quality and the dedication of the people who worked there. Thank you NASA and JPL for a wonderful research experience and for hosting me at for the duration of the project! Thanks are also due to other members of the SESWG who made my stay both welcoming and academically stimulating. They include Ron Blom, Robert Crippen, Eric Fielding, Margaret Glasscoe, Erik Ivins, Zhen Liu, and Paul Lundgren. Listening to Ron's recollection of his discovery of the lost city of Ubar with Sir Ranulph Fiennes over lunch at the JPL café was a highlight that I will always keep with me.

I was also lucky to have been given the opportunity to work on a four-month internship during the latter part of 2012 at the Japan Space Agency, more formally known as the Japan Aerospace and Exploration Agency (JAXA). I was only one of three foreign nationals at that

time working at the Tsukuba Space Centre, which is situated an hour away by train from Tokyo. Special thanks to Masanobu Shimada of the Advanced Land Observation Satellite (ALOS) group for making the internship possible, providing me with PALSAR data, a working area in the office, and for making me feel like part of the team. I would also like to acknowledge Manabu Watanabe of the Earth Observation Research Centre, JAXA, for technical assistance and for his support and encouragement during my stay at JAXA.

In January 2013 I spent a month in Sudan where I gained valuable experience on the ground taking part in the University of Michigan Nubian Expedition at El Kurru – a royal city of ancient Kush. I would like to extend my thanks to Geoff Emberling, the director of the work, for the chance to gain experience in the Nubian Desert, away from the comforts of an image-processing lab. It was a truly unique experience that I suspect few will ever get to experience. I was touched by the openness, hospitality, and friendliness of the Sudanese people.

Chapter 4 of this dissertation was presented as a paper at the International Society for Optics and Photonics (SPIE) conference held in Prague in April 2011 (SPIE 2011). I would like to thank The Queen's College, Keble College, and the Keble Association, for a generous award in support of the work. Travel expenses to and from the venue were paid for by a SPIE travel award. The National Aeronautics and Space Administration (NASA) generously provided a research grant for ASTER data through a program for approved educational use. Landsat-7 ETM+ and ASTER data were acquired through the Land Processes Distributed Active Archive Centre (LP DAAC), located at the U.S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) Centre (<https://lpdaac.usgs.gov/>). Thanks are also due to the Department of Earth Sciences, University of Hong Kong, for providing work facilities during the writing up of the paper. Finally, I would like to thank my D.Phil. supervisors John Baines and Gary Lock for their helpful comments and suggestions in the review of the work.

The palaeohydrological work is presented in chapter 5 of this dissertation. I would like to thank the NASA Jet Propulsion Laboratory (JPL) for the SRTM-1 restricted distribution data that formed the foundation for this research. Thanks are also due the USGS LP DAAC, NASA Earth Observing System Data and Information System (EOSDIS), and Japan's Earth Remote Sensing Data Analysis Centre (ERSDAC) for providing additional ASTER and PALSAR data.

I think it is safe to say that I probably would not have made it to Oxford had it not been for the quality of education I received during my undergraduate years in the United States, especially at the Junior College level at The Foothill – De Anza Community College District in the San Francisco Bay Area. The teaching was always of the highest quality and this was reflected through both their on-campus classes and their internet-based Massively Open Online Courses (MOOCs), of which Foothill has been the pioneer in this field since the beginning. Michael Loeff, of Foothill College (who at the time was also writing the screenplay for the popular TV series 24) should be credited for raising my interest in the study of Computer Science when I took his online class in the C programming language in the late 1990's. In addition, Mehran Sahami of the Department of Computer Science at Stanford University deserves mention as a teaching inspiration and for his eloquent explanations of software engineering principles and data structure algorithms using Java. I would also like to acknowledge my old college lecturers who got me interested in science in the first place: Claudio Vita-Finzi (Planetary Sciences, University College London) and Don Burt (Geology, Arizona State University). Claudio has since moved to the Natural History Museum, London.

Lastly, my mother deserves special mention. She has always given her fullest unconditional love, support, and encouragement. I have been a student for more years than I would like to admit but she has always been interested and never questioned my thirst for knowledge. For that I am eternally grateful. Without her initial support during my undergraduate years in the United States I would most likely not be writing this now. This dissertation is dedicated to her.

Thesis abstract

Detecting archaeological sites in the eastern Sahara using satellite remote sensing and digital image processing

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D.Phil. Archaeology, Hilary Term 2015

Advancements in remote sensing instrumentation are providing more detailed surveys of our planet using synoptic observations from a global, regional, and local perspective. This D.Phil. research project proposes novel techniques for detecting archaeological sites in the hyperarid desert regions and moisture-rich coastal areas of the eastern Sahara, by examining multispectral satellite imagery in the optical and microwave (radar) regions of the electromagnetic (EM) spectrum. The methodology uses sensors onboard spaceborne platforms (in contrast to airborne instruments or ground based geophysical survey) – weighted heavily towards an active radar approach. Landsat-7 ETM+, Shuttle Radar Topography Mission (SRTM), and PALSAR represent the principal imagery types used throughout this work.

Three case studies are presented, each setting out a comprehensive and well-documented protocol for archaeological site detection. The first uses Landsat ETM+ data to map and identify the distribution of ‘tell’ sites in the northwestern Nile Delta by applying a principal components transformation and a thresholding approach. The second case study produces a complete hydrologic map of the eastern Sahara from SRTM image (amplitude) and elevation data. Oases and ancient fluvial networks (palaeorivers) are mapped using the Normalized Difference Vegetation Index (NDVI) and from SRTM image data respectively. ASTER thermal infrared (TIR) is used to detect palaeolake deposits from their surface carbonate signatures. Additionally, topographic lake depressions and palaeoshoreline features are identified from SRTM DEM. The use of a DEM was found to provide a more favourable approach for mapping palaeolake systems compared to performing a spectral analysis. The final case study considers trading routes and their relationship to water sources. Imagery datasets produced over the course of the work are added to a Geographical Information System (GIS) in order to examine likely locations for new archaeological sites in Egypt's Western Desert. Results from these investigations indicate that a fully multispectral strategy is preferred when isolating spectral signatures from archaeological materials.

PART ONE

Chapter 1

Introduction

1.1 Scope and objectives

Since the early 1970s, with the advent of the first earth observation satellites, earth science data has routinely become available to members of the scientific community. Archaeologists have also benefitted from this new influx of imagery allowing for the first time a truly synoptic multispectral characterization of the landscape. Improvements in sensor design and the sophistication of image processing algorithms to process the massive amounts of newly acquired data have progressed at a swift rate. Many of the same techniques now used in archaeological remote sensing have been adopted and modified from those used in other disciplines, especially geophysics. It is therefore not uncommon to find remote sensing specialists “borrowed” from one of the physical sciences to specially work on archaeological problems. However, a lack of a robust workflow for the use of these techniques by archaeologists is widely apparent. As a result, a well-documented approach to the detection of archaeological sites using these new technologies has remained unrealized.

The objectives of this D.Phil. dissertation are as follows: (1) to describe methodologies for detecting new archaeological sites using multispectral remote sensing imagery acquired by satellite; (2) to present a well documented workflow for the processing of the imagery using digital image processing algorithms, and (3) to formulate strategies for the remote sensing (and therefore detection) of archaeological sites situated primarily in arid desert regions of the world, with special reference to the eastern Sahara.

It should be noted, therefore, that this study focuses primarily on the detection of archaeological sites rather than on the interpretation of the imagery for answering specific archaeological questions. As such, the focus of this work is on the methods for locating sites

using remote sensing technologies, given the advantage that high orbital imaging provides for regional based survey mapping.

A large part of this work relies on using existing digital image processing techniques, heavily borrowed from other fields, such as the Earth sciences (especially geophysics), and re-applying them to problems in archaeology, where little work has previously been carried out. It is hoped that archaeologists adopting such a strategy will be better able to interpret the nature of their own datasets, by relating them directly to the archaeological landscape. This in turn will help answer a range of questions, from the socio-economics of urban centres to the change in settlement patterns of these sites over time. It is assumed the reader has an elementary knowledge of the principles and concepts used in remote sensing. More specifically, some understanding of electromagnetic theory and its interaction with matter, passive and active remote sensing systems, sensor resolution, and elementary image processing are essential. Chapter 2 will cover some of these concepts in greater detail.

Initially, during the early stages of the D.Phil., the extent of the study area was limited to the desert regions and Nile floodplain of Egypt, but as work progressed, the study area expanded to cover the neighbouring countries of Sudan, Libya, and Chad – an area encompassing much of the eastern Sahara desert. Both the identification of features above ground (for example “tell” sites) and those below the surface (such as palaeorivers) are discussed and presented in three case studies, which comprise the major component of this dissertation.

Many of the techniques examined in this dissertation, in particular radar imaging, are particularly well suited to the remote sensing of arid regions, where little vegetation cover exists and where the conditions allow for a characterization of both surface roughness and subsurface signal penetration. As a result, the methodologies should adapt well to desert archaeology in other regions, especially other parts of the Sahara and the Middle East, where a similar dry environment may be encountered.

The work presented in this dissertation is timely due to the number and diversity of archaeological sites that are rapidly disappearing across the eastern Sahara. As time progresses many sites will come under threat due to increasing environmental pressures. Improvements made to desert transportation links will inevitably lead to many sites being more readily accessible. Furthermore, many of the more remoter sites are at risk from

modern-day recreational activities (“adventure tourism”), which use four-wheel drive vehicles to travel across the desert landscape often damaging and cutting up many of the preserved caravan routes. It is therefore imperative to locate, map, and protect sites for future generations before they disappear forever. I hope the methodologies presented in this dissertation will help contribute towards this aim.

1.2 A multispectral approach to locating sites

The detection of archaeological sites using remotely sensed data requires a fully multispectral, and if possible, automated, or at least a semi-automated approach. These strategies are necessary when working with large geographic regions and where little is known about the types of sites that may exist or their spatial positioning. Data should be acquired in as many wavebands of the electromagnetic spectrum as possible, including the visible / near infrared, thermal infrared, and microwave (active radar). After a comprehensive review of the imagery, regions of interest may be selected, and the survey can then continue from the ground using geophysical techniques, such as ground penetrating radar, resistivity, and if appropriate lidar. These types of survey all involve non-destructive means for locating sites. It is only after these methods have been exhausted that any on site excavation should take place. Excavation may initially begin by coring, for example, to get an idea of site distributions and time periods before moving on to trenching and other more invasive strategies.

When spaceborne data (acquired by orbiting satellite) first became available it was limited in its resolution and was typically expensive. Today we are spoiled for choice with access to high spectral and spatial resolution data from both optical and microwave (radar) sensors. However, most archaeological investigations do not take advantage of the multispectral component and limit themselves to studies in the visible, or at most, the near infrared regions of the spectrum. The various case studies in this work use a broad range of multispectral imagery from all relevant wavelength regions, including the thermal infrared and microwave.

1.3 Limitations of a remote sensing study

Remote sensing is never an exact science and should never be considered a panacea for the reconnaissance, detection, and mapping of archaeological sites. Therefore, the “ground-truthing” of satellite imagery, together with on-site field excavations have an equally important role to play in the detection process.

It is not always possible however to get access to the ground to visually check and investigate a potential site. This was the case with many of the sites mentioned in this dissertation. Sadly, due to the political situation in Egypt and many of the surrounding countries at the time of this research, it was impossible to undertake a field campaign for the purposes of ground-truthing the results. This was not too much of a problem for the first case study due to the large size, situation above ground level, and recognizable morphologies of the archaeological features (the so called “tell” sites). Many of these sites could be verified through the use of such applications as Google Earth, which employs very high-resolution imagery. However, remote sensing data without other ancillary data should be used with caution, and should not be relied upon without the accompaniment of supporting data sets. Ground-truthing should always (when possible) be used to confirm on the ground what the satellite sensor sees in the sky.

1.4 Overview of this thesis

Following this introduction, this document has been divided into the following key chapters:

2. Principles of satellite remote sensing

Chapter 2 provides an introduction to remote sensing so as to provide a solid foundation for later chapters. In this chapter, remote sensing is defined, and the process is put into an appropriate context. The applications of remote sensing in the fields of the exploratory sciences are briefly discussed, illustrating how far reaching the technology has come, and how archaeological remote sensing fits into this overall framework. Passive / active systems in addition to sensor resolution are considered, giving specific examples of sensor systems and types. The chapter also includes a brief introduction to electromagnetic theory due to its importance as the communications link between the sensor and the area of interest. The concepts of spectral reflectance and spectral signatures are highlighted in relation to surface studies, which are relevant to the first case study of this work (Chapter 4). Furthermore, the chapter is weighed quite heavily towards microwave theory, which is wholly relevant for an understanding of case study 2 (Chapter 5), which employs predominantly radar data. The final three sections form the bulk of the chapter and present a detailed examination of solid surface remote sensing in three different

electromagnetic (EM) wavelength regions: the visible / near infrared (VNIR), the thermal infrared (TIR), and the microwave regions using Synthetic Aperture Radar (SAR). Issues of resolution and calibration, in addition to approaches to image processing and analysis will be explored with regard to each of the imaging subsystems.

3. Methodology and approaches to locating archaeological sites

Whereas Chapter 2 introduced the principles of remote sensing and its applications, Chapter 3 focuses on the methodologies and approaches that can be used to detect new sites, with an emphasis placed on those situated in arid regions. The chapter opens with a review of past “space archaeology” accomplishments, giving a range of examples primarily from Egypt. The definition of ‘archaeological site’ is discussed, in addition to the types of sites that may be detectable using the current generation of spaceborne instruments. Furthermore, regions of the electromagnetic spectrum are considered as windows of opportunity in the detection of certain types of sites. The chapter summarizes the strategies for locating sites, emphasizing the search for water as a key factor when searching in arid regions. The geomorphology of Egypt is presented, contrasting the water-rich regions of the Delta and the floodplains to that of the arid desert areas, and how different approaches may be necessary depending on the search locations and conditions. The chapter continues with a discussion of image processing techniques often used to enhance archaeological anomalies in the imagery, such as Principal Components Analysis (PCA). Finally the chapter concludes with a discussion of data availability, the use of Google Earth as a data provider, and a brief examination of image processing applications available both commercially and from open source.

4. Case study 1: Detecting tell sites in the Egyptian Nile Delta using PCA

The fourth chapter presents the framework for the first case study, documenting a methodology and practical workflow for the detection of ancient Egyptian tell sites. The chapter begins by introducing the archaeology of tell sites and their importance in providing a better understanding of ancient settlement patterns. Previous tell surveys, including the Egyptian Exploration Society’s (EES) Delta Survey, are discussed, in

addition to the other data resources that are available. The second part of this chapter focuses on the mechanics of the case study, including a detailed look at the methodology, study area, principal remote sensing imagery used, and the image processing workflow employed. Principle components analysis (PCA), a multivariate statistical technique, is introduced and the theory of its use is explained. The Google Earth application as a tool for confirming sites on the ground (in the absence of ground truthing data) is also discussed. Finally, the results of the work are presented in addition to potential improvements that could be implemented in future work.

5. Case study 2: Mapping the palaeohydrology of the eastern Sahara: the search for water

The second case study moves away from the moisture rich regions of the Egyptian Nile Delta and examines strategies for locating archaeological sites in the arid regions of the eastern Sahara based on the distribution of ancient water sources. Therefore, a central theme in this case study is understanding the importance that water played in supporting local populations and the formation of settlement sites. The first part of this chapter introduces various types of desert water sources – both present and past, including the modern day oases / springs, and the former palaeoriver and palaeolake systems. The chapter continues with a more advanced treatment of subsurface radar imaging for the detection of relict palaeochannels, describing both the optimal conditions necessary for feature capture and those required to achieve maximum depth of signal penetration. The second part of the chapter presents a practical workflow for mapping regions of the Sahara to search for past evidence of flowing water. This includes the search for oases (using various vegetation indices derived from Landsat ETM+ data), palaeorivers (SRTM image data), and palaeolakes (ASTER thermal infrared for detecting surface deposits and SRTM data for locating depressions and palaeoshoreline features). The chapter concludes with a discussion of results of the findings.

6. Case study 3: Remote sensing of trading routes; archaeological site prediction using a GIS

The final case study consists of two parts. The first examines trading networks across the eastern Sahara and the potential for remote sensing satellites to identify and map them. The second part of the case study focuses on a practical study for archaeological

site prediction using a geographical information system (GIS). The chapter opens with an introduction to the trading routes of Egypt's Western Desert and the contribution that desert road archaeology has made in locating archaeological sites adjacent to them. A multispectral approach to identification is taken, using both visible near infrared, in addition to night-time thermal infrared (NTIR) imagery, to assist in the mapping of these surface lineaments. An analogy is made with the so-called "hollow ways" found throughout large regions of the Middle East and regions farther afield. The practical component of the case study uses spatial querying of a geographical information system (GIS) to predict regions throughout the Egyptian Western Desert where archaeological sites may be likely to exist using data gathered from earlier case studies. The chapter concludes with a discussion of the results and conclusions.

7. Conclusions

In this section the results from the three case studies are summarized. A critical analysis ties the work as a whole together with final concluding remarks and statements.

Chapter 2

Principles of satellite remote sensing

2.1 Introduction: definitions, applications, and benefits

Remote sensing is used in numerous applications ranging from medical imaging, radio astronomy, and archaeology. It can be broadly defined as the collection (and interpretation) of information about an object, area, or phenomenon without direct physical contact. The definition is usually implicit that the detecting and measuring medium is derived from electromagnetic energy, which acts as the communications link between the sensor and the study area. Consequently, all ground-based techniques, such as magnetometry, electrical resistivity, and ground penetrating radar, although often used in archaeology, tend to be described under the category of geophysical survey, as the detector needs to be in contact with or close to the ground surface. The definition also usually excludes the use of side scan sonar, often used in oceanographic studies, where the water column is used as the communications medium for the propagation of sound waves.

Remote sensing is not considered a scientific discipline in its own right, but can be considered a tool that has a great many applications, the majority of which are connected to earth observation. Typical examples for satellite delivered (spaceborne) applications are shown in Table 2.1 on the following page.

Remote sensing offers many advantages over other more conventional forms of data collection. Some of these key benefits include:

- Remotely sensed data is often acquired from a great distance – for example, tracking a weather system from a satellite orbit 36,000 km above the surface of the earth. Observations from this altitude allow for a synoptic view of our planet, which would normally be impossible to obtain by any other means.
- No field personnel need to be deployed and therefore images can be safely collected – for example, monitoring a dangerous volcanic eruption from the comfort of an image-processing lab located on the other side of the world.

Earth observation		Other
Land cover / land use mapping	Archaeology	Defence and military applications
Geology, forestry, and hydrology	Mineral and oil exploration	Imagery intelligence collection
Oceans and coastal monitoring	Digital elevation modelling	Police and law enforcement
Atmospheric research	Ground deformation studies	Space exploration and astronomy
Sea ice investigations	Change detection	War crime investigations
Weather imagery collection	Natural hazards monitoring	Cadastral (land ownership)
Table 2.1: Typical applications of spaceborne remote sensing		

- Imagery acquired from a satellite can be frequently updated and can therefore have great utility in time change studies – for example, weather satellite images can be updated every 15 minutes or less, which may be important for monitoring a typhoon as it rapidly approaches land. Some military reconnaissance satellites can be updated and operated in real time.
- Imagery collection using a remote sensing approach can bring a significant cost benefit and this is particularly the case when the surveying of large areas becomes necessary, which are normally calculated on a per unit area basis.
- Remote sensing instruments can study an object or phenomenon using a great many wavelengths of the electromagnetic spectrum when compared to an optical camera, which is normally sensitive to only a narrow waveband of the spectrum, such as only the visible / near infrared.

2.2 Basic theory and concepts

Remote sensing is performed using an instrument often referred to as a sensor. Sensors can be mounted on various platforms, including aircraft, spacecraft (for example the NASA Space Shuttle), and orbiting satellites. If the sensor is mounted on either a spacecraft or satellite, it is

often referred to as a spaceborne sensor. The type of platform and sensor used depends on the nature of the remote sensing investigation.

A remote sensing system consists of four components which are needed to measure and record data about an object or area: 1) a sensor; 2) an observable target; 3) an energy source which acts as the communication link (either passively received or actively transmitted); and 4) a transmission path to that target object. For satellite observations the transmission path will occur through the Earth's atmosphere. In contrast, an airborne sensor's transmission path will occur through a much narrower path of atmosphere, and in a geophysical survey, such as when using a ground penetrating radar system, the path will be through the ground. Figure 2.1 illustrates a simplified view of the remote sensing process.

As illustrated in Figure 2.1, electromagnetic energy, produced either from a natural source, such as from our Sun (1), or from a man-made source, such as a radar pulse from a satellite (4) radiates through the atmosphere (2) and illuminates a target of interest on the ground (3). The source of energy is electromagnetic in nature and will experience signal attenuation due to absorption as it passes through the atmosphere on its journey from or to the satellite sensor. If the satellite artificially generates the source of energy, the signal will pass through the atmosphere twice, encountering greater attenuation, as it travels from the satellite sensor to the ground and back again.

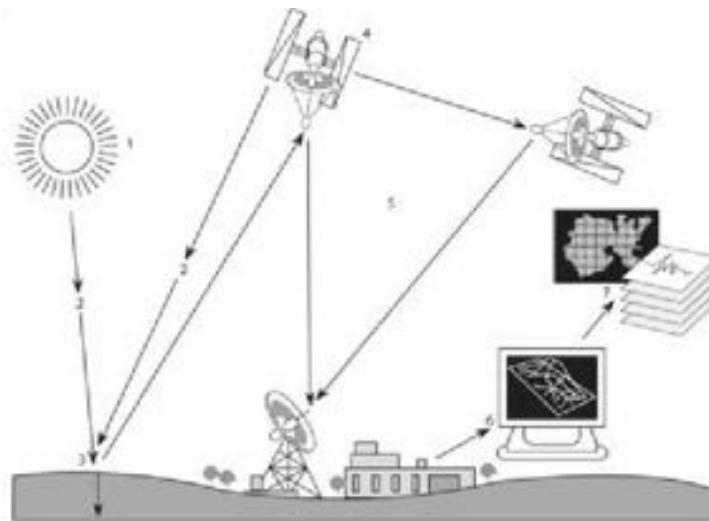


Fig. 2.1: The remote sensing process (Canada Centre for Remote Sensing)

After reaching the target a portion of the energy is reflected back to the sensor where it is recorded and transmitted to a ground station (5). The signal may need to be routed through a data relay satellite (in the case of a spaceborne instrument) if there are no ground stations directly visible from the satellite at the time of transmission (i.e., a clear line of sight is needed from the satellite or spacecraft in order to transmit a signal to a ground receiving station). After the data has been digitally transmitted to Earth it is checked for signal distortion and other sensor errors before it is pre-processed, by applying basic image processing algorithms. The data is subsequently distributed to dedicated image processing centres for further in house processing. Finally, the data is made available to third party users at universities, private research institutions, and public sites for the processing, analysis, and interpretation of the imagery (6). Information from the imagery can later be extracted, processed, and made available for presentation by the end user (7).

Several fundamental concepts will now be discussed, including the difference between passive and active systems, sensor resolution, and the fundamentals of electromagnetic energy, which are all relevant to the study of archaeological remote sensing.

2.3 Passive vs. active systems; multispectral vs. hyperspectral; satellite orbit

Sensors are subdivided into active or passive systems depending on how the energy source illuminating the target is produced.

A *passive* remote sensing system records energy that is naturally reflected or emitted from an object. The sensor therefore does not supply its own energy but relies on either naturally reflected energy (from the Sun), or thermal infrared energy (from the Earth). This latter source is collectively known as passive microwave. Examples of passive systems include aerial and space film cameras, multispectral and hyperspectral imagers, spectrometers, radiometers, atmospheric profilers or sounders, and Charge Coupled Devices (CCDs). They are all collectively termed ‘passive radiometers’, however the distinction between them can often be blurred.

Figure 2.2 illustrates a passive remote sensing system. The Sun provides the source of electromagnetic energy, which propagates to an object on the surface of the Earth (1).

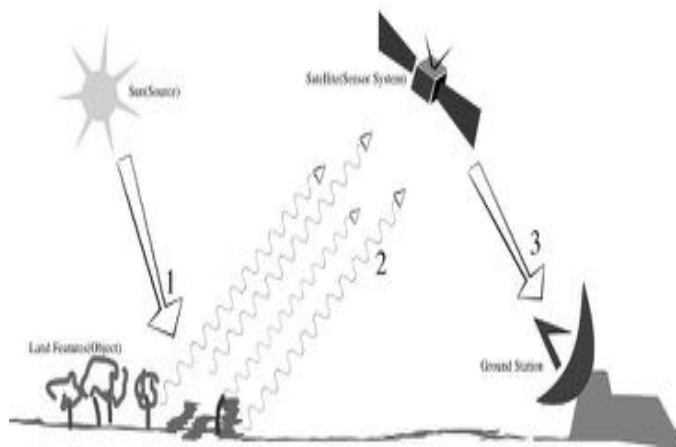


Fig. 2.2: A passive remote sensing system (Canada Centre for Remote Sensing)

A portion of the energy is reflected towards the satellite (2) and collected and recorded at the sensor, where it is transmitted to a ground station (3). These systems collect imagery in specific regions of the electromagnetic (EM) spectrum, including the visible, near infrared, shortwave infrared, and thermal infrared (collectively referred to as the optical range). The decision to acquire imagery using a particular wavelength depends on the nature of the investigation. Passive sensors may be described as either multispectral or hyperspectral depending on the number of bands they use to record energy. This is also known as an instrument's spectral resolution (see Subsection 2.4.2).

Multispectral devices record reflected and emitted electromagnetic energy using several channels (usually less than twenty). Typical multispectral instruments include the Enhanced Thematic Mapper Plus (ETM+) onboard the Landsat-7 satellite (collecting data in 8 discrete channels), the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) onboard the Terra satellite (14 discrete channels), the Advanced Very High Resolution Radiometer (AVHRR) onboard polar orbiting POES satellites (6 spectral bands), and various oceanographic and meteorological satellites (metsats). Multispectral imagers are used in many earth observation applications including the study of vegetation, land cover, clouds, aerosols, fires, and calculating sea surface temperature.

While multispectral instruments collect spectral data using several tens of bands at most, *hyperspectral* instruments (also known as *imaging spectrometers*) collect data using hundreds

of bands and therefore offer much higher spectral resolution. Hyperspectral imagers are therefore able to provide a much more detailed analysis by providing a spectral fingerprint of a target. They can identify for example whether an area of vegetation is healthy or under stress by examining its spectral profile in much greater detail. Examples of hyperspectral imagers include the Hyperion instrument, which records data in the visible near infrared and the short wave infrared using 220 spectral bands. Applications of hyperspectral imaging include rock type mapping and vegetation discrimination.

In contrast to a passive system, an *active* remote sensing system provides its own source of illumination. A pulse of microwave energy is emitted towards the target where it interacts with its surface. Depending on the surface characteristics (roughness, slope, water content etc.), a portion of the energy is backscattered and returned to the instrument where it is recorded by the sensor. A typical active system often used in remote sensing is Radio Detection and Ranging (RADAR). The radar signal can penetrate to a range of depths depending on the medium through which the signal passes. It has been shown to pass through up to four kilometres of Antarctic ice before reaching bedrock (Elachi, 1983).

Active sensing requires a two way travel time for the pulse as it travels from and to the sensor. In earth observation (EO) applications the signal must therefore pass through the atmosphere (or other medium) twice. This is important because a two way travel time attenuates and thus degrades the signal. RADAR, Light Detection and Ranging (LIDAR) and Sound Navigation and Ranging (SONAR) are all examples of active sensing technologies. A typical example of RADAR is the Side Looking Airborne Radar (SLAR). SLAR systems were deployed on several United States Space Shuttle missions. RADAR is also carried onboard aircraft and used in ground based geophysical surveys. When used in geophysical surveys they are known as either Ground Penetrating Radar (GPR) or Subsurface Imaging Radar (SIR) systems. The acquisition, processing, and interpretation of imagery acquired from a radar system is more complex than a conventional passive system and is covered in Section 2.8.

Figure 2.3 shows an active remote sensing system. In this example, an instrument onboard a satellite provides the energy source. It emits a pulse of microwave energy directed towards the ground (1), where it interacts with the surface of the object. Depending on the nature of the surface interaction, a percentage of the energy is backscattered back towards the sensor (2), where it is recorded, and transmitted to a ground station (3).

The advantages of using an active system, such as RADAR, are that it can record imagery in any weather conditions, including through clouds and rain and at any time of night or day. They therefore provide an all weather capability and are very useful for recording images in regions often affected by adverse weather conditions. Table 2.2 provides a quick look summary of the main categories of passive and active remote sensing technologies.

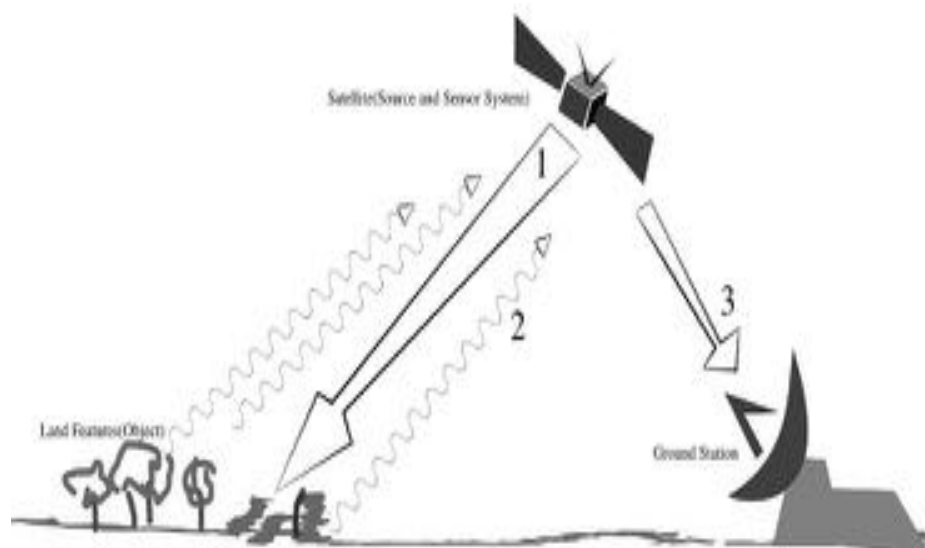


Fig. 2.3: An active remote sensing system (Canada Centre for Remote Sensing)

	Passive	Active
Optical	Optical imager Spectrometer (non imager)	LIDAR
Microwave	Microwave radiometer Microwave sounder (non imager)	RADAR / SAR
Sound	N/A	SONAR / SODAR
Table 2.2: Categories of remote sensing sensors		

Imaging sensors may be placed on a number of different platforms including ground vehicles, boats, balloons, unmanned aerial vehicles (UAVs), aircraft, and satellites, of which the latter is the focus of this thesis. Spaceborne sensors operate in a number of different orbits dependent on the type of data that they collect. Two of the most common include the geostationary (GEO) and the low earth orbit (LEO).

The geostationary satellites move in a circular orbit at approximately 36,000 km above the Earth's equator. Their orbital rotation matches that of the Earth (24 hour period) and as a result the satellite appears stationary in the sky above a fixed point on the equator. Geostationary satellites therefore view the same portion of the Earth's surface at all times. Weather (GOES – the Geostationary Operational Environmental Satellites, operated by NOAA), telecommunications, and Tracking and Data Relay (TDRS) satellites normally operate at these altitudes. They are able to continuously monitor the whole of the Earth's disk (high temporal resolution), however their spatial resolution tends to be low.

High spatial resolution sensors operate at much lower altitudes in Low Earth Orbit (LEO), typically less than 1,000 km. Data from these sensors are much more likely to be used for imagery reconnaissance and archaeological remote sensing studies. For earth observation at LEO the most commonly found sensors move around the Earth in near-polar orbits. In a near-Polar orbit the satellite follows a trajectory north-south which when combined with the Earth's rotation east-west allows for them to cover most of the Earth's surface over a fixed period of time. These satellites cross the equator multiple times per day and each time they are at the same angle with respect to the sun (sun-synchronous). Examples of near-polar low earth orbit satellites include NOAA's Polar-orbiting Operational Environmental Satellites (POES), NASA's Earth Observation System (EOS), Landsat 1-6, and SPOT. EOS is composed of the research satellites Aqua, Terra (which includes the MODIS and ASTER instruments), Landsat-7, and EO-1. All data used in this thesis was acquired from LEO satellites. Table 2.3 lists some of the characteristics of the different satellite orbits.

Orbit type	Altitude / km	Function / examples
Low Earth Orbit (LEO)	450 – 2,000	Earth observation / POES, EOS
Middle Earth Orbit (MEO)	2,000 – 35,786	GPS constellation
Geostationary Earth orbit (GEO)	36,000	Meteorological, telecommunication, TDRS
Table 2.3: Satellite orbit characteristics		

2.4 Sensor resolution

The resolution required to resolve a target on the ground is one of the primary factors in determining the suitability of a sensor for a given application. However, an understanding of the term ‘resolution’ in remote sensing is complicated by the fact that the word can convey four different meanings. Consequently, an image can be described in terms of its spatial, spectral, radiometric, and temporal resolutions. This section will discuss each of these four types.

2.4.1 Spatial resolution – Perhaps the most important and recognized parameter of an image is its spatial resolution. Again this is a vague term, as no single definition of its precise meaning exists. The spatial resolution may be described as the area on the ground represented by a single pixel in an image averaged to a single digital number (DN). The range of resolutions for different types of satellite imagery varies widely, on the order of kilometres for weather satellites, to less than half a metre for commercial earth observation satellites, to the order of centimetres for military operated intelligence gathering satellites.

It is important to understand that the higher the spatial resolution, the greater the detail that can be extracted from an image. However, there is usually a tradeoff due to the design limitations of the technology: a sensor offering high spatial resolution will often be limited to low or medium spectral resolution and vice versa. For example, a sensor may provide high spatial resolution in the visible / near infrared (VNIR) wavelengths, but will provide little to no capability in the shortwave infrared (SWIR) or thermal infrared (TIR) regions of the EM spectrum.

When working on a remote sensing project it is critical to choose a spatial resolution that is suited to the problem at hand. For regional archaeological applications, 30 m or better should ideally be the minimum. For site detection strategies, depending on the size of sites, 5 m or less, is considered the absolute minimum. This is achievable with current commercial satellites. It is only within the last 20 years that the civilian world has gained access to this level of resolution. This was in part due to legislation introduced by the United States in 1994 (Presidential Decision 23 signed by President Clinton), which allowed for civil commercial companies to develop, launch, and sell high-resolution satellite imaging services to the non military sector. This has resulted in the rapid expansion of the availability of high-resolution

commercially viable sensors. This rapid increase in the availability of high-resolution satellite imagery is proving a great asset to the archaeological community. As the spatial resolution approaches 1 m and better, satellite images are taking the place of aerial photographic maps, which are sorely lacking in many areas of the world.

The American Landsat series of satellites are considered the workhorses of the industry offering mid level resolution capabilities. The first satellite, Landsat-1, launched in 1971, used the Multispectral Scanner (MSS) and the Thematic Mapper (TM) sensors, and consisted of 5 spectral bands at 79 m spatial resolution. Landsat-7, launched in 1999 (and still in operation), utilizes the Enhanced Thematic Mapper Plus (ETM+), has 8 spectral bands providing resolutions of 30 m (multispectral) and 15 m (panchromatic). A panchromatic image records a scene in the visible range of the EM spectrum (0.4-0.7 μm), whereas the multispectral channels record in discrete wavelength regions. Landsat's latest generation instrument, Landsat-8, is the eighth satellite in the program (seventh to reach orbit), launched in February 2013, and provides moderate to higher resolution imagery from 15–100 m. These resolutions are still too coarse for high-resolution work, but nonetheless they have been useful in many remote sensing studies over the past 40 years.

Offering higher spatial resolutions compared to Landsat, the French owned Satellite Pour l'Observation de la Terre (SPOT) launched their first satellite, SPOT-1, in the mid 1980s. The latest generation satellites, SPOT-6 and SPOT-7, were launched in 2012 and 2014 respectively. Both sensors record EM energy within four spectral bands in addition to one panchromatic band and are capable of spatial resolutions of up to 6 m (multispectral) and 1.5 m (panchromatic). Unlike Landsat data, which is now free (see Subsection 3.9.1), SPOT imagery is expensive and may be of limited use due to its low spectral resolution.

For high-resolution work there are now several solutions available. Space Imaging launched the first high-resolution commercial satellite into orbit, IKONOS-2. Launched in 1999, IKONOS-2 represented a new era of privately produced and owned imaging systems, making intelligence quality imagery available to the civilian world for the first time. IKONOS-2 was equipped with four multispectral bands (red, green, blue, and near infrared), and one panchromatic band at a spatial resolution of 4 m multispectral and 1 m panchromatic.

Sensors that include a panchromatic band, in addition to lower resolution multispectral bands, can be pan-sharpened (see Section 3.6). Pan-sharpening makes it possible to produce a higher multispectral colour image by merging the high-resolution panchromatic band with the lower resolution multispectral bands (usually from the same sensor) to create a single high-resolution multispectral colour image. For example, pan-sharpening IKONOS imagery merges the 1 m panchromatic band with the 4 m multispectral bands to produce a high-resolution multispectral colour image at 1 m pixel resolution (Figure 2.4).

There are currently four commercially operating satellites that are capable of resolving objects at the scale of half a metre or less: WorldView-1, 2, 3 and GeoEye-1 (all owned and operated by DigitalGlobe). GeoEye (formally Space Imaging Corporation) was merged with DigitalGlobe in 2013. GeoEye-2, with a similar spatial resolution as WV-3 (but with a limited spectral resolution) is due for launch in 2016. Table 2.4 shows the specifications of the highest spatial resolution commercial satellites currently available. Prior to the launch of WorldView-3, WorldView-2 was the highest resolution satellite for civilian use offering eight separate spectral bands at a spatial resolution of 46 cm pan-sharpened. Its capabilities were superseded by the launch of WorldView-3 in August 2014 offering an unprecedented spatial resolution of 31 cm. The civilian world is unlikely to benefit from future increases in spatial resolution for the foreseeable future due to an operating license enforced by the U.S. Government*.



Fig. 2.4: pan-sharpened 1m IKONOS satellite image of St. Peter's Square, Rome, Italy (GeoEye)

* Due to recent government approval (June 2014), WorldView-3 (DigitalGlobe) will not be limited to the 50 cm restrictions of its predecessors. Currently this approval only applies to DigitalGlobe products. All other products will be resampled to 0.50 m (50 cm) due to imaging restrictions.

Name	Multispectral bands	Panchromatic band	Notes
IKONOS	3.2 m (3x VIS, 1x NIR)	0.82 m	Launched in 1999. First commercial satellite offering sub 1 m resolution.
QuickBird	2.4 m (3x VIS, 1x NIR)	0.61 m	Launched in 2002. Base imagery for Google Earth.
WorldView-1	None	0.46 m	Launched in 2007.
GeoEye-1	1.65 m (3x VIS, 1x NIR)	0.41 m	Launched in 2008.
WorldView-2	1.84 m (5x VIS, 3x NIR)	0.46 m	Launched in 2009. Prior to the launch of WorldView-3 was the highest resolution commercial satellite.
GeoEye-2 (renamed WorldView-4 after merger)	1.36 m (3x VIS, 1x NIR)	0.31 m	Date of launch scheduled for mid 2016. Once launched will offer highest spatial resolution.
WorldView-3	1.24 m (5x VIS, 2x NIR); 3.7 m (8x SWIR, 12x CAVIS)	0.31 m	Launched August 13, 2014. Currently offers the highest spatial and spectral resolution.
Table 2.4: Common high-resolution remote sensing systems. Current highest resolution commercial sensor shown in bold.			

2.4.2 Spectral resolution – The spectral resolution is the second most important attribute of a sensor. It refers to the number and the width of bands (also referred to as channels) that the sensor is capable of recording in within the EM spectrum. Generally the higher the spectral resolution of a sensor, the greater the number of wavelengths the instrument is sensitive to. Remote sensing systems are capable of recording data using many different wavelengths. For example, ASTER records in 14 separate channels, whereas Landsat ETM+ has 8 (including a panchromatic band). Hyperspectral instruments may record using hundreds of separate channels. Figure 2.5 show the respective spectral bands for ASTER and Landsat ETM+. Note the increased spectral resolution of the ASTER sensor in the shortwave infrared (bands 5–9) and the thermal infrared (bands 10–14) when compared to the Landsat sensor. Spectral resolutions for a selection of VNIR and TIR sensors can be found in Tables 2.8 and 2.10.

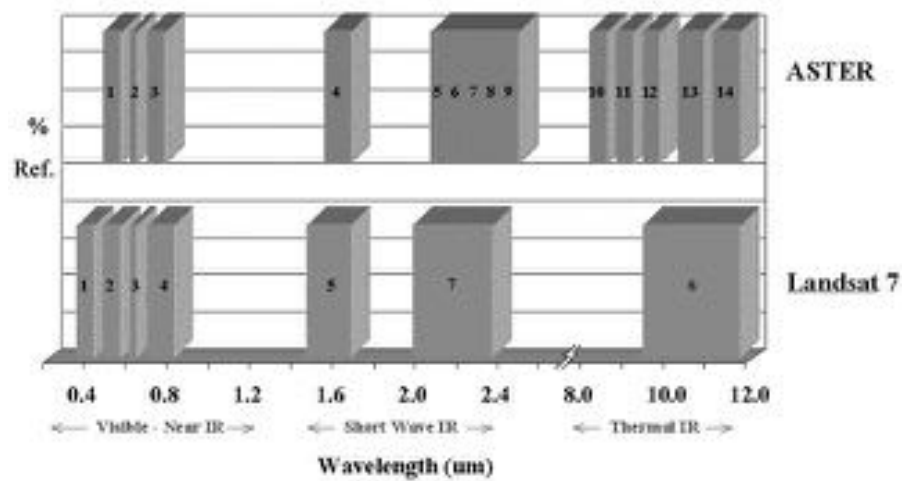


Figure 2.5: Spectral resolution for Landsat-7 ETM+ and TERRA ASTER (NASA)

2.4.3 Temporal resolution – The temporal resolution of a sensor refers to the frequency with which it is able to capture images over the same geographic area by each subsequent pass of the satellite (also known as its revisit period). This corresponds to the total time taken by a satellite to make a complete orbit around the Earth (in the case for a spaceborne sensor). The revisit time is usually on the order of several days (e.g., Landsat-7 and ASTER both have revisit periods of 16 days). The temporal resolution is determined from the orbital characteristics of the spacecraft and the swath width (width of the imaged area on the ground). Table 2.5 presents the temporal resolutions for several satellite sensors.

Instrument sensor	Temporal resolution / days
Landsat-7 / ASTER	16
IKONOS	3.5–5
WorldView-1	1.7
Table 2.5: Examples of sensors with different temporal resolutions	

The revisit time of a sensor is an important factor when performing change detection studies. This may involve examining before and after imagery taken of an archaeological site to identify looting activities or assessing damage to a region's infrastructure after a natural disaster, such as from an earthquake or tsunami. Recording imagery over several seasons may

show landscape changes over time. Crops, for example, have differential growth patterns depending on the time of the year. Varying sun angle during different seasons may also provide further information about a study area.

2.4.4 Radiometric resolution – Finally, the radiometric resolution refers to the quantization, or the number of gray levels used to display an image. This is often expressed as the number of digital levels used to make up the sensor output. For example, Landsat ETM+ data is quantized to 8 bits (256 levels of intensity). The digital numbers (DNs) of a Landsat image can therefore vary between 0 and 255, where a value of 0 represents black and that of 255 white. An increase in radiometric resolution is a double-edged sword: the image will benefit from higher contrast, however greater system resources will have to be allocated, as this will require larger amounts of data to be transmitted to a ground station. Examples of sensors with a variety of radiometric resolutions are shown in Table 2.6.

Instrument sensor	Radiometric resolution / bits
Landsat-7 ETM+	8
ASTER	VNIR / SWIR = 8 TIR = 12
SPOT-5	8
QuickBird / IKONOS	11
Table 2.6: Examples of sensors with different radiometric resolutions (8 bits = 256 levels; 12 bits = 4096 levels etc.)	

2.5 Electromagnetic energy: the communications link

Transfer of energy can take place through conduction, convection, or radiation. Remote sensing is primarily concerned with radiation because this is the method that electromagnetic energy uses to propagate through space. Electromagnetic (EM) radiation refers to all energy that travels at the speed of light (through a vacuum) in a harmonic wavelike motion. The EM wave consists of two oscillating waves - one electric and the other magnetic, both travelling through space perpendicular to each other (Figure 2.6). Electromagnetic radiation can be described from both a wave and a particle perspective. This is because the properties of light behave as both a wave and as a particle. In physics this is known as wave - particle duality. The definition of remote sensing requires that information be collected about a target from a

distance and without direct physical contact. Electromagnetic energy can therefore be said to act as the “communications link” providing a mechanism for the transference of the signal from target to sensor, even through a vacuum.

The wavelength (λ) describes the length of a wave (peak to peak or trough to trough), in metres (m), and the frequency (ν) describes the number of oscillations the wave makes per second in Hertz (Hz). One Hertz describes a frequency of one oscillation of one complete waveform every second (1 cycle per second). Frequency may also be expressed in units of Megahertz (MHz), and Gigahertz (GHz). Frequency is considered a more fundamental property as it remains constant as it travels through regions of different density. This is in contrast to the wavelength and velocity, which both change as a function of density. Units of wavelength used in optical and thermal radiation are usually described in microns ($1\ \mu\text{m} = 1\ \text{micrometre}$) or in units of wavenumber, which is the reciprocal of wavelength, usually expressed in cm^{-1} . Microwave energy (such as radar) is not normally referred to using units of wavelength but by military band designations, i.e., C-band or L-band (see Table 2.12 in Subsection 2.8.1).

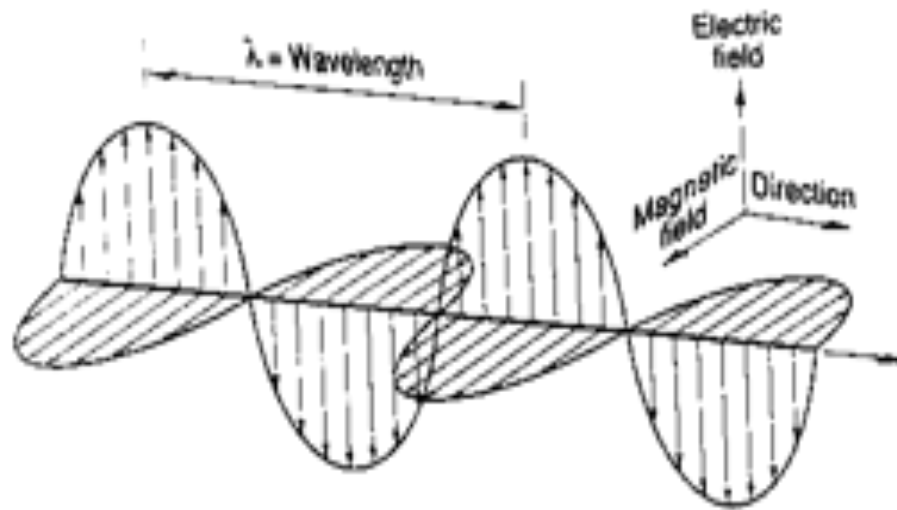


Figure 2.6: The electromagnetic waveform

Electromagnetic radiation is composed of many different forms of energy making up what is called the electromagnetic spectrum (EM). It is continuous in its distribution and is divided into arbitrary regions according to wavelength. At one end of the spectrum lie the high-energy cosmic, gamma, and X-rays of very small wavelength (10^{-12} μm) and at the opposite end are situated the low energy, very long wavelength, radio and television waves (10^9 μm). The distance between the two opposite ends of the EM spectrum represents a difference of greater than twenty orders of magnitude. In between these regions lie the more familiar ultraviolet, visible / near infrared, thermal infrared and microwave. Figure 2.7 illustrates the different regions of the electromagnetic spectrum.

There are a number of relationships that are important when considering radiative transfer theory. These include the Planck relationship, which shows that the energy of a photon is inversely proportional to its wavelength; the Stefan-Boltzmann law, which describes the amount of energy emitted by an object (radiance) as a function of its temperature; and Wien's Displacement law, used to determine the radiation's dominant wavelength. These relationships will not be discussed further mainly because the details can be found in more quantitative texts. For a more detailed examination the reader is directed to Lillesand et al. (2007) and Jensen (2004).

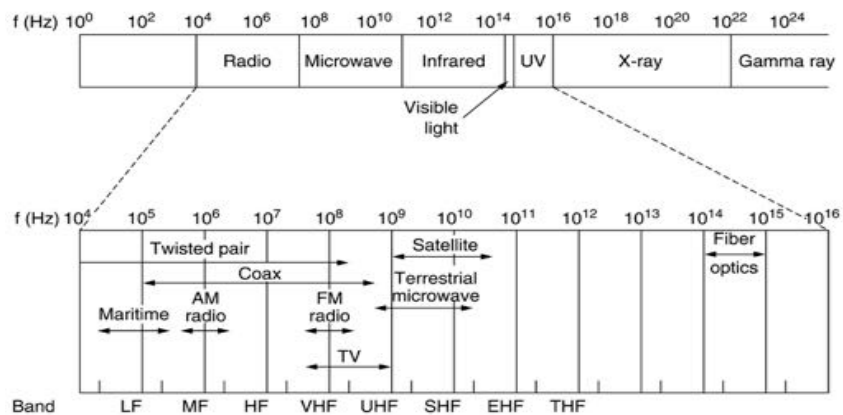


Figure 2.7: The electromagnetic spectrum

One of the principal advantages of acquiring imagery using a multispectral approach is that data can be recorded from many different wavelengths of the EM spectrum simultaneously, including regions that are invisible to the human eye. However, gases and suspended particles in the atmosphere (such as water vapour, carbon dioxide, and ozone), tend to be efficient absorbers of EM energy. They affect specific wavelengths and as a result are not normally used. Remote sensing instrumentation is therefore designed to examine specific locations of the spectrum where the signal is allowed to pass through with little attenuation. These specific regions that allow radiation to pass through relatively undisturbed are called "atmospheric windows". For example, optical sensors acquire image data at several wavelengths, i.e., the visible / near infrared (VNIR), the shortwave infrared (SWIR), and the thermal infrared (TIR) by taking advantage of these absorption-free locations. EM regions relevant to archaeological remote sensing include the VNIR, SWIR, TIR, and Radar (Table 2.7).

The remainder of this chapter (Sections 2.6–2.8) examines specific locations of the EM spectrum considered relevant to archaeological remote sensing. These are broken down into three regions: at the shorter wavelengths of the VNIR (0.4–1.3 μm), the signal received at the sensor is due to reflected sunlight; at the longer wavelengths of the TIR (3.0–50 μm), the signal is emitted due to heat energy from within the Earth; and in the even longer microwave regions (> 1 mm), the signal is generated using radar antennas mounted on a satellite / aircraft.

EMR	Wavelength (λ)	Notes
Ultraviolet	0.3–0.4 μm	Photographic ultraviolet
Visible (VIS)	0.4–0.7 μm	Visible light
Near infrared (NIR)	0.7–3.0 μm	Infrared sensitive film emulsion
Middle infrared (SWIR)	3.0–8.0 μm	Reflected solar radiation
Far infrared (thermal, TIR)	8.0–1000 μm	Terrestrial thermal emission
Microwave (radar, SAR)	1 mm–100 cm	Terrestrial emission and radar
Table 2.7: Wavelength regions of the electromagnetic spectrum		

2.6 Solid surface sensing: visible and near infrared (VNIR)

2.6.1 Introduction

Prior to the development of the satellite much of the early work in remote sensing was carried out using aerial photography. Cameras were attached to kites, hot-air balloons, and even pigeons to acquire a perspective of a site from above ground level. Wilson (1982) presents a comprehensive overview of photographic interpretation of archaeological sites using black and white aerial photography, which has had a long and rich history. The majority of these early studies used the visible and near infrared (VNIR) region of the EM spectrum almost exclusively, i.e., blue (0.4–0.5 μm), green (0.5–0.6 μm), red (0.6–0.7 μm), and the reflected near infrared (0.7–3 μm). These wavelength regions can provide useful information about the surface and vegetation cover of a site. However, as technology improved and sensors were mounted at increasingly higher elevations and eventually onboard satellites, the spatial resolutions became good enough to replace aerial photography in their entirety and provided the additional advantage of increased spectral resolutions.

In contrast to the visible region, which represents a scene in true colour, two regions of the NIR ($\sim$ 0.76–0.90 μm and 1.55–1.75 μm) can also be useful in archaeological investigations. These can be used to determine vegetation type, health (vigour), and biomass content, in addition to vegetation and soil moisture content. For highly vegetated regions, such as Egypt's Nile Delta, floodplain, and desert oases, the two most promising EM regions for detecting archaeological features are at the chlorophyll peak of 0.56 μm , and the red edge at 0.67–0.72 μm (Bassani et al., 2009). This is because healthy vegetation reflects strongly in the NIR when compared to the visible wavelengths, making this region particularly useful for detecting surface archaeological features, such as crop or soil marks. Crop marks appear due to the differential growth rates of vegetation cover and can be indicative of a surface or subsurface archaeological site. Remains above ground level may also be identified through their features in relief in addition to shadowing effects due to the Sun.

Surveying large areas of ground using the highest resolution sensors can be prohibitively expensive. Researchers have found that using a combination of lower resolution imagery, such as Landsat ETM+ and ASTER (Fujisada, 1995; Yamaguchi et al., 1998), in combination

with higher resolution products, such as Corona spy photography (Ur, 2003; USGS, 2011b), for confirmation of site locations, can offer a more cost effective solution.

Complimenting imagery from satellites such as Landsat, declassified spy satellite photography from the American Corona series (USGS, 2011b) and Russian KVR missions (Lavrov, 2000), offer a valuable optical resource for archaeologists. They have been found to be particularly useful for the reconnaissance of sites in the Middle East where data availability is usually a problem. Collected in the 1960's and 1970's using black and white film, and delivered as a single panchromatic channel, Corona can be used in the same way as an aerial photograph and holds enormous potential as a source of archival material for visualizing archaeological sites and landscapes that have changed over time. Imagery from the Corona KH-4B series camera (operated between 1967 – 1972) holds the most potential for work in Egypt due to its high spatial resolution (~ 1.8 metres), wide geographic coverage of Egypt, and low cost. When used in combination with other data products, it has been instrumental in identifying such features as hollow ways (see Chapters 3 and 6), canals, and archaeological sites in Iraq (Altaweel, 2005), and the mapping of ancient tell sites in Egypt (Parcak, 2007).

2.6.2 Sensor resolution

The majority of remote sensing satellites employ VNIR capabilities. The most popular are listed in Table 2.8. Higher resolution optical instruments were discussed separately in Subsection 2.4.1 (Table 2.4). Amongst the medium resolution sensors useful in archaeological reconnaissance are the Landsat series of satellites, such as the Multispectral Scanner (MSS), Thematic Mapper (TM), and Enhanced Thematic Mapper Plus (ETM+), in addition to the TERRA ASTER instrument, offering resolutions between 15 – 30 metres. Imagery from these assets are available online at little or no cost (see Section 3.9 and the Appendices at the end of this thesis for further information on data availability, download resources, and a review of software packages that can be used to view them).

Sensor / Platform	Years	Resolution (m)	Number of bands	VNIR wavelength (m)	Swath (km)
Landsat-8 LDCM OLI (S)	2013 –	15, 30	8 + Pan	0.43–2.29	185
Landsat-7 ETM+	1999 –	30, 60	7 + Pan	0.45–2.35	185
Landsat MSS (S)	1972–1992	80	4	0.5–1.1	100
Landsat TM (S)	1982 –	30	6	0.4–2.4	100
ASTER (S)	1999 –	15, 30	9	0.5–2.4	60
SPOT (S)	1986 –	2.5–20	4 + Pan	0.5–1.7	60
MODIS (S)	1999 –	250–1000	19	0.4–2.2	2330
AVIRIS (A)	1987 –	~ 20	224	0.4–2.5	~ 10
Table 2.8: Common visible near infrared remote sensing systems					

LDCM, Landsat Data Continuity Mission; OLI, Operational Land Imager; MSS, Multispectral Scanner; TM, Thematic Mapper; ASTER, Advanced Spaceborne Thermal Emission and Reflection Radiometer; SPOT, Satellite Pour l'Observation de la Terre; MODIS, Moderate Resolution Imaging Spectroradiometer; AVIRIS, Airborne Visible / Infrared Imaging Spectrometer; A/S: Airborne / Spaceborne Systems.

2.6.3 Spectral reflectance and signature characteristics

VNIR systems can be used to collect spectral information of the surface composition of geologic materials. Many earth surface materials, i.e., rocks, soils, and minerals, have diagnostic absorption features located in the visible and near infrared. Differences in spectral reflectivity between different types of materials have been recorded on the basis of the spectral distribution of energy as a function of wavelength. Due to many geologic materials having characteristic reflectance distributions in given wavebands, diagnostic signatures have been compiled into spectral libraries and are available for download. For example the ASTER spectral library is a compilation of over 2,400 spectra of natural and manmade materials and includes data from three sources: the John's Hopkins University (JHU) Spectral Library, the

Jet Propulsion Laboratory (JPL) Spectral Library, and the United States Geological Survey (USGS – Reston) Spectral Library (ASTER Spectral Library Version 2.0, <http://speclib.jpl.nasa.gov/>).

Ideally, the best way to identify a given material would be to acquire spectral data for each sample pixel across a large range of wavelengths of the EM spectrum – including the VNIR, SWIR, and TIR. However, data may not be available across the whole of the spectrum and in any event the data handling and image processing requirements may become prohibitive. It is therefore more usual to identify a material by concentrating on specific diagnostic regions. For example, minerals typically associated with hydrothermal alteration (OH group minerals) can be usually identified in the 2.0 to 2.4 μm region (Elachi and Van Zyl, 2006). The first case study in this dissertation used Landsat and ASTER data to identify mud brick contained in Egyptian 'tell sites' using their spectral characteristics in the VNIR and SWIR (Chapter 4).

2.6.4 Calibration and imagery analysis

Optical (VNIR) satellite images need to be radiometrically and atmospherically corrected before any meaningful quantitative information can be extracted from them. This is usually performed in the pre-processing phase of a project. For example, if many contiguous scenes acquired at different dates and / or from different sensors are to be combined into a single scene (a process called mosaicking), then they first need to be radiometrically corrected (a process also called normalization). This process converts the raw uncalibrated digital number (DN) values for each pixel to either physical units of spectral radiance or unitless values of reflectance. Spectral radiance is a radiometric quantity restricted by wavelength and the angle of observation (units of $\text{W m}^{-2} \text{sr}^{-1} \mu\text{m}^{-1}$), whereas reflectance is a ratio of the incident and reflected energies. Depending on the task it is usually better to convert uncalibrated DNs to reflectance values. This adjusts each scene according to its illumination and sensor gain settings and provides a common illumination so that there is less variation between images from different dates. Radiometric processing is often not performed in the literature resulting in inaccurate results, but it is considered an essential step if the imagery is to be calibrated correctly. Radiometric correction requires the gain settings for the sensor, which are unique to each instrument, in addition to the illumination metadata, which is unique to each scene. These values can usually be found in the header file for each image.

In addition to performing a radiometric correction, usually an atmospheric correction should also be applied. The EM signal that is recorded by VNIR sensors passes through and interacts with molecular gases in the atmosphere (H_2O , CO_2 , and O_3), and therefore the effects of atmospheric absorption and scattering need to be considered, especially if the received reflectance spectra are to be directly compared to laboratory-derived spectra. Standard atmospheric models exist, including the Moderate Resolution Atmospheric Transmission (MODTRAN) correction algorithm (Hooke et al., 1999), but they are not easy for the end user to use. This is because many of the scene parameters that are required for the calculation are not normally found in the image header files. Specialist software is also needed to perform an atmospheric correction, which are not usually included (even as an add-on), to the general tools provided in most remote sensing software suites.

If atmospheric model parameters are not available then radiative transfer codes cannot be used to perform a full atmospheric correction of the imagery. A very basic correction may be performed using radiometric normalization, where as previously mentioned, quantized pixel values (digital numbers) are converted to reflectance values. Another technique, dark-object subtraction, may also be used to correct VNIR imagery for the effects of atmospheric scattering. Dark-object subtraction should be performed on the raw digital data (DN values) and should only be used as a rough approximation to an atmospheric correction. Dark-object / pixel subtraction works by assuming there is a high probability that there are pixels within the image that are black (i.e., zero radiance, with DN values close to zero). Dark pixels may correspond to regions on the ground that are in shadow, such as in areas of high topographic relief, or from pixels lying underneath significant cloud cover. They may also occur in areas of deep water, especially when observed in the NIR. It is assumed these pixel DN values should be zero but due to atmospheric scattering the imaging system records non-zero values. In the dark-pixel subtraction technique, these low value DNs are subtracted from all pixel values for each spectral band to remove the scattering component. However this technique has its limitations because if this is done for each spectral band it may introduce errors in the spectral relationship between the bands. Subsequent researchers have improved upon this technique by modelling the appropriate atmospheric conditions (Chavez, 1989, 1988).

2.6.5 The Landsat Enhanced Thematic Mapper Plus (ETM+)

The Landsat Enhanced Thematic Mapper Plus (ETM+) instrument onboard Landsat-7 is typically used in medium resolution VNIR studies. It offers 8 multispectral channels and is a good general-purpose sensor with separate channels in the visible near infrared, shortwave infrared, and thermal infrared, with spatial resolutions of 30 m (VNIR and SWIR) and 60 m (TIR). It also offers a high-resolution panchromatic band able to resolve features down to 15 m (Table 2.9).

Band	Wavelength (µm)	Spectral location	Principal applications
1	0.45–0.515	Blue	Water body penetration – potential uses for underwater archaeology; soil / vegetation discrimination; forest type mapping; cultural feature identification
2	0.525–0.605	Green	Green reflectance peak for vegetation; vegetation discrimination and vigour assessment; cultural feature identification
3	0.63–0.690	Red	Chlorophyll absorption region; cultural feature identification
4	0.75–0.90	Near infrared	Vegetation type, vigour and biomass content; soil moisture discrimination
5	1.55–1.75	Mid infrared	Vegetation and soil moisture content; discrimination of mineral and rock types differentiation of snow and clouds
6	10.40–12.5	Thermal infrared	Thermal mapping applications; spectral mapping of archaeological materials; discrimination of mineral and rock types; cultural feature identification
7	2.09–2.35	Mid infrared	Vegetation and soil moisture content; discrimination of mineral and rock types cloud and snow discrimination
8	0.52–0.90	Panchromatic	Higher resolution work; can use this band to pan-sharpen the multispectral bands
Table 2.9: Landsat 7 Enhanced Thematic Mapper Plus spectral bands			

2.7 Solid surface sensing: thermal infrared (TIR)

As discussed previously, the Visible (VIS) wavelengths of the EM spectrum provide high-resolution coverage of a region in true colour, in contrast to the NIR, which is more sensitive to vegetation health and vigour. Furthermore, the NIR channels can be used to locate water sources and associated crop marks often indicative of the presence of archaeological sites. Complementing the VNIR is the thermal infrared (TIR), which although heavily used in other research areas, such as geological mapping, has been underutilized in the archaeological sciences. While the VNIR bands are sensitive to vegetation cover and moisture content, the thermal infrared (TIR), and to a lesser extent the SWIR, are more sensitive to soil, mineral, and rock geology (composition), and can help distinguish materials that may be spectrally unresolvable in the VNIR (provided that the diagnostic absorption bands are present at these wavelengths). Consequently, the use of the TIR wavelengths have the potential for detecting subtle archaeological features both on the ground surface and in the shallow subsurface due to the object's thermal properties.

2.7.1 Theory and concepts

At the longer wavelengths of the thermal infrared ($\sim 3\text{--}50\text{ }\mu\text{m}$), the energy collected by the sensor does not originate from reflected energy from the Sun, but predominately consists of emitted heat radiation from the Earth. Of this region two rather narrow thermal infrared wavebands from $3\text{--}5\text{ }\mu\text{m}$ and $8\text{--}14\text{ }\mu\text{m}$ are used in remote sensing. The air in these “atmospheric windows” is relatively transparent and the radiation is little affected by absorption of atmospheric gases, such as water vapour and carbon dioxide.

TIR sensors can measure several useful attributes about a remotely sensed scene, including its temperature, emissivity, and thermal inertia. Determining the radiating temperature (measured in Kelvin) can be useful in understanding differential heating patterns in the surface or near surface and may help provide clues to the presence of archaeological features within a site. This is because archaeological materials at or below ground level can affect the temperature of their surroundings (i.e., different materials cool at different rates). The second quantity, emissivity, is a unitless value described as the ratio of radiant energy of a source to that of a black body at the same temperature. It provides information about the spectral component (composition) of the signal. TIR emissivity data has often been used in geological remote

sensing for the identification and mapping of various rock types and rock forming minerals and is particularly sensitive to silicate composition (Corrie et al., 2010). This can be useful when determining the composition of different materials. A third quantity that can be derived from TIR data is the thermal inertia, which measures the thermal response (or resistance) of a material to temperature changes (see Subsection 2.7.3 for a discussion of each of these quantities and methods of calculation).

The utilization of TIR data in archaeological investigations has produced positive results, including the discovery of an Anasazi road network using the 5 metre Thermal Infrared Multispectral Sensor (TIMS) in Chaco Canyon, New Mexico (Sever and Wagner, 1991; Sever and Wiseman, 1985); the detection of road networks in the rainforests of Costa Rica using a range of thermal and other techniques (Sheets and Sever, 1991); and the detection of subsurface features using emissivity data from the Airborne Thematic Mapper (ATM) and the Multispectral Infrared and Visible Imaging Spectrometer (MIVIS) in the Arpi archaeological area of southern Italy (Bassani et al., 2009). In addition to this, TIR may be useful in the mapping of desert lineaments, such as trading and caravan routes (Chapter 6).

2.7.2 TIR sensors; spatial resolution

There are a limited number of spaceborne thermal infrared sensors offering high enough spatial and spectral resolution to be of interest to archaeological remote sensing. The flux from thermal infrared energy is much less than that from reflected energy of VNIR systems and therefore the resolution of TIR systems tend to produce images of smaller spatial and spectral resolutions. Archaeological features tend to be small (on the order of a few metres for walls for example, and up to several tens of metres for buildings) and therefore coarser data may be of limited use. TIR data may be acquired through airborne higher resolution data, however, airborne systems although offering higher spatial resolutions are limited in their swath width and geographic coverage. Table 2.10 lists the currently operational spaceborne (S) and airborne (A) TIR sensors that may be of potential use in archaeological remote sensing.

Sensor / Platform	Years	Resolution (m)	Number of bands	Wavelength (m)	Swath (km)
Landsat-8 LDCM / TIRS (S)	2013–	100	2	10.6–12.51	185
Landsat-7 ETM+ (S)	1999–	60	1	10.4–12.5	100
Landsat TM (S)	1982–	120	1	10.4–12.5	100
ASTER (S)	1999–	90	5	8.1–11.6	60
MODIS (S)	1999–	1000	16	3.7–14.4	2330
TIMS (A)	1982–1999	10	6	8.2–12.6	~ 10
MASTER (A)	1998–	10	25	3.1–12.9	~ 10
SEBASS (A)	1999–	2	256	3.0–13.5	0.25
Table 2.10: Common thermal infrared remote sensing systems					

TIRS, Thermal Infrared Scanner; TM, Thematic Mapper; ASTER, Advanced Spaceborne Thermal Emission and Reflection Radiometer; MODIS, Moderate Resolution Imaging Spectroradiometer; TIMS, Thermal Infrared Multispectral Scanner; MASTER, MODIS / ASTER airborne simulator; SEBASS, Spatially Enhanced Broadband Array Spectrograph System. A/S: Airborne/Spaceborne Systems.

Spaceborne TIR systems include band 6 of the Landsat Enhanced Thematic Mapper Plus (ETM+) and the TIR array of the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), offering spatial resolutions of 60 m and 90 m respectively. One advantage of the ASTER dataset is that it includes five TIR spectral bands compared to Landsat's one. Consequently, ASTER's higher spectral resolution may help to improve spectral signature collection when used for material identification (see Section 4.6).

2.7.3 Calibration and imagery analysis

TIR wavelengths are considerably more affected by the atmospheric effects of water vapour and other atmospheric species compared to the VNIR. Processing of these images is therefore more time consuming and computationally complex due to having to perform an atmospheric correction during the post-processing of the imagery. Similar algorithms that can be used to

atmospherically correct VNIR images can also be used to correct TIR data, including MODTRAN etc. (see Subsection 2.6.4).

As mentioned earlier, several important quantities can be derived from TIR images. The extraction of the spectral component (emissivity) of an image is usually the most important. However the surface temperature produces a strong masking effect, which needs to be removed before calculating emissivity. There are several methods to calculate emissivity including using a temperature and emissivity separation algorithm (Gillespie et al., 1998; Hook et al., 1999), applying an alpha-residual technique (Salisbury and D'Aria, 1992; Hook et al., 1999) or performing a decorrelation stretch (Gillespie et al., 1984, 1986). A decorrelation stretch is an algorithm readily available in most image processing software packages and works in a similar fashion to Principal Components Analysis (PCA). It works by removing the high correlation commonly found in multispectral datasets by decreasing the temperature component and emphasizing the variations in emissivity. Both a decorrelation stretch and the use of PCA have been used in this work to atmospherically correct TIR images and to reduce both the variance and dimensionality of VNIR datasets.

Mapping the thermal inertia of a region may also be of potential benefit. Essentially thermal inertia is a measure of a material's ability to resist changes in temperature and is related to the material's volumetric (rather than surficial properties), including its density, specific heat capacity, and thermal conductivity (Schieldge et al., 1980). In essence, the denser the material, the higher the thermal inertia. Studies undertaken during this research has shown that creating maps of thermal inertia has been useful in the identification of several roads and trading routes (see Section 6.3; Fig. 6.9). VNIR imagery of the same area failed to show any trace of the lineament – effectively remaining invisible to detection. The calculation of thermal inertia requires two thermal infrared images taken at different times of the day. Ideally the images should be acquired from the same sensor during periods of maximum heating and cooling – i.e., early afternoon and pre-dawn. The images are then differenced and then corrected for physical albedo differences (Farr, 2011).

The output of thermal imagery to a computer display depends on the number of channels available. Many remote sensing systems include at least one thermal band, however if less than 3 bands are available, they are typically loaded up individually on a display and

displayed in greyscale. Areas of brightness represent warm regions, whereas dark regions represent cooler areas. If there are 3 or more TIR channels available then combinations of 3 bands become possible, which can be displayed in false colour using the red, green, and blue colour guns. For example because ASTER provides five channels in the TIR, it becomes possible to create 60 different colour combinations ($5 * 4 * 3$) by selecting the greyscale images to be sent to 1 of 3 colour guns. The choice of bands to use when displaying a false colour composite image should be based on the statistical characteristics of the individual channels and the degree of inter band correlation.

2.7.4 The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER)

Launched onboard the TERRA satellite in 1999, ASTER is a cooperative effort between NASA, Japan's Earth Remote Sensing Data Analysis Centre (ERSDAC), and MITI –Japan's Ministry of International Trade and Industry (Fujisada, 1995; Yamaguchi et al., 1998). ASTER is composed of three optical imaging subsystems acquiring a total of fourteen multispectral bands, three in the VNIR, six in the SWIR, and five in the TIR, achieving spatial resolutions of 15 metres, 30 metres, and 90 metres respectively (Fujisada, 1995). It should be noted that there is no blue band included in the ASTER dataset and therefore viewing imagery in true colour is not possible.

ASTER is unique in having five thermal infrared channels covering 8–12 μm at a spatial resolution of 90 metres (in contrast, Landsat ETM+ has only one thermal band at 60 metres). At a resolution of 90 metres, ASTER TIR is not ideal for locating buried structures, but its increased spectral capabilities should prove useful in locating archaeological features on a larger scale. The thermal infrared channels of the ASTER instrument are shown in Table 2.11, including the specifications for the single Landsat ETM+ TIR subsystem for comparison purposes.

Sub-system	Band number	Spectral range (μm)	Centre λ (μm)	Spatial resolution (m)
ASTER TIR	10	8.125–8.475	8.3	90
	11	8.475–8.825	8.65	
	12	8.925–9.275	9.1	
	13	10.25–10.95	10.6	
	14	10.95–11.65	11.3	
Landsat-7 ETM+	6	10.40–12.50	11.45	60
Table 2.11: ASTER and Landsat ETM+ instrument characteristics				

2.8 Solid surface sensing: microwave – Synthetic Aperture Radar (SAR)

This section provides a general introduction to the principles of radar imaging, relevant to Case study 2 (Chapter 4), which relies heavily on an active radar imaging approach. Section 5.2 covers advanced topics on using radar for subsurface imaging in arid regions.

Whereas optical imagery at the shorter wavelengths (VNIR, SWIR, and TIR) provides spectral information on material composition, radar is more sensitive to surface roughness (when viewed at scales of the observing wavelength) and the dielectric constant (a function of rock density and moisture content). Although the use of optical imagery has been at the forefront of most archaeological investigations, radar remote sensing in recent years has proved to be an equally important asset for locating sites, especially when acquired in combination. Optical and radar imagery can be regarded as complimentary datasets providing different information about the same area of coverage.

Radar remote sensing has been successfully used in many parts of the world for site detection purposes, including assisting in the discovery of the lost city of Ubar, Saudia Arabia (Blom et al., 1997; Fiennes, 1992); mapping previously unknown structures at the Angkor Wat temple complex, Cambodia (Moore, Freeman, and Hensley, 2007); mapping distributions of ruins along the legendary Silk Road, northwestern China (Holcomb, 1992); discovering new settlement sites around the Maya site of El Zotz (Garrison et al., 2011); and the identification of human occupation sites along the shorelines of palaeolakes and rivers of Egypt and Sudan (McHugh et al., 1989, 1988a, and 1988b). Many of these discoveries have been possible due to airborne radar systems. However, the next generation spaceborne radar systems, with

equivalent or better spatial resolution, are beginning to come online and enabling high-resolution mapping from satellite orbit (for example the Japanese PALSAR-1 and the recent launch of PALSAR-2).

2.8.1 Primer on radar imaging; contrast to optical imagery

Microwave sensors are classed as either active (radar) or passive (microwave radiometer) in their design. This work uses an active approach using RADAR (Radio Detection and Ranging). Passive microwave systems, although useful in other disciplines will not be mentioned further.

Although it is beyond the scope of this work to discuss the physics of radar imaging in any great depth, it is useful to examine the basic principles, including the specialized terminology that is often encountered. The basics of radar imaging are very straightforward: a transmitting antenna mounted on the side of a moving platform – either aircraft or satellite, emits a short duration pulse of microwave energy. The radar uses a side-looking geometry and as a result the EM pulse is transmitted perpendicular to the motion of the satellite (this is in contrast to an optical instrument that uses a nadir-pointing (straight down) sensor). The radar pulse illuminates the ground at an oblique angle enhancing variations in both surface roughness and texture (Figure 2.8).

As mentioned earlier, unlike optical sensors, which passively receive energy reflected from or emitted by an object, active microwave sensors provide their own energy source. The signal travels at the speed of light and illuminates an area of interest on the ground. A portion of the energy is reflected back (backscattered) to the instrument and is collected at a receiving antenna, where the signal's intensity (amplitude), time delay, and phase shift (polarization) are recorded. A surface that scatters a large part of the signal back to the antenna has a high radar return, and the radar image appears brighter in those regions, whereas a surface that reflects the signal away from the antenna has a low radar return, and the image appears darker.

The variation in tone of a radar image is caused by changes in the signal strength (amplitude) of the returned signal, which is directly related to the geometric and electromagnetic interactions between the radar wave and the surface (Robinson, 1998). These interactions are a function of the target's slope, surface roughness, and dielectric properties (of which the last

factor is dominated by moisture content). Other components that influence radar backscatter include the radar look-angle (discussed in the next paragraph), the signal wavelength, and the polarization, i.e., if the signal is like or cross-polarized (Robinson, 1998).

The special geometry of a radar instrument introduces a number of descriptive terms, including the depression, look, and incidence angles (Figure 2.8). The depression angle is the angle between the radar beam and the horizontal, whereas the look angle is the complement of the depression angle. Finally, the incidence angle at the target is the angle between the radar beam and the surface normal. For low altitudes from an airborne instrument, the incidence angle is approximately equal to the look angle (for horizontal terrain). However, from satellite orbit the angles are not equal as the incidence angle is affected by planetary curvature. The angle at the target may also be influenced by the terrain (look angle in addition to local

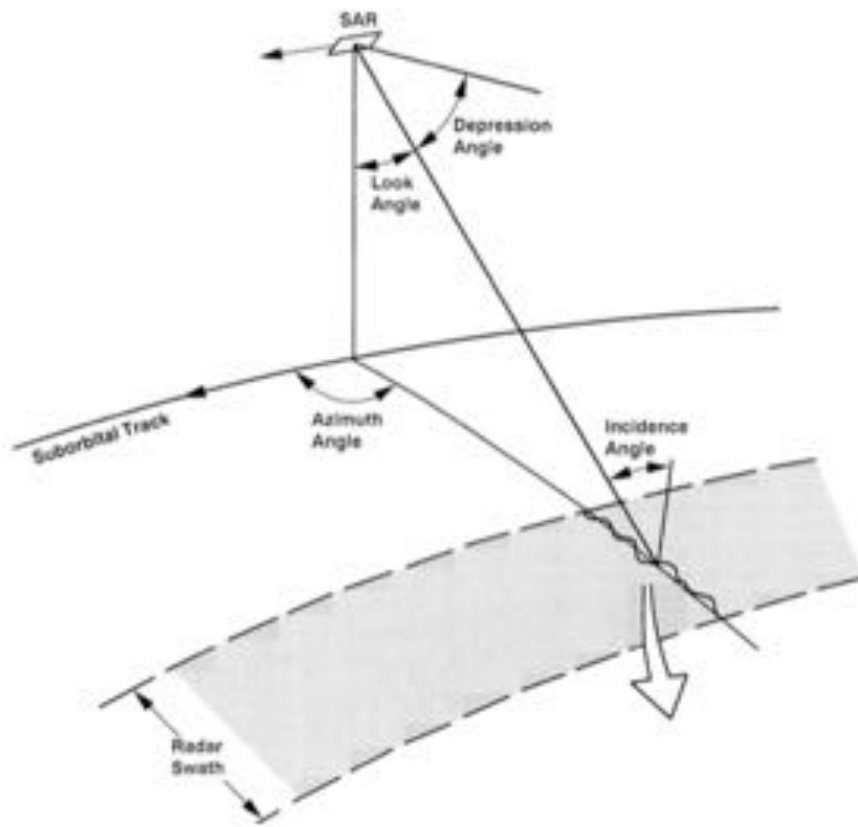


Figure 2.8: Viewing geometry of a radar system (after Farr, 1993)

variations) to produce a local incidence angle (Farr, 1993). Additionally, two orientations in relation to the satellite sensor are often discussed in the literature, including the ground-range (often called the across-track direction) and the azimuth (along-track direction).

Imaging from the side eliminates left-right ambiguities during image capture, however it does introduce significant distortion that has to be corrected for, i.e., slant range geometry needs to be corrected to ground range due to the compression of the image in the near-range dimension (Figure 2.9). This is due to the distance being measured from the antenna to the target, and is not a true representation of the distance along the ground from the platform ground track to the target. This is a natural result of radar range measurements. Slant range to ground range processing can be achieved using a simple transformation available in most radar image processing software. This is implemented by multiplying the slant range by the inverse of the cosine of the depression angle (simple trigonometry).

Elementary math can be used to solve the direct distance between the transmitter and the object in the cross-track direction (slant range, $\overline{SR}$), as the round trip travel time (range) of the pulse is known, in addition to its speed (the speed of light). The distance can therefore be easily calculated using the equation:

$$\overline{SR} = \frac{ct}{2} \quad (\text{Equation 2.1})$$

The factor of 2 enters into the equation due to the two-way travel time of the signal as it passes from the sensor to the ground and back again.

where $\overline{SR}$ = direct distance between transmitter and object (m)
c = speed of light ($3 \times 10^8 \text{ ms}^{-1}$)
t = time between pulse transmission and reception (s)

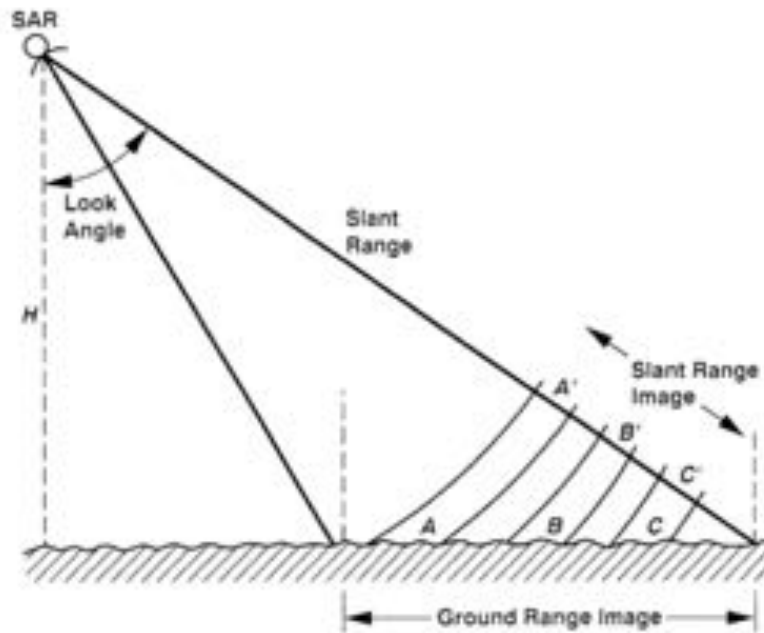


Figure 2.9: Slant and ground range acquisition (after Farr, 1993)

Radar sensors operate at the longer microwave regions of the EM spectrum (measured in cm), and are identified by letter code. Radar band identifiers were developed during the Second World War and the convention has remained to this day. Table 2.12 lists the wavelength regions, which range from the long wavelength P-band to the shorter wavelength Ka band. Radar sensors can therefore acquire imagery using a number of different wavelengths (multi-wavelength capability). The choice of waveband will depend on the application and the environmental conditions of the study area. For example, L-band imagery may be selected if high spatial resolution is not a priority, and depth of penetration is considered of high importance (and the environmental conditions allow for it).

Band	Wavelength (cm)
P	30–107
L	15–30
S	7.50–15
C	3.75–7.50
X	2.40–3.75
Ku	1.67–2.4
K	1.18–1.67
Ka	0.75–1.18
Table 2.12: Radar band designations	

In addition to choosing a suitable wavelength, SAR imagery may also be acquired using a number of discrete polarizations (multi-polarization capability). Different polarizations may be used to emphasize archaeological features of interest, which may be more clearly visible using one polarization when compared to another. Because imaging radars produce their own coherent source of illumination (similar in principle to a laser), the phase of the signal is recorded and it becomes possible to select different polarization settings for the transmitted beam. Radar systems can be configured to transmit or receive either vertically (V) or horizontally (H). Four configurations therefore become possible: HH (horizontal transmit and receive), VH (vertical transmit, horizontal receive), VV, and HH. Most radar systems transmit and receive using linear (i.e., HH or HV) or dual (i.e., HH / HV) polarizations. Some SAR systems may acquire imagery using all four polarizations (i.e., HH / HV / VV / VH), and these systems are said to have quad polarization capability (quad-polar or quad-pol). Fully quad-polar sensors include SIR-C (USA) and PALSAR-1 and 2 (JAPAN).

Radar systems offer a number of significant advantages when compared to passive optical instruments. Due to providing their own energy source (active system), they are not dependent on energy provided by the Sun, and can therefore operate during both night and day. Radar can also operate in any weather conditions, and are able to penetrate through most types of cloud, dust, and haze. It is therefore the sensor of choice for regions often hidden by cloud cover due to poor weather conditions or from atmospheric out-gassing due to volcanic eruptions. An additional benefit of radar, when operating at longer wavelengths, is its ability in arid environments to penetrate up to 2 metres of sand given optimal conditions, i.e.,

extremely dry, fine-grained, clay-free sand (Robinson, 1998). This can be very useful for locating desert palaeochannels, also known as “radar rivers” - see Case study 2 (Chapters 5), and for detecting arid subsurface archaeological structures. A disadvantage of radar, which was discussed earlier, is that the side-looking geometry introduces a number of significant distortions into the imagery, including both layover and foreshortening of the image (see Subsection 2.8.3), in addition to compression of the image in the near range. Complex image processing needs to be applied to correct for these distortions, including the removal of noise (speckle). Furthermore, the interpretation of the imagery may need to be carried out by trained analysts, as the mechanics of radar imaging are quite different when compared to acquiring optical data.

2.8.2 Radar sensors; spatial resolution

Due to the complex imaging geometry acquired by a radar system, the spatial resolution of a sensor differs in the range (cross track) and azimuth (along track) directions. The range and azimuth resolutions are both dependent on the pulse duration (time measurement for each pulse) and the depression angle. However the range resolution is acquired from the pulse transmission, whereas the azimuth resolution is obtained from the sum of pulses using a synthetic aperture (SAR) technique. Most imaging radars today use Synthetic Aperture Radar (SAR) to calculate resolution in the azimuth direction since it overcomes the resolution limitations of earlier Real Aperture Radar (RAR), also known as “brute force” systems. This is achieved by using the motion of the satellite and principles of Doppler shift to synthesize a much larger antenna length and thus a significantly higher resolution. SAR allows for the acquisition of high-resolution radar imagery independent of platform altitude (Farr, 2011). The strength (amplitude) of the signal resolved in both the range and azimuth dimensions are then used to synthesize the radar image.

The most commonly used radar sensors include the U.S. Shuttle Imaging Radar series of satellites – flown over three separate missions (SIR-A, B, and C); the European Space Agency’s ERS and ENVISAT; Canada’s RADARSAT, and the Japanese sensors JERS and PALSAR. SIR-C radar had good coverage, albeit discontinuous, of most of Egypt, parts of Libya and Sudan, imaging approximately 10% of the Earth’s surface. The specifications of the most common radar sensors are summarized in Table 2.13.

Sensor / Platform	Years	Resolution (m)	Band / Polarization	Swath (km)
Seasat	1978	25	L-HH	100
SIR-A	1981	25	L-HH	50
SIR-B	1984	25	L-HH	~50
SIR-C / X-SAR	1994	25	C-quad, L-quad, X-VV	~50
Envisat	1998–	25	C-VV, C-HH	100
JERS	1992–1998	20	L-HH	75
Radarsat	1995–	10–100	C-HH	45–500
PALSAR	2006–2011	10–100	L-quad	40–350
SRTM	2000	30	C-HH, C-VV	N/A
TerraSAR-X	2007–	1–16	X-HH, HV, VV, VH	5–100
PALSAR-2	Date of launch expected 2014	1–100	L-quad	25–350
Table 2.13: Common radar remote sensing systems				

2.8.3 Calibration and imagery analysis; distortion and interpretation

The calibration and interpretation of radar data is very different to that of optical. There are therefore a number of pre-processing steps that have to be applied in order to process a raw SAR dataset into an interpretable image before analysis can be carried out. This process is computationally expensive and includes compressing the image in both the range and azimuth directions. These procedures are normally handled by the image processing software during the data import stage, but nonetheless it is important for the user to be aware of the process and not to treat it like a black box. McCandless and Jackson (2004) offer a concise treatment on the processing of SAR imagery. A detailed description of these steps is beyond the scope of this work as the procedures have been well documented in many remote sensing textbooks, including Elachi and Van Zyl (2006) and Lillesand, Kiefer, and Chipman (2007).

As mentioned earlier, significant geometric distortion of the imagery occurs due to the side looking direction of the radar antenna as it records data. This results in the distortion of both the position and the proportions of objects. The greatest distortion occurs when imaging

regions of high topographic relief. If not too extreme, these can be corrected using a range of image processing techniques.

Three of the most significant distortions include layover, foreshortening, and shadowing (Figure 2.10). Foreshortening occurs when imaging very steep sloped terrain resulting in a mountain's near-range slope being compressed, extending the dimension of the back slope (Figure 2.10a). The case of layover is an extreme example of foreshortening and occurs with small look angles combined with steep slopes. In this case the radar beam reaches the base of the mountain first before it reaches the top (Figure 2.10b). Slope AB will appear compressed and its length will be represented incorrectly. The amount of distortion depends on the incidence angle of the radar beam with the mountain slope. Finally, radar shadowing occurs when information in the shadow area is lost due to larger look angles (Figure 2.10c). Further information on topographic distortions can be found in Farr (2011, 1993) and Elachi and Van Zyl (2006).

Another consideration when processing radar images is that they are inherently noisy. This is the result of constructive and destructive interference patterns made by the SAR pulse by different scatterers within a single resolution cell. This manifests itself as speckle - a grainy "salt and pepper" like appearance found throughout the image. Speckle can be removed using one of several techniques, including a speckle reduction filter and multi-look processing. Multi-look processing is when several "looks" are taken of a target in a single radar sweep, which are then averaged together.

2.8.4 The Phased Array L-band Synthetic Aperture Radar (PALSAR)

The Phased Array L-band Synthetic Aperture Radar (PALSAR) is one of the "next generation" radar sensors. Launched onboard the Advanced Land Observing Satellite (ALOS) in January 2006, PALSAR was jointly developed by The Ministry of Economic Trade and Industry (METI) of Japan and The Japan Aerospace and Exploration Agency (JAXA). PALSAR replaced the SAR sensor on board the Japanese Earth Resource Satellite, JERS-1, and provided higher spatial resolution, variable off-nadir angles, full polarimetry (quad polar), in addition to a ScanSAR mode.

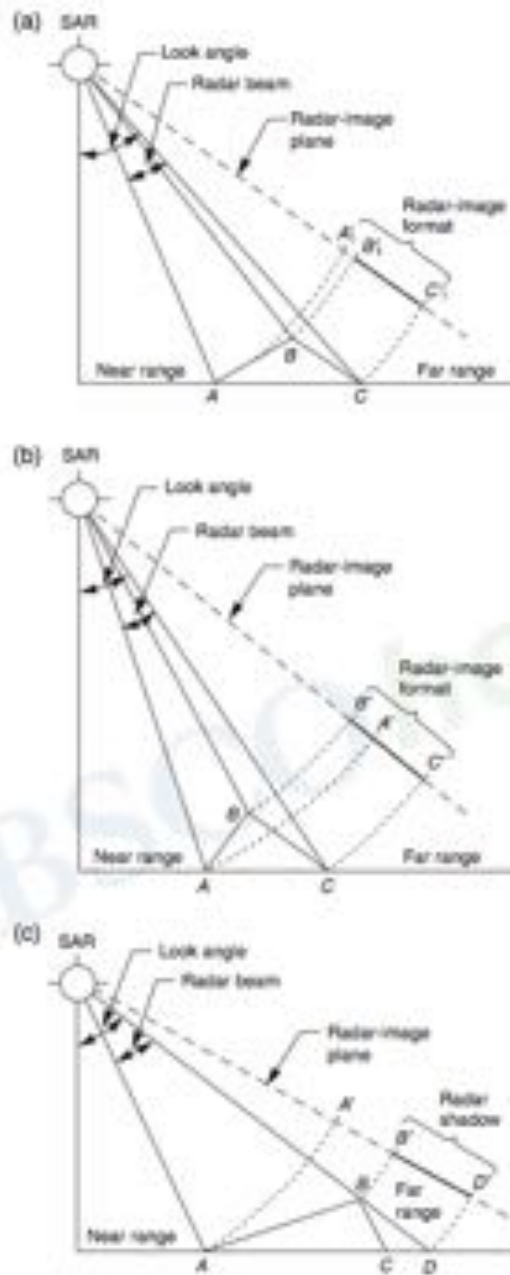


Figure 2.10: Geometry of side-looking radar illustrating image distortion due to signal obliqueness. (a) Foreshortening – Slope AB appears foreshortened compared to BC due radar using signal time delay; (b) Layover – Extreme foreshortening resulting in data loss of AB where top of mountain (B) is in front of its base (A); (c) Shadowing – Typical of radar systems with high look angles often resulting in shadowing and loss of data in the far slope BC (after Farr, 2011).

The ScanSAR mode of PALSAR produces a swath width of up to 350 km and can be used in an initial survey where high resolution may not be necessary. Once suitable study areas have been identified, higher resolution radar imagery can then be acquired. PALSAR offers many firsts, including the world's only spaceborne SAR system currently operating at L-band frequencies (1.27 GHz, 23.6 cm wavelength) with full polarimetry observation capability, and a world-class ground resolution of 10 metres. PALSAR additionally features steerable off nadir angles from 9.7 to 50.8 degrees and a temporal resolution of 5 days. The four principal observation modes and resolution capabilities are shown in Table 2.14.

PALSAR-2 was launched in May 2014 and provides a number of key improvements over PALSAR-1 including increased spatial resolution (1–3 m) and improved observation frequency (1–2 days). PALSAR-2 with its long wavelength L-band SAR, quad polar capability and increased spatial resolution offers great potential for locating buried archaeological sites in the desert regions of the world.

Mode	Ground resolution (m)	Polarization	Swath (km)
Fine (single polar)	10	HH or HV	40–70
Fine (dual polar)	20	HH+HV or VV+VH	40–70
Full polarimetry (quad polar)	30	HH+HV+VH+VV	20–65
ScanSAR	100	HH or VV	250–350
Table 2.14: PALSAR observation modes			

2.9 The Digital Elevation Model (DEM)

An additional resource often employed in remote sensing analysis and not yet discussed is the digital elevation model (DEM). A DEM is a three-dimensional representation of a terrain's surface and is stored either as a raster or vector-based model. The raster model uses a grid of cells (or pixels) to represent a three-dimensional surface, in contrast to the vector model, which uses a data structure called a triangulated irregular network (TIN). In the raster model, each pixel stores an elevation value (normally in metres with reference to sea level). Two of the most commonly used DEM raster datasets include ASTER GDEM and the Shuttle Radar

Topography Mission (SRTM). SRTM is discussed at length in later chapters (see Subsections 5.3.1 and 5.3.2).

Figure 2.11 shows SRTM elevation data for the west bank of the Nile. The imagery is from the SRTM1 dataset, with a horizontal spatial resolution of 1 arc second (30 metres) and less than or equal to 16 metres vertical resolution. The image extends approximately 70 kilometres from Cairo in the north to Al Maqatfiyyah in the south. This region covers the “pyramid zone”, where a large number of pyramid structures were built west of the Nile during the Old and Middle Kingdoms. It is believed that some collapsed or unfinished pyramids may still be found in this area. For example, the pyramids of several 7th–10th Dynasty rulers are still unaccounted for (see Section 3.2 and a discussion about the pyramids discovered by Robert Schiestl in this region in 2006). The two insets in the figure show that even at this relatively coarse resolution several pyramids can be observed. These structures are visible not due to their spectral characteristics but due to differences in elevation. These include the Giza Pyramids - the Great Pyramid of Khufu and Khafre's Pyramid at Giza (A), and further south - Sneferu's North (Red) and Bent pyramids at Dahshur (B). These are some of the largest pyramids ever constructed in this region. To provide a sense of scale, the base length and elevation of the Great Pyramid measure approximately 230 metres and 145 metres respectively.

This chapter has provided an overview of some of the principles and techniques employed in remote sensing and in archaeological remote sensing in particular. Its main focus has been to provide the reader with enough terminology and concepts to help towards gaining an understanding of the later chapters. The language used in remote sensing is unfortunately quite terse with many abbreviations. Therefore, to help the reader, I have included a list of acronyms in the ‘Appendices and references’ section at the back of this dissertation. In the next chapter, the discipline of space archaeology is introduced in addition to the methodologies and strategies that can be applied when searching for sites in arid regions.

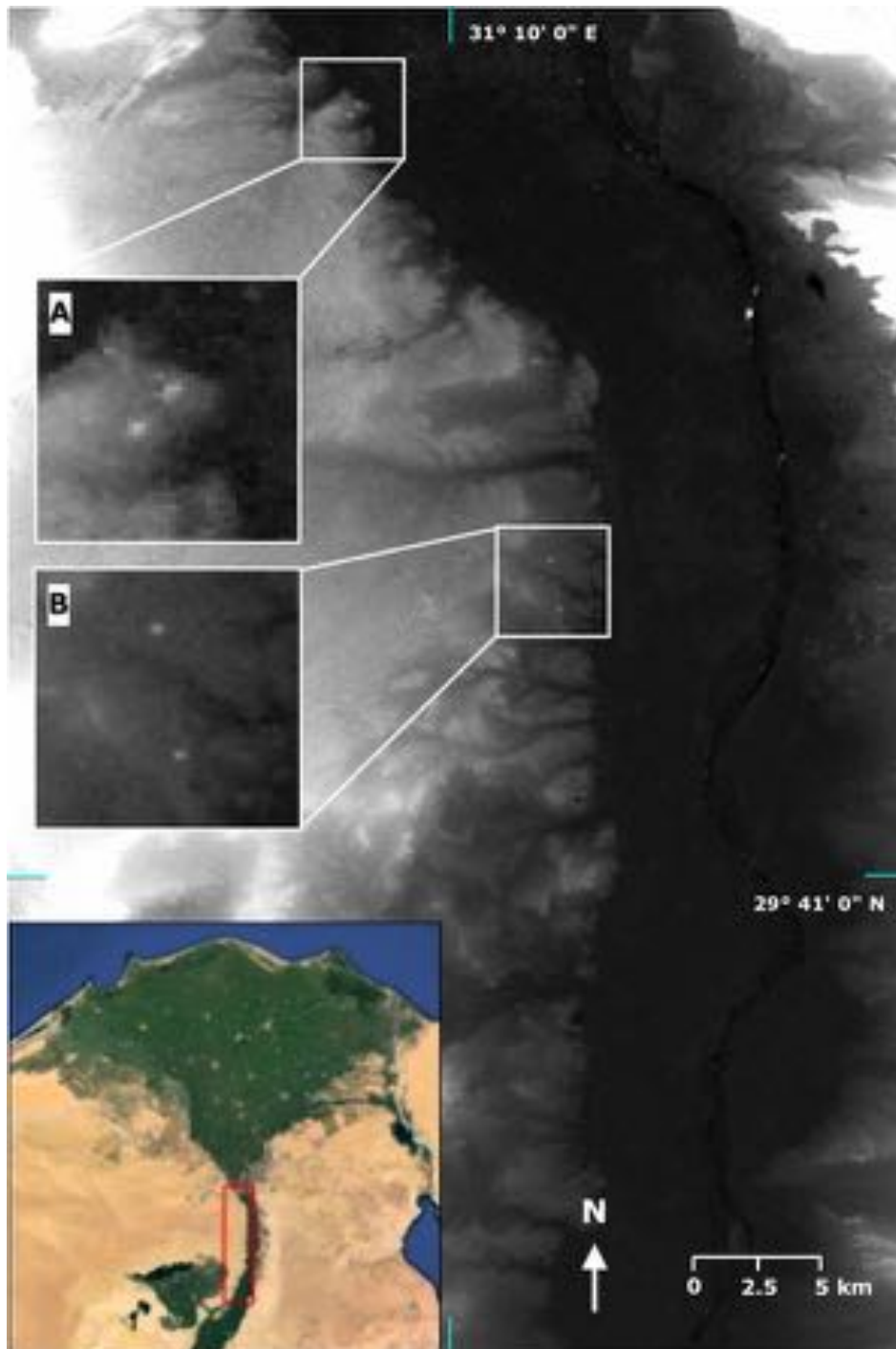


Fig. 2.11: SRTM1 DEM (30 metres) of the Nile West Bank (Pyramid Zone)

Chapter 3

Methodology and approaches to locating archaeological sites

3.1 Introduction

In order to detect new sites there needs to be an understanding of how a site is defined, what types of sites may exist, where to look for them, and whether satellite imaging can be used to detect them. When answering these kinds of questions, it is crucial to develop and adopt a robust methodology that can be implemented to maximize the chances of success. The objectives of this chapter are therefore to highlight what such a methodology may look like based on the current tools that remote sensing possesses. First however, before site detection methodologies are discussed, it seems appropriate to provide a short history of “space archaeology” so as to put the technique into an appropriate context.

3.2 Space archaeology: detecting cultural remains from satellite orbit

Space archaeology is considered to be an emerging field that uses satellite imagery to locate archaeological cultural remains either on the surface or in the shallow subsurface of the earth. The advantages of using satellites to examine large swaths of earth not only benefit our ability to locate new sites, but given their synoptic view of an area also add to our knowledge and understanding of the local, regional, and larger scale settlement patterns, densities, communication, and transportation links of a region.

Researchers at the Tokai University Research and Information Centre (TRIC), in collaboration with the Institute of Egyptology at Waseda University in Japan, are considered to be the first research group in the world to have detected an archaeological site primarily through the use of satellite imagery analysis. TRIC has been using remote sensing techniques for archaeological exploration since 1994 and detected their first site in Egypt in 1996 using a combination of optical and microwave imagery. The discovery was made in the “pyramid zone” on the Nile’s west bank, south of Saqqara, in a region where it was believed several pyramids still lay undiscovered. For example, the locations of the pyramids of Neferkare (7th–8th Dynasty) and Ity (9th–10th Dynasty) still remain undiscovered. The site was named “Dahshur North” and was determined to be a mud brick tomb from the New Kingdom (late

18th to early 19th Dynasty, ca. 1330–1250 BCE). Positioned on a central hilltop, the super structure of the tomb had long since disappeared, leaving scattered remains of limestone fragments on the surface. Excavations of the site lead to the discovery of a ramp, courtyards, and a chapel with side rooms. Subsequent excavations have uncovered a necropolis with further tomb chapels, shaft tombs, and simple burial pits. These are the first New Kingdom monuments to be found in this region, where most of the surrounding archaeology is from the Old and Middle Kingdoms (Etaya, Sudo, and Sakata, 2000; Etaya et al., 1997; Yoshimura et al., 1997).

Important archaeological sites are continuing to be uncovered using satellite imaging. As recently as 2006, Robert Schiestl, an archaeologist with the German Archaeological Institute, Cairo, detected the remains of two previously unknown 13th Dynasty pyramids in the South Saqqara region west of the Nile using QuickBird imagery from Google Earth (Alexanian, Schiestl, and Seidlmayer, 2009). The two sites are identified as SAK S 3 and SAK S 7 (SAK is short for South of Saqqara). Two further pyramids visible in the QuickBird image (Figure 3.1) – the Khendjer pyramid and the “Unfinished pyramid” (identified as SAK S 5 and SAK S 6 respectively), are also dated to the 13th Dynasty, and were discovered in the early 19th Century (Lepsius) and later excavated by Gustave Jéquier in 1929–1931 (Jéquier, 1933). Jéquier’s excavation ramps (triangular shaped features) can still be seen adjacent to the sites.

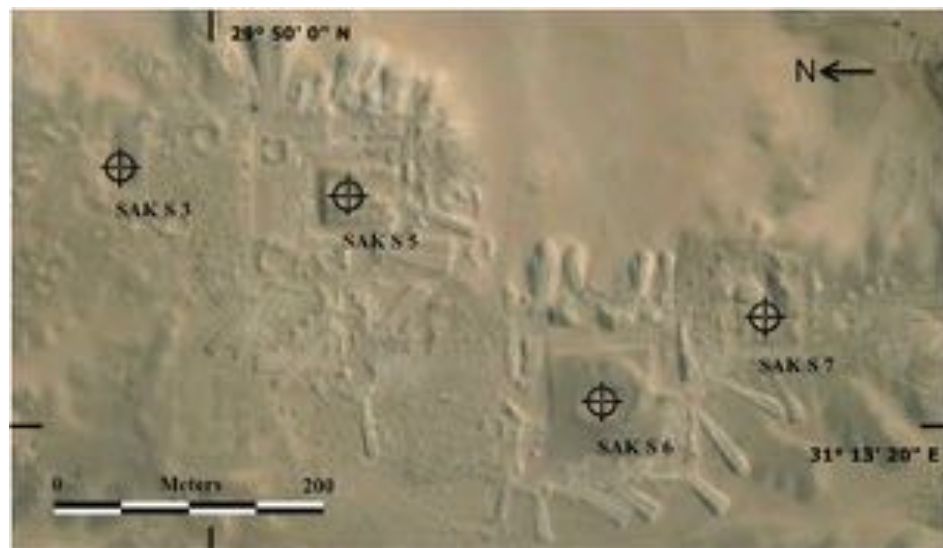


Fig. 3.1: Recent pyramid discoveries in South Saqqara (SAK S3 and SAK S7). QuickBird image courtesy of Google Earth.

Furthermore, a group at Cairo University in 2008 may have rediscovered the missing pyramid of Menkauhor (5th Dynasty), which had been originally discovered by Lepsius in 1842, but later lost due to the movement of shifting sands (Kratovac, 2008). These recent discoveries demonstrate the utility of using satellite remote sensing as a tool for site detection, even in areas thought to contain no new finds.

More recently there have been several high profile campaigns to use satellite imagery to search for lost archaeological remains in other regions of the world. One of these named The “Valley of the Khans” Project, lead by Albert Yu-Min Lin, uses a combination of high-resolution imagery from the GeoEye Foundation (DigitalGlobe), combined with Unmanned Autonomous Vehicles (UAVs), ground penetrating radar, and crowd sourcing techniques, to locate the tomb of Genghis Khan in Mongolia. Genghis Khan was one of history’s most enigmatic leaders, whose Mongol Empire spanned across the entire continent of Eurasia. After 3 years the project is still on going with many archaeological sites having been mapped, including multiple Bronze Age burial mounds (Lin et al., 2011). The exact location of the site however still remains uncertain.

The role of space archaeology as an emerging discipline should be recognized as providing an additional component to a rapidly expanding technical toolset allowing archaeologists to locate new sites by means normally unavailable using more traditional ground-based techniques.

3.3 Defining an archaeological site; types of sites

The definition of ‘site’ differs widely among archaeologists, however it is generally understood to represent a location that preserves evidence of past human activity. In a traditional sense the idea of an archaeological site conjures up images of large-scale structures. In Egypt examples of these include the funerary architecture such as the Old and Middle Kingdom pyramids, temples, and the royal tombs constructed on a grand scale. Many of the remains may be in various states of preservation, collapsed or simply unfinished (often found with pyramids and tombs). Other types of sites include cemeteries, smaller scale tombs (such as the mastaba), tomb chapels, pit burials, and settlement sites such as tell sites (see below) and towns. A “mastaba” is an Arabic word for a mud bench, and was a type of prestige tomb. It consisted of an above ground rectangular structure with a flat roof and

outward sloping sides called the superstructure (this has normally disappeared over time). One or more burial chambers are normally found beneath the superstructure to a depth of several metres.

Archaeological sites however can also exist on a much smaller scale – for example the scattering of ceramic fragments across the surface of the ground may also be considered a site, or at least perhaps indicative of the presence of a site close by. In Egypt and other areas of the Middle East, a ground scatter of potsherds is sometimes found in association with a tell site. A 'tell' is an ancient settlement site composed of mud brick, and usually forming a large mound due to multiple levels of occupation over time. Strategies for using remote sensing to detect this type of site will be discussed in Case study 1 (Chapter 4).

Without further investigation it would be impossible to determine the true extent of a site. What appears on the surface of the ground may consist of just a fraction of what is hidden beneath its surface. Alternatively, the cultural remains found on the surface may have travelled great distances due to processes of weathering and erosion, or may simply have been dropped by a traveller in antiquity and therefore can potentially mislead as to the true nature of a site. Evidence of whether a location is host to a site will of course come through a campaign of surveying and site excavation. This could include the use of several remote sensing techniques, including a high-resolution aerial survey using a camera mounted on an unmanned aerial vehicle (UAV) to record a site's surrounding topography, or perhaps various geophysical approaches, such as ground penetrating radar or magnetometry. More invasive strategies may include coring and trenching to examine a site's distribution and age through time.

Not all sites can be detectable by a satellite sensor. This is dependent on a number of factors, including the size of the site, its stratigraphic position in the landscape (i.e., its depth of burial), its state of preservation, and its spectral characteristics when compared to the matrix of material that surrounds it. Many sites may be undetectable simply because they are too deeply buried under the foundations of modern sites, or they may be hidden due to the relentless shifting of the Nile sands due to both fluvial and aeolian events. Many sites may have been destroyed and removed over time, in which case there may not be enough ancient

material left to be detected. Of course the spatial and spectral resolutions of the chosen sensor are also of paramount importance and should be carefully selected.

It is unclear how many archaeological sites remain undiscovered in Egypt. Regional survey work is helping to answer this question. According to Sarah Parcak, an Egyptologist at the University of Alabama, Birmingham, “only 1/100th of one percent of archaeological sites in Egypt have been discovered” (Parcak, 2008), whereas Zahi Hawass, former secretary general of Egypt’s Supreme Council of Antiquities, has estimated it to be in the region of 30 percent (Hawass, 2001). Ultimately, it is impossible to estimate the number of sites remaining to be found. However, following a satellite, airborne, and ground-based remote sensing approach the archaeologist has the best chance of uncovering further sites in the most efficient manner.

3.4 The Electromagnetic spectrum: archaeological windows of opportunity

There needs to be a fully multispectral approach to locating sites with wavelength regions carefully chosen that are appropriate to the type of material to be detected. Often times examining a region using a range of wavelengths can provide additional information that cannot be obtained using a single wavelength.

The amount of emitted and reflected radiation from different earth surface materials varies as a function of wavelength, resulting in a unique spectral signature for different earth surface materials. The spectral signatures for different mineral and rock types are well known and have been compiled into spectral libraries (United States Geological Survey, 2011a, 2011b). The libraries are available for free and can be download online from several sources including the United States Geological Survey (USGS) and the NASA Jet Propulsion Laboratory (JPL).

Remote sensing data with greater spatial and spectral resolution is becoming more freely available. For the first time data utilizing all major wavelengths can be acquired free of charge from the major clearinghouses. These include all Landsat legacy data (MSS, TM, ETM+) and ASTER offering VNIR, SWIR, and TIR capabilities. Additionally, for the first time microwave data is available from the Shuttle Imaging Radar (SIR-A/B/C) and PALSAR-1 will become available later this year. These datasets provide a wealth of complementary information and can be seen as windows of opportunity.

3.5 Strategies for locating sites in arid regions

Fundamental to any remote sensing survey is the development of strategies that best maximize the chances of searching in high probability locations. Egypt, for example, is a very large country covering well over one million square kilometres, much of it consisting of sparsely inhabited and inhospitable sands of the Sahara Desert. It would be impractical and a waste of resources to simply begin searching in a random location without having data to support such an endeavour. It is therefore important to design search algorithms, also known as protocols, which can be applied to an area in a methodological and logical manner.

One criterion when considering arid regions is to search imagery for sources of water that were both large enough in size and perennial in their nature to adequately supply a significant population. This would seem like a reasonable and sensible approach given the scarcity of water in desert locations. Populated areas often grow up around the edges of water sources – rivers, lakes, and oases. It is therefore logical to focus on areas where there was a ready supply close at hand. Furthermore, areas of vegetation are commonly associated with water and these vegetation patterns can be mapped using optical satellite imagery. The spectral reflection of water absorbs energy in the near infrared wavelengths and spectral bands can be chosen to map these features. Satellite imagery can be searched for sources of vegetation using the Normalized Difference Vegetation Index (NDVI). The NDVI is a spectral ratio of the difference between near infrared and red intensities of light to the total light being reflected, and provides a good sensitivity to changes in vegetation cover. The mapping of oases and vegetation is discussed in the second case study of this dissertation (Chapter 5).

The most precious resource in Egypt has always been the River Nile. Until the mid 1960's the Nile experienced regular flooding, overflowing its banks annually. This occurred between late July and early October bringing with it rich nutrients that made the surrounding earth fertile. This event was predictable, leaving an average deposit of about 1 millimetre of silt a year, preventing the lowest lying sections of the Nile Valley and delta from becoming permanently settled (Butzer, 1976). It is safe to assume that temples, tombs and other structures would have been constructed above major flood levels so as to allow sufficient access to buildings and to avoid excessive water damage. Flooding the Nile using “digital water” can help identify regions that are unlikely to contain sites due to their position below the flood level,

and these areas can be excluded from further consideration when conducting an archaeological survey. One complication in estimating historical water levels is that the position of the Nile is not stationary. Like all water bodies it has evolved by gradually changing its shape and position over time as it moves across the floodplain and delta. Studies have shown that the rate of migration is different depending on location. Data from borehole survey, satellite imagery, and historical maps suggest that the Delta head was further south in antiquity and that on average the Nile in parts of Upper Egypt has been migrating eastwards at a rate of up to 9 km every thousand years (Jeffreys, 2008; Lutley and Bunbury, 2008; Hillier, Bunbury, and Graham, 2007). Scholarly journals usually do not consider the migration of the Nile over time, and draw its position in antiquity close to its present day location. However, its shifting movement should be taken into account as this can have an impact on where to search for sites.

In addition to its immense size, Egypt is also one of the most densely populated countries in the world, with an estimated 80 million people inhabiting the banks of the River Nile in a space of just forty thousand square kilometres. The landscape is therefore changing rapidly due to an ever increasing and expanding population. Greater numbers of archaeological sites are increasingly at risk from levelling and complete destruction or from being built over by modern developments. There is therefore a necessity for the detection and mapping of these sites (and Egypt is just one example) to move quickly given the time constraints to find them. The use of historical photographic imagery from the American Corona and former Soviet KVR-1000 reconnaissance satellites can help to visualize how the archaeological landscape has changed over the past 40+ years.

Mapping arid desert regions using microwave wavelengths (radar) is essential when searching for ancient water sources. Radar has the ability to penetrate several metres of dry sand, given the right environmental conditions, and is a useful tool when looking for interface changes in strata that could indicate cultural remains. Furthermore, radar imaging (especially long wavelength L-band) is particularly useful for mapping ancient river channels, of which there are many found buried in the eastern Sahara. The identification of palaeorivers can therefore provide an indicator to the location of past settlement sites. Results from the first Shuttle Imaging Radar (SIR-A) mission onboard the November 1981 flight of the Space Shuttle Columbia provided the first regional scale subsurface images of previously unknown valleys

and palaeochannels buried beneath the Selima Sand Sheet of the eastern Sahara Desert of Egypt and the Sudan (Wendorf, Close, and Schild, 1987; McCauley et al., 1982, 1986). These features, named “radar rivers”, are detectable using radar but are invisible from the ground and undetectable using optical sensors, such as Landsat. The presence of many present day oases, including the Kharga, Dakhla, Fayyum, and Siwa of the Egyptian Western Desert can be attributed to these palaeo-drainage networks buried deep under the sand. Many of these oases served as the crossroads for caravan routes transporting luxury goods, including ivory, spices, in addition to animals and slaves. The remote sensing of trading routes is discussed in the final case study (Chapter 6).

In areas devoid of vegetation spectral based remote sensing is particularly effective for mapping carbonate deposits left over from the surface depressions of large ancient lakes. Without the cover of vegetation, it becomes easier using medium to high-resolution instruments, to map the mineralogy and rock type of a region without the signal being contaminated by the vegetation component. Furthermore, instruments such as ASTER, with its 11 bands in the SWIR and TIR, are especially well suited to spectral mapping due to many of its channel sensitivities coinciding with the diagnostic spectra of carbonate and silicate minerals. This of course was no coincidence; the design of wavelength sensitivities for each ASTER channel were carefully planned around the locations of peak mineral spectra. One promising area of research is mapping carbonate deposits in large desert regions, which could indicate the presence of ancient water sources, such as palaeolakes. This area of research will be examined in some detail in the second case study (Chapter 5) primarily using ASTER and Landsat ETM+ imagery.

Another criterion for locating sites in desert regions is to search for travel pathways (caravan and trading routes) that are often found to converge at settlement sites and water sources. VNIR and TIR imagery have been successfully used in previous studies to identify ancient roads and tracks (hollow ways) in the Near East where they were used to map the spatial distributions of settlement sites (Wilkinson et al., 2010). First identified by Wilkinson and Tucker in the North Jazira, Iraq (Wilkinson and Tucker, 1995), hollow ways represent shallow linear depressions in the landscape resulting from a millennia of human and animal foot traffic. Hollow ways are not as commonly found in the eastern Sahara perhaps due to the

absence of sufficient moisture content of the sand. This is further discussed in Chapter 6 on the remote sensing of desert lineaments (Section 6.3).

Finally, high-resolution optical imagery can be used to look for further surface evidence of site remains, such as hill forts, protective fortresses, and ancient walls. Many of these types of sites can be found adjacent to caravan routes to protect the transportation of high value goods. The remains of other sites, such as cemeteries, may also be visible. Many sites have only become visible in recent years due to the appearance of looters' spoil heaps or excavation pits dug into the landscape by modern day treasure seekers. This type of activity often appears as a characteristic pockmark feature on the landscape. The use of Google Earth with its high-resolution imagery is a useful asset when searching for these types of sites. Ancillary sources of information may also be collated, including historical maps and previous survey records.

Search protocols should include a Geographical Information System (GIS) to merge the separate data into one central dataset. A GIS allows spatial analysis to be performed such as the defining of buffer zones of a predetermined distance around water sources and travel ways. Locations inside buffered zones indicate regions of increased probability for the location of an archaeological site. This is the subject for Case study 3 where inputs into the GIS include vector layers of surface water (oases), subsurface palaeorivers / channels, trading routes, and palaeolakes. These layers are overlain on top of a SRTM digital elevation model base map.

In conclusion, the presence (or absence) of water and the category and size of the site, will guide the remote sensing methodology used when surveying archaeology in arid regions. However, the limitations of remote sensing technology should be understood. Perhaps remotely sensed images are not appropriate and cannot be used in certain instances. This may be because archaeological remains are located too far beneath the ground surface, too small to be detected, or cannot be sufficiently differentiated from surrounding materials due to possessing a similar spectral profile. Therefore the results from the imagery analysis may be inconclusive. For this reason, a remote sensing survey should never be conducted in total isolation. It is vital to follow up with a ground-based confirmation of imagery results. This should ideally involve a geophysical survey, coring, and when appropriate, excavation.

3.6 Image processing techniques for archaeological site detection: searching for anomalies in the imagery

The primary objective of remote sensing is to detect changes in contrast between the area of interest and its surrounding matrix. The contrast difference is named an “anomaly” until it can be identified, either directly through further image processing, or most usually through a campaign of ground-based investigation (also known as ground-truthing). Ground-truthing provides a way to compare what is shown in the imagery to what is physically located on the ground. If possible this should always be carried out; often what is presented in the imagery is not always confirmed when examined from the ground.

Digital image processing enhances the imagery to make it more interpretable. There are many types of imagery enhancement techniques, including radiometric (modifying values of individual pixels), spectral (transforming pixel values on a multiband basis), and spatial (modifying pixel values based on the values of surrounding (neighbourhood) pixels). Examples of these techniques include an atmospheric correction, principal components analysis (PCA), and convolution filtering respectively. Further examples for each category of enhancement are shown in Table 3.1. In the remainder of this section and sections 3.7–3.8 various techniques are discussed for enhancing remote sensing imagery. These include simple band combinations for imagery visualization, pan-sharpening to increase multispectral resolution, and principal components analysis for reducing spectral redundancy due to inter-band correlation. For a more complete treatment of enhancement techniques used in digital image processing the reader is directed to Lillesand, Kiefer, and Chipman, 2007.

Radiometric	Spectral	Spatial
Image restoration	Density slice	Geometric correction
Radiometric normalization	Contrast stretch	Low pass / high pass filters
Atmospheric correction	Band ratios (spectral indices)	Edge enhancement filter
*	<i>Principal Components Analysis</i>	Frequency domain filters (FFT)
*	Decorrelation stretch	<i>Resolution merge</i>
Table 3.1: Digital image enhancement techniques. Italicized entries are described in further detail following this table.		

One problem often encountered when using image-processing software is that only three channels of data can be displayed at any one time (where a single channel is sent to the red, green, and blue colour guns of the display monitor). However, multispectral satellite imagery consists of multiple bands of data, where each band is sensitive to a different region of the EM spectrum. For example Landsat ETM+ data consists of 8 bands, while Terra ASTER consists of 14 separate channels. Different band combinations enhance different features in the landscape, such as vegetation patterns, geological features, or archaeological anomalies. Therefore a choice has to be made about which three bands to use to best display the particular features of interest.

Popular band combinations using Landsat TM / ETM+ data include 3, 2, 1 (R, G, B); 4, 3, 2 (NIR, R, G); and 7, 3, 2 (SWIR, R, G). The band combination of 3, 2, 1 is also known as “true colour” as it displays the scene using the same red, green, and blue wavelengths of light that our eyes are sensitive to, thus helping to create a more natural looking image. Archaeologists often display crop marks and other surface vegetation patterns using the combination 4, 3, 2. Vegetation appears red in this combination due to the near-infrared channel being sent to the red colour gun. This is because healthy vegetation reflects strongly at near-infrared wavelengths. A third combination, 7, 3, 2, is often used in geological interpretation of rocks and mineral types, and may also be useful in archaeological interpretation. Non-true colour images are often referred to as “false-colour composites” (FCC) because the band combinations give an artificial representation of the landscape. Other imagery products will have similar band combinations depending on their band-wavelength allocations.

A second example of using image processing techniques to enhance imagery is the pan-sharpening algorithm. In addition to lower spatial resolution multispectral (colour) data, many imagery products also include a higher resolution panchromatic (greyscale) band. Landsat ETM+, SPOT-5, IKONOS, and QuickBird, all include separate panchromatic bands. For these datasets a method called pan-sharpening can be used to increase the spatial resolution of the multispectral channels. This can be achieved by merging their colour information with the geometric information from the panchromatic band, resulting in high-resolution multispectral imagery. For example, the 15 m panchromatic band from Landsat ETM+ can be merged with the six 30 m multispectral bands, resulting in six multispectral (colour) bands each at 15 m spatial resolution. In addition to combining bands from a single satellite, it is also possible to

combine bands from two different satellites (e.g., the 5 m panchromatic band from SPOT-5 with the 30 m multispectral bands from Landsat ETM+). There are a number of pan-sharpening algorithms available within image processing software including intensity hue saturation (IHS), Brovey transform, principal component analysis, and wavelet-based techniques. A quantitative study comparing different algorithms has shown that the wavelet based method offers better results most of the time (Vijayaraj, Younan, and O'Hara, 2006).

The final image processing technique presented here is principal components analysis (PCA). PCA is used extensively in the methodology of Case study 1 (Chapter 4). It is also widely used in other disciplines including physics and digital signals processing (DSP). Therefore PCA is given its own section where it is discussed in some detail.

3.7 Principal Components Analysis (PCA)

A problem often encountered when analyzing satellite imagery is deciding how to extract the most useful information from a multidimensional dataset. This is because there is a tendency for the channels of the multispectral data to be highly correlated when the wavelengths of the displayed spectral bands are located close together. If two bands are correlated they share some of the same information and displaying these bands in the same output display may not be the best way to display the data. For example, Landsat ETM+ bands 1 and 2 are highly correlated because the wavelength regions are spectrally close together, whereas bands 1 and 4 are less so because they are spectrally further apart (refer to Figure 2.5). Principal components analysis (PCA) – also known as Karhunen-Loeve analysis, including similar techniques, such as the decorrelation stretch and canonical analysis, may be used to reduce the redundancy and dimensionality of a dataset. These techniques transform the bands into a smaller number of non-correlated principal components, which when displayed, are often more interpretable than the original source data. As a result PCA is often applied to a dataset before further image processing is performed so as to rearrange the data to show the most variation. PCA is therefore a practical tool for analyzing data consisting of multiple bands of information and tends to be of greater benefit when the dataset has a large number of channels. It can be applied to multispectral datasets such as Landsat and ASTER for example, but the real benefit is realized when PCA is applied to hyperspectral datasets, some of which consist of hundreds of bands. Hyperion for example has 220 contiguous spectral bands, 70 of which are in the VNIR and 172 in the SWIR.

PCA is a widely used statistical based technique for transforming a multivariable dataset consisting of a large number of correlated bands into a smaller number of uncorrelated variables called principal components (PCs). For example, applying PCA to multiple bands of data may reduce the dataset to just three channels. These three PCs may contain 99% of the total variance of the original dataset and can be displayed as one complete image by sending them to each of the three colour guns of the display. In summary, PCA has three common uses: decorrelating a set of highly correlated images, reducing the dimensionality of a large dataset, and improving imagery interpretation.

The principal components of an image can be found by using the following steps (summarized in Jensen, 2004). For simplification purposes the example given is performed on a two-band dataset.

1. PCA is applied to a correlated multispectral (or hyperspectral) dataset. A hypothetical 2-dimensional set of pixel values, i.e., Landsat ETM+ Band₁ vs. Band₂, arranged as a scatterplot is shown in Figure 3.2a. The first dimension is shown along the x-axis (X_1) whereas the second is shown along the y-axis (X_2), where the amplitudes of both axes represent pixel brightness values. Mean values for X_1 and X_2 are calculated and plotted on the graph as μ_1 and μ_2 respectively. The centre point where the two means intersect is the average pixel brightness value for the two channels. The variance (spread) of the data points indicates the degree of correlation between the different dimensions. A scatterplot displaying a wide spread of data points indicates a high degree of correlation, whereas dimensions showing little variation will be clustered in a tight region. In this example there is a wide spread of data that shows the two bands are correlated to one another.
2. A new coordinate system is created by translating the original axes from X_1 , X_2 to X_1' , X_2' . This translation may involve a simple relationship such as $X_1' = X_1 - \mu_1$, and $X_2' = X_2 - \mu_2$. This will move the origin of the original coordinate space to the location of both means (Figure 3.2b).

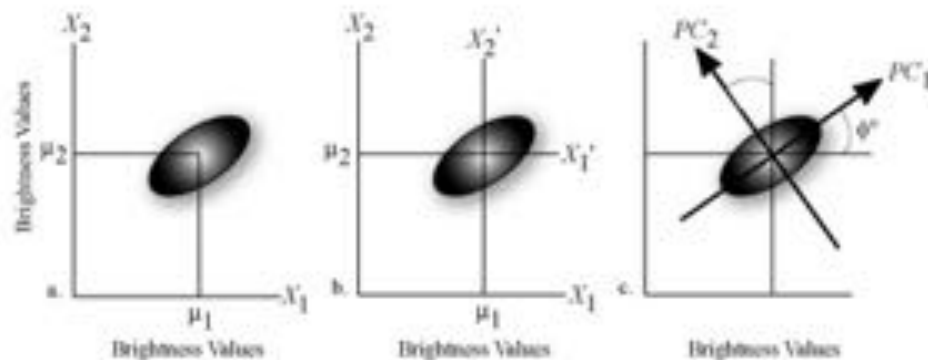


Fig. 3.2: Spatial relationship between an original set of axes and two of their principal components. (a) Original coordinate space; (b) New coordinate space defined; (c) Coordinate space rotated around origin with 2 principal components shown (After Jensen, 2004).

3. In this example, the new coordinate system is rotated about the new origin, μ_1 , μ_2 (Figure 3.2c). In this example two principal components are created (PC_1 and PC_2). The variances of both PCs are at a maximum and their axes are perpendicular to one another.

Applying PCA to an imagery dataset produces the same number of output components as bands in the original data. The first principal component (PC_1) contains the maximum amount of variation, with each successive component displaying less variation. For example, in Landsat ETM+ data, usually the first two components account for over 90% of the total variance found in the original data, while the first three may account for almost all of the variation. If the remaining PCs contain no useful information, they may be safely discarded. However, even higher order PCs can sometimes contain valuable information, and should therefore be examined before being discounted. Either the components can be viewed individually in greyscale, or a FCC can be generated, by sending the components to the display. The first case study of this dissertation demonstrates the utility of PCA when applied to detecting tell sites in the northwestern region of Egypt using Landsat imagery. Further information on the PCA methodology and a practical workflow on how to calculate it can be found there (Section 4.9).

3.8 Automating detection using pattern recognition

Automated detection strategies, such as pattern recognition, should form an integral component in a remote sensing survey. Pattern recognition applied to archaeology is the

identification of cultural features using imagery derived from ground, air or space where the detection is automated in its approach. It can be divided into three key areas: (1) detection of features based on the patterns of their DN (spectral classification), (2) identification of shapes and patterns due to their spatial relationship with neighbouring pixels (spatial classification / textural analysis), and (3) determination of changes in features using multi temporal data (temporal classification / change detection).

Spectral classification is considered the most common approach to computer assisted mapping. Individual pixels within a matrix are assigned a finite number of classes based on their spectral characteristics (i.e., when comparing values of spectral emissivity / reflectance) and usually on a multispectral basis. Classification may therefore be seen as a means of compressing image data by reducing the massive range of DN values often present in many spectral bands, to a few classes in a single image. Spectral based classification was used in Case study 1 (Chapter 4) as one technique to differentiate ancient settlements (tell sites) from modern sites.

Prior to classification the imagery should ideally undergo several pre-processing steps. These may include an atmospheric correction to eliminate the atmospheric component of the signal, radiometric correction to radiometrically normalize the dataset, band-ratioing to suppress topographic variation in the data, and PCA to reduce the dimensionality and inter-band correlation of the dataset (see Subsection 2.6.4). Once the imagery has been pre-processed, ancillary data should be collected for the study area (if available) The amount of information known about the study area will determine the type of classification scheme to be used, i.e., whether unsupervised, supervised or hybrid approaches are used.

A supervised classification is normally selected when the analyst has some prior knowledge of the region (the analyst is said to "supervise" the pixel categorization). Knowledge about the area can be gathered from aerial photographs that have detailed annotated maps or from prior fieldwork and ground-truthing experience. Supervised methods tend to produce more accurate results. This is because more information is known about the data although it does require greater user interaction, as the number of classes and their associated training regions are to be determined before the classification is run. A "training area" is selected for each class from a group of homogeneous pixels representative of that class in the image. Each training area in

the image can be correlated to a known area on the ground and is representative of the spectral characteristics for that class. As a general rule, for any n -dimensional dataset, normally a minimum of $(n + 1)$ pixels is required to form a training area in the classified image to be considered a representative sample. A suitable classifier algorithm is used in the classification process. These include the maximum likelihood classifier (this is the most commonly used), the minimum distance to means (also known as the centroid classifier), and the parallelepiped classifier.

Alternatively, an unsupervised classification (also known as clustering analysis) can be used when little is known about the image data (i.e., no training data exists to aid in the classification process). The classification is therefore entirely dependent on the statistics of the pixel data for the definition of the classes. Whereas a supervised classification will use the similarity between pixel data and training data as the basis for a classification, an unsupervised classification uses cluster analysis to form separate classes of land cover. Clustering is the process of forming classes (clusters) of pixels based only on their similarities in spectral space using image statistics only. It is the responsibility of the analyst to attach meaning to the resulting classes after the classification has run. Several algorithms are available including ISODATA, K-means, and RGB clustering.

The Iterative Self-Organizing Data Analysis Technique (ISODATA) is the clustering algorithm used in the software suite ERDAS IMAGINE and was used in the practical components of this dissertation. It is an iterative approach that repeatedly performs a classification after which the image statistics are recalculated. After each iteration a new mean is calculated and the positions of pixels are reclassified with respect to the new means. This process continues until the change in the number of pixels assigned to each class is less than the pixel change threshold (set at the beginning of the classification). Parameters entered into the ISODATA algorithm include the minimum and maximum number of classes desired, the maximum number of iterations, and the percent pixel change threshold. The ISODATA algorithm tends to produce good results for data that are not normally distributed, however it is slow and tends to overlook pixel homogeneity.

An alternate to carrying out an unsupervised or supervised classification is the adoption of a hybrid approach, which combines a spectral classification with an object-based strategy. The

image is segmented into objects which are assigned classes based on their spectral information and shape / contextual relationships. A hybrid strategy tends to work well when classifying medium to high-resolution imagery.

Classification often produces a "salt and pepper" or speckled appearance to the classified image. This is where there are large numbers of small clusters of pixels. Some of the isolated pixels may be the result of misclassification. This is an unwanted artifact left over from the classification process and should be corrected for. They can be removed by applying a smoothing (averaging) filter, such as the majority filter, which consists of a 5 x 5 or 7 x 7 moving window. They are also known as convolution filters. After smoothing, the classified image will appear more homogeneous in appearance. Classification and smoothing can be performed within most standard GIS applications, such as ArcGIS (or a remote sensing package with vector add-on module, such as Leica ERDAS IMAGINE). Finally, one of the most common methods of assessing classification accuracy is to prepare an error matrix, also known as a confusion matrix. This quantitative approach determines the number of incorrectly labelled pixels in the classified image and uses a numerical indicator representing the degree of accuracy (Schowengerdt, 2007). A qualitative approach may also be undertaken where the classified image is simply compared to reference images or maps of the area.

3.9 Acquiring imagery and choosing the correct tools

Acquiring the most appropriate imagery and software tools are important considerations when conducting a remote sensing survey. This section discusses the types of satellite imagery that are available, the criteria for choosing them, and how to select the most suitable software tools when performing the imagery analysis.

3.9.1 Satellite data resources

There are a large number of imagery products available offering varying levels of spatial and spectral resolutions. The resources considered here are principally derived from spaceborne systems and may be acquired for free or at little cost to the end user and do not require a license agreement. Optical systems include Terra ASTER, Landsat-7 ETM+, Corona and KVR-1000 spy photography, and various commercial high-resolution imagery products streamed through Google Earth. Radar systems include imagery products from SRTM and

PALSAR. Finally, two digital elevation model data sets are considered from SRTM and ASTER.

ASTER (<http://asterweb.jpl.nasa.gov/>) onboard the Terra satellite is a very versatile instrument, offering adequate spatial and spectral resolution (depending on what you want to image), with 14 spectral channels, including three in the VNIR (15 m spatial resolution), six in the SWIR (30 m), and five in the TIR (90 m). This may be suitable for larger scale mapping projects, but it is somewhat limited for site detection purposes in the VNIR wavelengths, and would have to be complemented with a higher resolution instrument, such as from one of the older generation US spy satellites, such as Corona, or one of the higher cost commercial sensors, such as QuickBird. ASTER is a resource that has been vastly underutilized by the archaeological community and holds great potential in the future, especially when a medium spatial resolution sensor with good SWIR and TIR spectral coverage is needed. ASTER imagery, although not free, is available at approximately USD 70 per scene. Applications can be made by either university (worldwide) or NASA affiliated researchers to request free access to the database.

Landsat legacy products (<http://landsat.usgs.gov/>) also offer a rich collection of current and historical imagery. The Landsat series of satellites have been the workhorses of the remote sensing industry since the 1970s (the first Landsat satellite – the Earth Resources Technology Satellite was launched on July 23, 1972), producing three generations of sensors: the Multispectral Scanner (MSS), the Thematic Mapper (TM), and the Enhanced Thematic Mapper (ETM+). The ETM+ sensor onboard Landsat-7 offers general-purpose capabilities with a swath width of 185 x 185 kilometres and 6 bands in the VNIR and SWIR at medium resolution (30 m) and a single band in the TIR (60 m). ETM+ also includes a panchromatic band with a spatial resolution of 15 m that can be used to pan-sharpen the data set (see Sections 3.6 and 4.5). Since April 21, 2008 all archived scenes from all generations of Landsat legacy satellites can be downloaded free of charge. The latest generation Landsat-8, launched in 2013, ensures the continuity of the satellite, and utilizes a two-sensor payload: the Operational Land Imager (OLI) and the Thermal InfraRed Sensor (TIRS). OLI offers nine VNIR / SWIR / PAN bands with similar resolutions as ETM+, whereas TIRS offers two TIR bands at a resolution of 100 m. Data from the Landsat-8 is also freely available for download.

High resolution reconnaissance imagery from the 1960's–1970's have been declassified and released into the public domain from both the US and former Soviet reconnaissance programs (Corona and KVR-1000 respectively). They have a range of resolutions and are available at cost as either film negatives or as scanned TIFF images. Corona and the KVR-1000 were previously discussed in Subsection 2.6.1.

In addition to the previously mentioned sensors there is also a large choice of commercial high-resolution imagery, but it is expensive and may well be out of reach of most archaeological budgets, especially when large numbers of scenes are required. Commercial imagery is normally charged per square kilometre (rather than per satellite scene) and this can substantially add to the overall cost. Currently the highest commercially available imagery is provided by DigitalGlobe's WorldView-3 satellite (www.digitalglobe.com/), recently launched in August 2014, with a spatial resolution of 31 cm (panchromatic at 0.31 m). It is also unique in providing eight multispectral bands in the VNIR and SWIR (with a resolution of 1.24 m) and twelve Clouds, Aerosols, Vapours, Ice, and Snow (CAVIS) bands at 30 m resolution. Other high-resolution satellites with resolutions better than 1 m include QuickBird, WorldView-1, GeoEye-1 and WorldView-2 (See Table 2.4 in Subsection 2.4.1). GeoEye's next generation satellite, GeoEye-2, was renamed to WorldView-4 and is being held in storage for a launch in 2016.

As was noted earlier, the cost of acquiring large amounts of commercial high-resolution satellite imagery for regional survey purposes can often be prohibitive. Although data costs have come down in recent years, pricing is still beyond the reach of most university research budgets. For example, the cost of the WorldView-2 Basic Bundle, consisting of the full complement of spectral bands (1 panchromatic and 8 multispectral) costs over US\$8,000 for a single scene (correct as of July 2010). This price is for imagery that is currently archived and does not require re-tasking of the satellite. Re-tasking of the satellite would incur further costs. In the past this has meant that researchers have had to rely on lower resolution imagery, i.e., Landsat ETM+ and similar datasets, and order higher resolution data only when essential. High resolution Corona imagery is available at reasonable cost, however it is not multispectral, consisting of just a single channel. This prevents its use in any advanced image processing operations.

There are a wealth of other resources utilizing a range of wavelengths that can be downloaded free of charge, including those from both airborne and hyperspectral sensors. Some of these assets have been made freely available by organizations such as NASA and the USGS. Table 3.2 shows examples of remote sensing and digital elevation model datasets relevant for archaeological applications. Technical specifications and pricing for each sensor are also included.

3.9.2 Google earth as a data provider

Applications providing high-resolution imagery, such as Google Earth (GE), are causing a mini-revolution in the way that scientists, professionals, and private individuals collect and use satellite data of the Earth. GE servers are designed to stream imagery over a broadband Internet connection to a remote user anywhere in the world. For the first time both professional and amateur researchers have free access to large amounts of high-resolution data (although only consisting of a single band) and usually at a global coverage. The imagery is provided at varying levels of spatial resolution with the majority of the imagery updated in the last 1–3 years. Base imagery of the world is provided using pan-sharpened Landsat ETM+ data with a spatial resolution of 15 m. Landsat coverage is gradually being replaced by higher resolution imagery such as SPOT (2.5–10 m) and QuickBird-2, (QB-2, 60 cm). The QB-2 satellite currently covers about 70% of Egypt, with the remaining 30% covered by SPOT.

GE offers several advanced features including the ability to use historical (multi-temporal) imagery to view regions of the Earth at different dates. This is useful for several reasons. Firstly, if many archived images of the same area are available they can show how the landscape has changed over time. This can provide valuable information for example in change detection studies - such as modelling the effects of urban expansion on a landscape. Secondly, as discussed earlier, the Delta and floodplain regions of Egypt can exhibit unique vegetation patterns, such as soil and crop marks, that may indicate the presence of archaeological remains. Depending on the time of year that the satellite image was acquired, these marks may or may not be visible. GE therefore allows the user to select imagery from a different date that may be more appropriate to the types of questions being asked.

Satellite sensor	Subsystem with number of bands	Spatial resolution (m)	Cost (USD)
Landsat ETM+	VNIR (4) SWIR (2) TIR (1) PAN (1)	30 30 60 15	Entire Landsat legacy data set available free of charge as of April 21, 2008
ASTER	VNIR (3) SWIR (6) TIR (5)	15 30 90	Free for coverage in the United States. Coverage outside the US is charged at ~ USD 80 per ASTER scene
SPOT-5	PAN (1) VNIR (4) SWIR (1)	2.5–5 10 20	USD 1,700 for old archive imagery, and 7,800 for 2.5 m pan data (3,600 km ² scene)
Corona 4B	VIS (1)	1.8	USD 30 for scanned frame
KVR-1000	VIS (1)	2–3	USD 1,000 –4,000 per frame
IKONOS	VNIR (4) PAN (1)	4 1	From USD 10 per km ² for archived imagery
GeoEye-1	VNIR (4) PAN (1)	1.65 0.5	From USD 12.50 per km ² for archived imagery
QuickBird-2	VNIR (4) PAN (1)	2.4 0.6	From USD 18 per km ² for archived imagery
WorldView-2	VNIR (8) PAN (1)	1.84 0.5	From USD 14 per km ² for archived imagery
Hyperion	VNIR–SWIR (220)	30	Free as of August 5, 2009
Shuttle Imaging Radar (SIR)	SAR / C-band	30	Free
PALSAR-1	SAR L-band	10–100	JPY 4,000 - 20,000 per scene. 3 different scan modes available
PALSAR-2	SAR / L-band	1–100	JPY 150,000 - 500,000 per scene 9 different scan modes available
Shuttle Radar Topography Mapper (SRTM)	DEM	15 vertical / 30 horizontal	Free for SRTM1 data of the United States and world. SRTM3 data. SRTM1 data outside of the United States is currently restricted and not available
ASTER GDEM	DEM	20 vertical / 15 horizontal	Free
Table 3.2: Satellite sensor specifications for use in archaeology			

Another feature found in GE is the ability to change the angle of the Sun and the surface lighting parameters on-the-fly when the scene is displayed in the viewer. The time of day that the scene was acquired can be an important factor when examining archaeological features. Usually imagery in Google Earth and other remote sensing software is displayed with no vertical exaggeration; the imagery is displayed from directly overhead. This is not particularly helpful when the elevation of the land varies widely. For example, tell sites and burial structures can often be identified based on their characteristic shape and the effects of their shadowing which is dependent on the position of the sun. Data from digital elevation models (DEMs), such as NASA's SRTM, can be added as a separate layer within GE. Once remote sensing imagery is draped over the DEM, tell sites and other elevated features can be easily identified and an algorithm can be written to automatically detect them.

Although GE is a good source for remotely sensed data, it does come with some disadvantages, especially if relied upon as the primary imagery provider. Some of the disadvantages include: 1) the imagery provides no multispectral capability, other than in the visible region of the EM spectrum. The channels in the near, shortwave, or thermal infrared that are normally present in a commercial release have been truncated. This limits the user to applications in the visible region only; 2) the visible channels have been merged into a single band and displayed in "true colour". This forces the user to examine the imagery under a specific band combination; 3) imagery from GE (or Google Maps) can only be saved as a jpeg file and at a limited resolution – up to 4,800 pixels for the professional version, compared to 1,000 pixels for the free version. Once saved, the image needs to be imported (and geo-referenced) into a remote sensing or a GIS package for further processing; and finally 4) the spatial and spectral resolution of the imagery has been degraded due to the use of compression algorithms for reducing the file size when streaming the imagery over the internet. Therefore, although GE is very good at presenting imagery at very high resolution in the visible bands, it cannot substitute for the full spectral capabilities of imagery that are available from remote sensing providers. They can provide imagery with a full compliment of channels that can be easily manipulated for further analysis using digital image processing operations. This would be impossible from with GE.

Two versions of GE are available (free and professional) which can be downloaded from <http://www.google.com/earth/index.html/>. GE Pro is a commercial product providing extra

features, including the ability to save and print at higher resolutions, import vector files, and calculate 3D measurements. Competing products offering similar functionality include: NASA's World Wind (<http://worldwind.arc.nasa.gov/>), USGS Earth Explorer (<http://earthexplorer.usgs.gov/>), ArcGIS Explorer (<http://www.esri.com/software/arcgis/explorer/>), and SkylineGlobe (<http://www.skylinesoft.com/>). These products are proprietary, except for World Wind, which is open-source and uses data that is freely available and in the public domain.

3.9.3 Commercial and freely available software

There are a large number of choices when it comes to selecting remote sensing and image processing software. However, applications tend to range in capability and sophistication depending on their cost. The commercial "Big Three" which currently dominate the market are ERDAS IMAGINE, ER MAPPER, and ENVI. IMAGINE and ER MAPPER are owned by Hexagon Geospatial / Intergraph (www.hexagongeospatial.com) while ENVI is licensed under Exelis Visual Information Solutions (www.exelisvis.com). Both IMAGINE, ER MAPPER, and ENVI offer similar functionalities but may use different implementations of algorithms that can vary in efficiency. It is therefore essential to understand the underlying implementation of how the algorithm works before applying it. ER MAPPER is unusual in that it uses a different workflow compared to other applications when performing image-processing operations, which takes time to understand (such as the concept of a running algorithm). ER MAPPER additionally includes many wizards and batch processing capabilities for the automation of certain procedures. ENVI (the ENvironment for Visualizing Images) was not used in this dissertation and will not be discussed further.

ER MAPPER was acquired by ERDAS in 2007 and comes bundled with the IMAGINE Professional license. An advantage of using ER MAPPER over other software packages is that it includes a proprietary Enhanced Compressed Wavelet (ECW) format that has been optimized for aerial and satellite imagery. This format compresses very large images while still retaining visual quality. Saving an image in an ECW format allows compression ratios from between 50:1 to 20:1 to be achieved, resulting in the ability to interactively view images of large file size in real time. This ability is essential when many scenes are to be mosaicked together, which can result in very large file sizes, i.e., a 10 GB image can be reduced to 500 MB or smaller in size. The Multi Resolution Seamless Image Database (MrSID) format,

developed at the Los Alamos National Laboratory (LizardTech) is the only other standard able to achieve similar compression rates.

Other popular packages include PCI Geomatica (www.pcigeomatics.com/) and IDRISI (www.clarklabs.org/). Free and open source software include GRASS – the Geographic Resources Analysis Support System (grass.osgeo.org/), and Opticks (<http://opticks.org/>), which was originally developed by Ball Aerospace for the U.S. Air Force and is particularly strong in processing hyperspectral imagery.

The processing of radar imagery typically requires more specialized software although all three of the commercial applications do have add on modules with basic processing functionality (IMAGINE includes a Radar module with its professional license, and Sarmap (www.sarmap.ch/) provides SARscape as an ENVI add on module). There are several free radar and optical utilities that have been made available by the European Space Agency (ESA), including the Polarimetric SAR Data Processing and Educational Tool (PolsarPro), the Basic ERS and Envisat (A) ATSR and MERIS Toolbox (BEAM), the Basic ERS and Envisat SAR Toolbox (BEST), the Basic ERS and Envisat Atmospheric Toolbox (BEAT), the Basic Radar Altimeter Toolbox (BRAT), and the Next ESA SAR Toolbox (NEST). PolsarPro is particularly useful as it is able to import many SAR imagery formats including fully polarimetric data from various satellite sensors, including SIR-C and PALSAR. The ESA toolboxes can be downloaded from earth.esa.int/web/guest/software-tools/. Polsarpro was used almost exclusively in this work for the processing of SIR-C and PALSAR imagery.

The most popular application for GIS analysis is ArcGIS, produced by The Environmental Systems Research Institute (ESRI), and can be downloaded from www.esri.com/software/arcgis/. In addition to the commercially available ArcGIS, there are other free (albeit less capable) GIS applications, including, GRASS, and QGIS (www.qgis.org/).

The software used to complete the image processing sections of this dissertation include ER MAPPER and ERDAS IMAGINE (Professional) for satellite imagery analysis, PolsarPro for the processing of SAR imagery, Golden Software's Surfer (version 11) (www.goldensoftware.com/products/surfer/) for DEM contouring and water filling, and ESRI ArcView and ESRI ArcGIS for geospatial analysis.

PART TWO

Introduction – Part two of this dissertation presents three case studies in practical format for the identification of archaeological sites in the eastern Sahara using current operational technology and digital image processing techniques. The methodologies described here should be relevant and applicable to other regions of Saharan Africa (the western Sahara) and similar environments found throughout the world, such as the Middle East, where a comparable arid environment is encountered.

The first case study focuses on the northwestern Nile Delta, using Landsat ETM+ and ASTER imagery to detect “tell sites”. Tell sites are found throughout Egypt’s Nile Delta and floodplain regions (they are also commonly found in other regions throughout the world), and are the remains of ancient settlement mounds formed from many centuries or millennia of occupation. Due to their construction above ground level, tell sites appear in satellite imagery as topographically high regions. Furthermore, due to their mud brick construction, they present a unique spectral signature, which differs from those of modern day building materials, and which may even differ between tell sites in different locations. These two attributes (topographic profile and spectral signature) provide a means for their identification. The content in this chapter describes the second approach, i.e., tell site detection through spectral classification.

The results from this initial study demonstrate that principal components analysis (PCA), when used in combination with a thresholding approach, was capable of isolating and detecting ancient tell sites. Furthermore, it was found that a higher order component – principal component 5 (PC5), contained the spectral variation needed to separate the characteristics of tell sites in the northwestern Delta. It still needs to be determined if the same methodology can be successfully applied to other regions of the Nile Delta, or if it can translate well to regions outside of the Delta, namely in the floodplain regions of Middle

Egypt. Detecting tell sites in other locations based on their spectral characteristics may need a different approach due to differing surface conditions and moisture content of the mud clay.

Many tell sites are at risk from urban, industrial, and agricultural expansion, in addition to looting and vandalism. Therefore, part of this work constitutes an important first step for mapping the spatial distribution of tell sites, which in turn will help to provide a window into urban land distribution and settlement patterns at a time of the first emerging communities. It is therefore important to document these sites before they completely disappear from the archaeological record. The results of this work were presented at the 2011 International Society for Optics and Photonics (SPIE) Remote Sensing conference in Prague, in addition to being published in the SPIE Proceedings (Corrie, 2011).

While the first case study examined site detection strategies at a local scale (i.e., the Nile Delta), the second case study considers regional scale strategies applied to the eastern Sahara Desert, primarily Egypt, Sudan, Libya, and Chad. The primary water sources are mapped using a range of imagery. The following map layers are constructed: (1) Surface desert water sources (oases), which are identified and mapped using spectral indices, including a variant of the Normalized Difference Vegetation Index (NDVI); (2) Subsurface palaeorivers (the remains of fluvial valleys that lie buried beneath the surface sand sheet, identified using long wavelength radar data from the SRTM mission and the Japanese PALSAR instrument; and finally, (3) Surface palaeolakes. The locations of palaeolakes were identified and mapped on the basis of their spectral characteristics and surface topography. Carbonates often indicative of lacustrine deposits were mapped using Ninomiya's (Geological Survey of Japan) ASTER thermal infrared band ratios. Finally, SRTM1 restricted data was used to search for potential lake depressions where water may have collected, in addition to their associated palaeoshoreline features, which are often observed surrounding many palaeolake systems.

The final case study discusses the remote sensing of trading routes in Egypt's Western Desert and archaeological site prediction using a GIS applied to the eastern Sahara. A region in Egypt's Western Desert was used as a testing ground for performing spatial analysis with a geographical information system. Map layers created from earlier case studies were used as inputs. These datasets included (1) surface water / oases (ASTER / Landsat NDVI); (2) near surface palaeorivers (SRTM / PALSAR); (3) maps of slope and aspect

derived from the SRTM DEM; and (4) trading routes and historical roads (ASTER VNIR / TIR, Landsat ETM+, and historical maps). Proximity analysis (buffering) was performed using the raster and vector layers to produce a new map highlighting the locations where archaeological sites are likely to occur. Finally, the Google Earth application was used for visualization purposes and for zooming into potential areas of interest.

Chapter 4

Case study 1: Detecting tell sites in the Egyptian Nile Delta using principal components analysis and thresholding techniques *

4.1 Introduction

Detecting archaeological sites from the ground is often impractical due to the large amounts of time and costs involved. Furthermore, many locations remain off limits to a ground-based campaign due to ongoing political unrest and heightened security concerns. This is often true of tell sites (“tell” is an Arabic word for a settlement mound), many of which are found in isolated desert regions across large swaths of North Africa and the Middle East. In contrast, the synoptic approach provided by the satellite sensor covers much larger areas, in greater spectral detail, and more cost effectively. As a result, satellite remote sensing is playing an increasingly important role in the detection of new tell sites and in the environmental monitoring of previously known sites. Mapping the distribution of tell sites is crucial to gaining a better understanding of their settlement patterns in an ever changing landscape.

In this case study, an area in the northwestern Nile Delta is surveyed using a variety of remotely sensed data, including Landsat ETM+ and ASTER imagery. The area was chosen due to its large number of settlement sites, both modern and ancient, that are found scattered throughout the region. The Google Earth application is used to highlight the archaeology both from a regional and a local perspective. Image processing algorithms were applied to the imagery in an attempt to differentiate ancient tell sites from modern developments. Results were compared to a database of known sites, where it was found that principal components analysis (PCA), combined with a thresholding technique, was best able to detect and differentiate tell sites from their modern counterparts. The tell site detection methodology described in this chapter focuses on Egypt but could be applied, with reasonable caution, to other areas of the world, where a similar arid environment is encountered, including other countries in the eastern Sahara and farther afield in the Middle East.

* The results from this case study were presented at the SPIE conference in 2011 and published in the Proc. SPIE 8181, Earth Resources and Environmental Remote Sensing / GIS Applications II, 81811B (27 October 2011); doi: 10.1117/12.898230

4.2 Egyptian tell site archaeology

The exploration and cataloguing of ancient Egyptian sites from the ground began with the French invasion of Egypt under Napoleon Bonaparte in 1798-1801 (Jornard, 1809). This initial work was followed by several further surveys, most notably the Prussian expedition under the German Egyptologist Karl Richard Lepsius in 1842-1845 (Lepsius, 1849), and British led surveys under Francis L. Griffith and Flinders Petrie in 1891-1910 (Griffith, 1912) and 1883-1927 (Petrie, 1932) respectively. These and similar campaigns set out to establish a comprehensive record of the known archaeological sites. However, many sites were completely missed, badly interpreted, or incompletely recorded, lacking an appropriate spatial context, due in part to the limited perspective offered by ground-based investigations.

Prior to the Space Age, archaeological remote sensing in Egypt had its origins in aerial photography using camera film sensitive to the visible and near-infrared wavelengths of the electromagnetic spectrum (Engelbach, 1929). The value of these and other aerial surveys from around the world was well recognized, given their advantage of providing unrestricted and unbiased views of archaeological features from the air. They provided complimentary information to the earlier expeditions that were carried out up to half a century earlier. However, limited spectral capability, in addition to poor geographical coverage, limited their full effectiveness.

Thousands of ancient settlement mounds, or “tells”, can be found scattered throughout the landscape of the Egyptian Nile Delta and Nile Valley floodplain. The Arabic word ‘tell’ (‘kom’ is also frequently used in Egypt) describes the remnants of an ancient town or city that formed over centuries or millennia of occupation and consists of a series of levels that slowly built up over time. Tell sites are not unique to Egypt, being commonly found throughout much of the Near East (Syria, Iraq, Iran, Turkey), including parts of Balkan Europe, and northwestern India. In Egypt, they range in size from a few tens of square metres up to many square kilometres and date from the late prehistoric through to the Roman periods and beyond.

Tell sites used to be a common feature found throughout Egypt, however due to rapid urban expansion many sites have been completely levelled to make way for agricultural fields, in addition to being buried under modern developments; this is especially true for many tell sites throughout Middle Egypt. Tells are also under threat from local farmers, who use the mud brick as a fertilizer (known as sebbakh) as they are naturally rich in phosphates. Figure 4.1 shows a typical tell site, Kom Awad, located in the northwestern Nile Delta, three kilometres east of Abu Hummus. A large number of mud bricks, in addition to sherds, can clearly be seen on the surface. The site consists of three mounds, with the largest covering approximately 200 x 160 m, rising about 6 metres above the surrounding fields. Kom Awad is relatively small compared to other tell sites in the area, some of which can reach several square kilometres in size. These images were taken by Penny Wilson, of Durham University, as part of the Egypt Exploration Society's (EES) Delta Survey, in 2005.

Tell sites are representative of some of the first emerging communities that were the ultimate precursors to modern cities. Further study can provide valuable insight into the evolution of

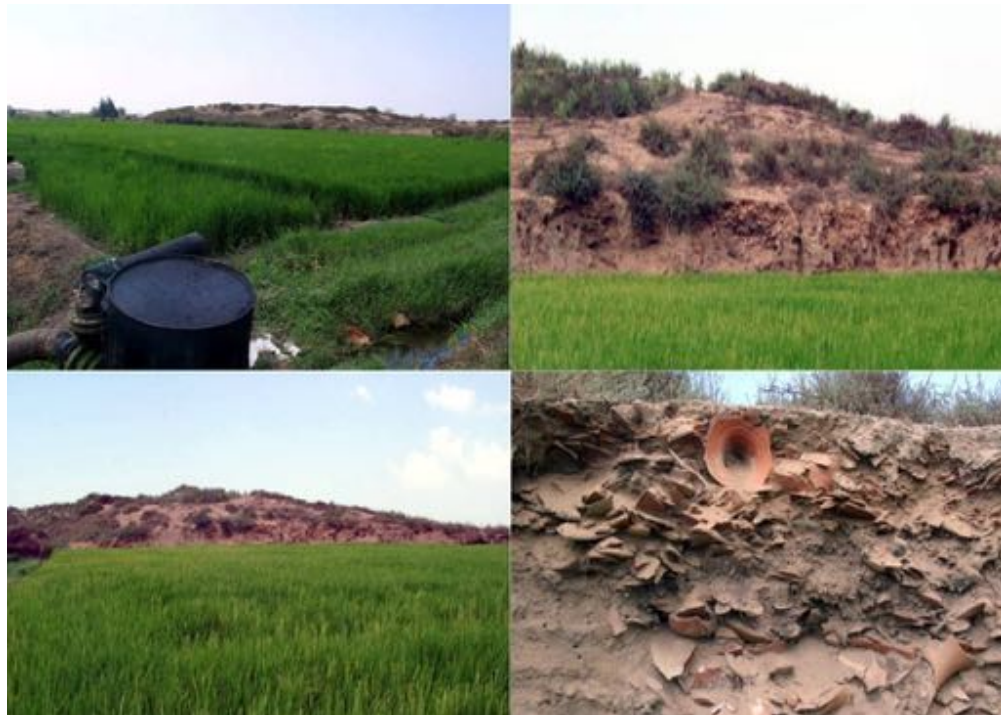


Fig. 4.1: Tell site Kom Awad (Egypt Exploration Society)

their settlement patterns and their systems of social organization. However, after 200 years of study there remains no comprehensive record detailing their exact locations or antiquity. Of the sites that are known, only a small number have been surveyed, and of those an even smaller number excavated. A regional based remote sensing survey, which is the focus of this case study, provides some first steps towards a more extensive methodology for documenting these ancient monuments.

4.3 The Egypt Exploration Society's (EES) Delta Survey

Although the Delta has not been extensively surveyed, many tell sites have been mapped, unlike much of the Nile Valley in Upper Egypt, where few examples still survive. A number of resources relating to tell sites have been made available online, including work of the Egypt Exploration Society's (EES) Delta Survey Project (<http://www.deltasurvey.ees.ac.uk/>), and Uppsala University's Ancient Near Eastern sites database (http://www.lingfil.uu.se/staff/olof_pedersen/Google_Earth/). The Delta Survey Project, led by Jeffrey Spencer of the British Museum, describes over 700 tell sites, providing information on the site name, location (in latitude and longitude), size, notable surface features, dating information, and links to external references. The Uppsala University database has compiled 2,500 archaeological sites across the whole of the Near East, including tell sites in Egypt. Both databases can be downloaded as KML files and added as separate layers in Google Earth. KML, the Keyhole Markup Language, is a Google Earth file format for storing geographic features, such as points, lines, and polygons, images, and models, which can be displayed over Google Earth base imagery.

Several researchers have worked on tell sites in the Delta, including Penny Wilson (Durham University), who was involved in survey work at the city of Sais (Sa el-Hagar, <http://www.dur.ac.uk/penelope.wilson/sais.html>), and the Western Nile Delta Regional Survey (<http://www.dur.ac.uk/penelope.wilson/Delta/Survey.html>). Further work has been carried out by Joanne Rowland (Freie Universität, Berlin), around Quesna, in the Central Delta, and by Neil Spencer (British Museum), at Kom Firin in the Western Delta (http://www.britishmuseum.org/research/research_projects/all_current_projects/kom_firin,egypt.aspx).

4.4 Remote sensing of tell sites: imagery analysis using Google Earth

When examining the Nile Delta using satellite data and comparing areas in the imagery with known tell site locations, it is readily apparent that the landscape contains large numbers of both ancient and modern settlement sites. Both types of sites often coexist in close proximity with one another. Indeed, many modern settlements have expanded outwards from the tell site, often leading to its eventual demise. The question that needs to be asked is: can satellite imagery be used to differentiate tell sites from modern sites, and can it be done in an automated or semi-automated manner?

To answer this question, the physical and spectral characteristics of tell sites need to be examined. Two attributes of tell sites may allow them to be detected using remote sensing satellites. Firstly, due to the nature of their construction, many sites have formed a large mound, or several mounds, that rise above the surrounding landscape. Tell sites therefore present as topographically high regions when examined using digital elevation models. As a result, modelling landscape morphologies may assist in their detection. A second method of identification is to examine the properties of their building materials, which is normally mud brick. Tell sites may be detectable from the spectral characteristics of the “tell earth” of which they are composed. The mud brick may possess a suitably different spectral pattern, compared to that of modern and natural surrounding materials. This case study examines tell site detection using the latter approach, i.e., using the spectral domain.

When conducting remote sensing in the spectral domain choosing an appropriate dataset that provides the necessary spatial and spectral resolution (in terms of number and width of bands) becomes vital. If satellite data is first examined using Google Earth (GE) imagery, the type of image rendered in the display depends on the scale, and therefore the resolution, of the scene being viewed. At more regional scales, to a maximum of 15 m spatial resolution, the scenes are usually displayed using pan-sharpened Landsat 7 ETM+ imagery. Examining the imagery in the visible range of the spectrum displays the scene in true colour using the red, green, and blue wavelengths. This is how you would expect to observe the landscape if looking out the window of the Orbiter of the Space Shuttle, for example.



Fig. 4.2: Wide area coverage of the western Nile Delta showing densely populated urban areas. Modern cities have been marked. Boxed area shows a region that is enlarged in Fig. 4.3 (GE Landsat ETM+ imagery).

Observing large swaths of the Nile Delta, the full extent of both modern and ancient urban development on the landscape becomes apparent (Figure 4.2). The lush vegetation of the Delta appears as a dark green colour, Nile tributaries a dark blue, and tell sites, modern urban centres, and roadways, a light shade of grey. Thousands of ancient and modern urban centres are scattered throughout the landscape in globular clusters, connected by linear networks of roadways. However, the differentiation of tells from modern sites appears impossible when viewed using Google Earth imagery.

Zooming in further, the Google Earth imagery, Landsat ETM+ data is seamlessly exchanged for higher resolution data – such as from the French satellite SPOT, capable of resolutions of up to a few metres. At these resolutions, the larger tell sites become more recognizable. Figure 4.3 shows an enlargement taken from the boxed area in Figure 4.2. In this image several tell sites are visible and are identified by their name and a small red or yellow square (see Section 4.5 for colour significance). The tell sites appear to have a different texture and darker colour when compared to modern sites.



Fig. 4.3: GE imagery showing tell sites marked in red and yellow, several of which are adjacent to modern settlements. Boxed area discussed in text (see Figure 4.4).

Zooming still further into the imagery, high-resolution imagery (QuickBird-2), with a spatial resolution of approximately half a metre (60 centimetres), takes the place of SPOT or equivalent resolution data. At these resolutions, recognition of buildings and other similar sized features become possible. Figure 4.4 shows the tell site Tell ed-Daba (boxed region from Figure 4.3) at an even larger scale. On closer examination, due to the much higher resolution, subtle differences in both texture and colour of the tell site become more apparent. At these resolutions, tell sites take on a smoother and darker appearance, compared to the lighter, speckled appearance of modern developments. Even so, examining satellite imagery only in the visible wavelengths, even at high spatial resolution, tell sites cannot be easily separated on the basis of their spectral characteristics from surrounding sites. It would take great effort to examine large areas of satellite imagery in the visible range at high resolution in order to identify them.



Fig. 4.4: QuickBird-2 image showing differences in colour and texture between tell site Tell ed-Daba (red square) and surrounding modern developments. The tell site is located in the northwestern Nile Delta and listed in both the EES (number 269) and UU catalogues. It was first visited in 1990 and mapped in 2011 by the EES Delta survey.

Google Earth imagery is restricted in some respects due to the limited number of channels that it can use when rendering an image (see Section 3.6). When viewing Landsat ETM+ imagery, for example, only the first three bands (RGB: 3, 2, 1), representing the visible wavelengths of the spectrum, are displayed, where band 3 is sent to the red colour gun, band 2 to the green, and band 1 to the blue. All other multispectral channels in the Landsat data set are truncated and not used in the final display. Moreover, the order in which the three channels are sent to the colour guns cannot be changed. It is only when satellite imagery is viewed from a truly multispectral perspective – using regions beyond the visible – into the shortwave infrared and thermal infrared, do tell sites become more spectrally distinct. Being able to use the full multispectral capability of a data set and change the combinations of bands is essential when interpreting imagery. Google Earth is therefore severely restricted in this respect as a multispectral imaging tool.

In summary, when using Google Earth to view the landscape in the visible region of the spectrum, at various levels of spatial resolution, tell sites are difficult to differentiate from modern structures. When viewed at low spatial resolutions, as in Figure 4.2, tell sites appear identical to modern settlements. At much higher spatial resolutions, tell sites become more visually distinct in both colour and texture (Figures 4.3 - 4.4). However, mapping tell sites using a rapid scan of the eye is time-consuming, subjective, and not particularly accurate. A stronger quantitative approach is needed, taking advantage of a multispectral data set, in combination with digital image processing algorithms. This is the subject of the next section.

4.5 Study area; imagery data set; pre-processing

The remainder of this chapter describes a methodology for the detection of tell sites using Egypt's northwestern Nile Delta as a case study. This region was selected due to the large number of surviving sites, many of which have been mapped by prior surveys (this is in contrast to tell sites in Middle Egypt which are poorly represented). The objective was to determine if satellite imagery could be used to detect previously known sites, in addition to locating new sites for future investigation. A fully multispectral approach using imagery from Landsat ETM+, ASTER, and Google Earth data is presented. The remote sensing performed in this case study complements and advances the work undertaken by Sarah Parcak (University of Alabama, Birmingham), who first suggested that principal components analysis (PCA) could be used to detect tell sites in the eastern Nile Delta (Parcak, 2007).

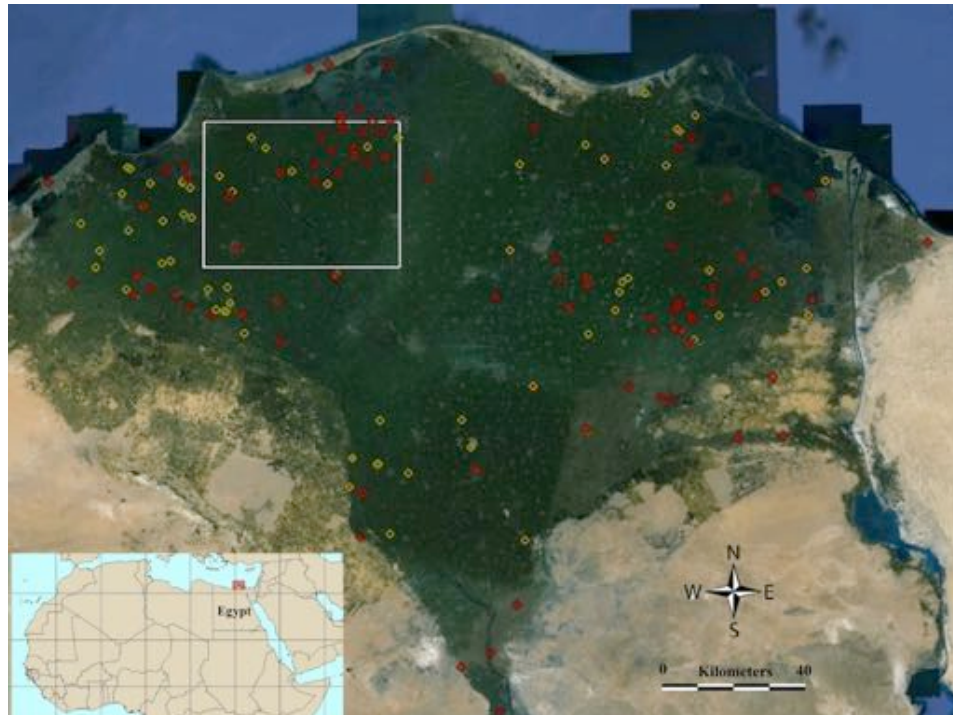


Fig. 4.5: GE image (Landsat ETM+) of the Nile Delta with boxed study area and tell site overlay (catalogue of sites acquired early 2001)

The work presented here goes beyond Parcak's work by using the northwestern Delta as a case study to develop a methodology for tell site detection, taking advantage of higher spatial and spectral resolution satellite data and novel image processing techniques.

Known tell sites contained in two Google Earth KML files were added as separate layers to GE base imagery. These data sets included location data from both the EES Delta Survey (EES) and from the Uppsala University (UU) catalogues, marked in yellow and red respectively, in Figure 4.5. The white box in the northwestern region of the Nile Delta indicates the 50 x 40 km study area, centred at 31° 5' North latitude, 30° 46' East longitude. This region contained a total of twenty-four known tell sites – nine from the EES and fifteen from the UU catalogues, located in the northern region of the Rosetta branch of the Nile (Figure 4.6). It should be noted that the two catalogues used in this work did not employ satellite imagery to locate tell sites but were based on a campaign of ground surveys. Furthermore, the EES GE database, although reasonably complete, did not include all known tell sites and therefore did not represent a complete record for the area.

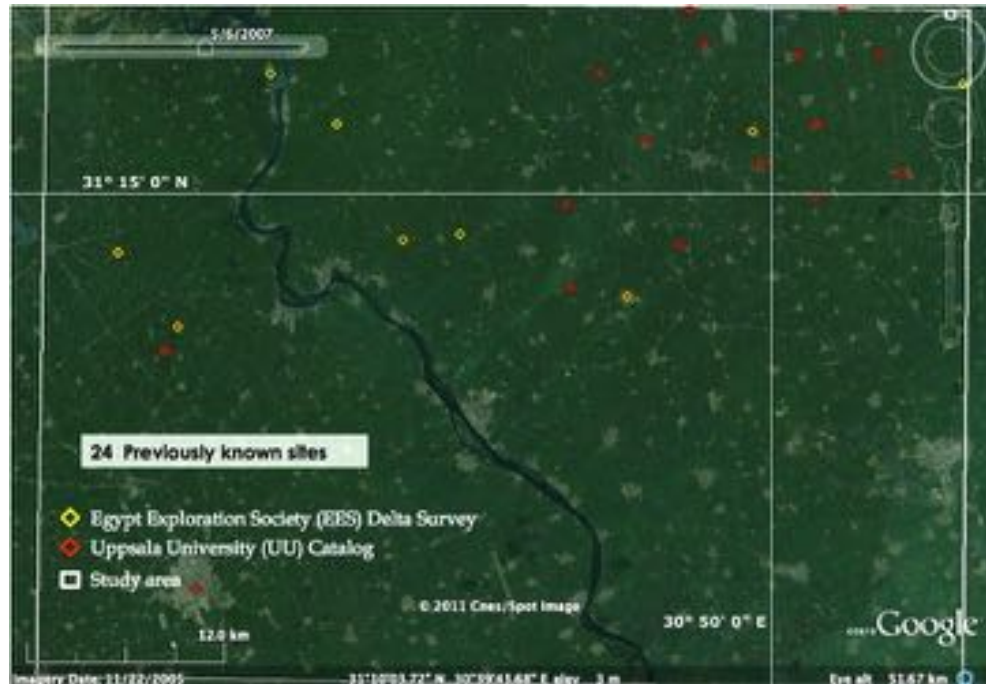
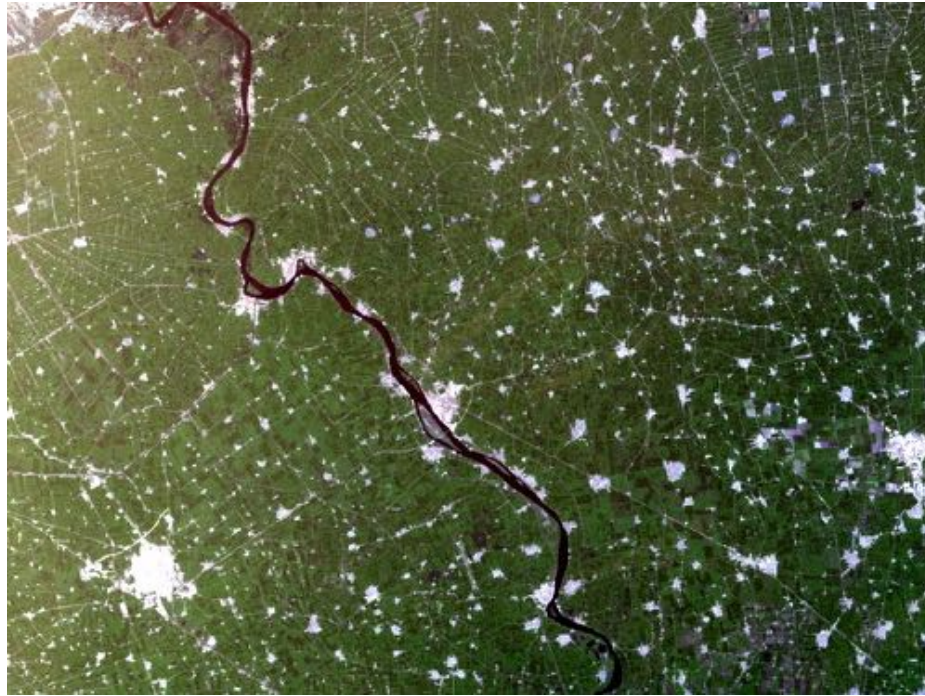


Fig. 4.6: Google Earth image of the study area with EES and UU tell site overlay (catalogue of sites acquired early 2001).

It has been shown that increased moisture content in mud brick can be a key factor for successfully locate tell sites (Parcak, 2007). In Egypt, December through February are considered the wettest months of the year and data acquired during this time provide optimal conditions for imagery analysis. Therefore imagery was selected from a subset of data that was recorded between these months.

A single Landsat-7 ETM+ scene (Path 177, Row 38), acquired by the satellite on January 27, 2003, was downloaded from the Land Processes Distributed Active Archive Centre (LP DAAC, <https://lpdaac.usgs.gov/>), using WIST - the NASA Warehouse Inventory Search Tool. Although the Landsat scene had a relatively high cloud content (about 25%), the clouds were restricted to regions over the ocean, in the northern half of the satellite scene, and did not affect the image processing workflow. Figure 4.7 shows a subset of the full scene, corresponding to the study area, displayed in true colour (channels 3, 2, 1). The subset scene was unaffected by the aforementioned cloud coverage.



Sensor	Bands used	Path / Row	Date	Cloud coverage
Landsat ETM+	1, 2, 3, 4, 5, 7, 8	177 / 38	January 27, 2003 (SLC-on)	25.57%

Fig. 4.7: Landsat ETM+ subset of the study area displayed in true colour (RGB: 3, 2, 1)

A full ETM+ data set (Table 4.1) consists of eight channels, including four in the VNIR (bands 1 - 4), two in the SWIR (bands 5 and 7), one in the TIR (band 6), and one high-resolution panchromatic channel (band 8). All bands were used except for the TIR, which was discarded due to being incompatible with the reflected bands, and much coarser in spatial resolution (60 vs. 30 m).

Pre-processing of the imagery involved the following steps: 1) Data import: Bands were imported from GeoTIFF format (.tif) into ERDAS IMAGINE's native file format (.img); 2) Layer stacking: After importing the data, the individual channels were layer-stacked (excluding band 8) as a single multilayer .img file. Each of the six bands (1, 2, 3, 4, 5, and 7) had a spatial resolution of 30 m and therefore no resampling was required;

Band Number	Spectral range (μm)	Description	Resolution(m)
1	0.45–0.52	VIS / Blue - green	30
2	0.52–0.60	VIS / Green	30
3	0.63–0.69	VIS / Red	30
4	0.76–0.90	Near IR	30
5	1.55–1.75	Shortwave IR	30
6	10.40–12.50	Thermal IR	60
7	2.08–2.35	Shortwave IR	30
8	0.52–0.90	Panchromatic	15
Table 4.1: Landsat-7 ETM+ sensor specifications			

3) Quality control: Each channel within the layer stack was displayed in greyscale and visually inspected for bad detector response or errors resulting from the data recording and transmission process, such as banding or dropped scan lines; 4) Subsetting: The Landsat scene (the multispectral and panchromatic data sets) was subset to the geographic extents of the study area; and 5) Radiometric correction: The digital number (DN) of each pixel in each band was converted to at-satellite reflectance. In some cases step 5 was not applied so as to preserve the original radiometry of the scene. An optional step involved pan-sharpening the imagery using the 15 m high resolution band. This was usually not necessary if viewing it in true colour as the Google earth imagery could be used at much higher resolutions. However for other non-standard band combinations this was an option.

Figure 4.7 shows the Landsat image after pre-processing has been applied, where the scene has been subset to the study area, radiometrically corrected, pan-sharpened, and displayed in true colour (3, 2, 1 band combination). Image statistics for the raw DN values were recorded, including the minimum, maximum, mean, and the standard deviation for each of the six channels (Table 4.2). Calculating image statistics were important so as to be able to compute the Optimum Index Factor (OIF) and for running the Principal Components Analysis (PCA); see Sections 4.7 and 4.9 respectively.

Band #	Spectral region	Min	Max	Mean	Std. dev.
1	Blue-green	35	83	42.921	2.851
2	Green	24	83	34.071	2.909
3	Red	18	97	28.814	5.303
4	NIR	22	169	111.698	22.190
5	SWIR	9	96	38.726	5.790
7	SWIR	6	221	23.014	5.184
Table 4.2: Univariate statistics for Landsat-7 ETM+ image shown in Fig. 4.7					

Converting the raw, uncalibrated DNs to reflectance values (radiometric correction) is a two-step calculation. The DNs are first converted to radiance at sensor values, with units of $\text{W m}^{-2} \text{sr}^{-1} \mu\text{m}^{-1}$ (spectral radiance). This requires the gain and bias parameters of the sensor, which can be found in the metadata file, included with the data set (named with a .MTL extension for Landsat-7 data). This calculation can be performed using one of two equations. The choice of which equation to use depends on the type of calibration data available in the metadata file. One equation uses the gain and bias, while the second uses the LMin and LMax spectral radiance factors. The two conversion factors are as follows:

$$L_{\lambda} = \text{gain} \times \text{DN} + \text{bias} \quad (\text{Equation 4.1})$$

where, L_{λ} = spectral radiance cell value at the sensor's aperture
($\text{W m}^{-2} \text{sr}^{-1} \mu\text{m}^{-1}$)

Gain = gain value for the specific band ($\text{W m}^{-2} \text{sr}^{-1} \mu\text{m}^{-1}$)

DN = digital number cell value (dimensionless)

Bias = bias value for the specific band ($\text{W m}^{-2} \text{sr}^{-1} \mu\text{m}^{-1}$)

$$L_{\lambda} = \left(\frac{LMAX_{\lambda} - LMIN_{\lambda}}{QCALMAX - QCALMIN} \right) \times (QCAL - QCALMIN) + LMIN_{\lambda} \quad (\text{Equation 4.2})$$

where L_{λ} = spectral radiance cell value at the sensor's aperture
($\text{W m}^{-2} \text{sr}^{-1} \mu\text{m}^{-1}$)

QCAL = quantized calibrated pixel value in DN (dimensionless)

LMIN _{λ} = spectral radiance, scaled to QCALMIN

$$\begin{aligned}
& \text{(W m}^{-2} \text{ sr}^{-1} \mu\text{m}^{-1}\text{)} \\
\text{LMAX}_i &= \text{spectral radiance, scaled to QCALMAX} \\
& \text{(W m}^{-2} \text{ sr}^{-1} \mu\text{m}^{-1}\text{)} \\
\text{QCALMIN} &= \text{minimum quantized calibrated pixel value in DN} \\
\text{QCALMAX} &= \text{maximum quantized calibrated pixel value in DN}
\end{aligned}$$

Landsat ETM+ uses the LMin_i and LMax_i values in its .MTL metadata file to represent the spectral radiance scaling factors. These values can be found under the heading of GROUP = MIN_MAX_RADIANCE. Each band minimum and maximum scaling factor is designated as LMIN_BANDx and LMAX_BANDx, where x can be substituted for the band number.

The second radiometric correction step involves converting from spectral radiance to exoatmospheric (apparent) reflectance, which is a dimensionless value, representing the ratio of upwelling to downwelling radiation, measured on a scale between 0 and 1 (or 0 – 100 %). This calculation requires scene-specific parameters, including the solar zenith angle (in degrees), and the mean Earth-Sun distance (in astronomical units). Converting from spectral radiance to reflectance can be computed using Equation 4.3:

$$\rho_p = \frac{\pi \times L_\lambda \times d^2}{ESUN_\lambda \times \cos \theta_s} \quad \text{(Equation 4.3)}$$

where	ρ_p	=	Exoatmospheric (planetary) reflectance (dimensionless)
	L_λ	=	Spectral radiance at the sensor's aperture (W m ⁻² sr ⁻¹ μm ⁻¹)
	d	=	Earth - Sun distance (astronomical units, AU)
	ESUN _λ	=	Mean Solar exoatmospheric irradiance (W m ⁻²)
	θ _s	=	Solar zenith angle (degrees)

When computing reflectance, the radiance image is used on a per pixel basis as the input for radiance values (L_λ). The other parameters required from Eq. 4.3 can be found either in the metadata file, i.e., the Solar zenith angle or in the Landsat-7 Science Data Users Handbook (NASA, 2011), i.e., the Earth to Sun distance and the mean Solar irradiance. For Landsat-7 ETM+ data, the Solar zenith angle can be calculated from the SUN_ELEVATION entry in the metadata file (90 – Sun elevation angle). Utilities for converting from DNs to radiance values are usually included in most professional remote sensing applications. During the conversion process parameters have to be entered in manually from the above sources. Other imagery products, such as ASTER, may be automatically corrected for you when they are imported, and this should be stated in the help file. Nevertheless it is important to understand

the process, including the units of the quantities, so as to not treat it as a black box. Satellite imagery acquired by other sensors may not have a utility built into the remote sensing software to perform radiometric correction and will therefore need to be corrected manually using tools such as the Spatial Modeler in ERDAS IMAGINE or the Band Math tool in ENVI.

As discussed (Subsection 2.6.4) the decision to perform a radiometric correction is an important consideration. Although not strictly required when working with a single scene, it is essential when quantitatively comparing spectral information between scenes of a multi-scene – and therefore multi-temporal data set. This is because the data is uncalibrated so that when several scenes taken at different dates are combined, the DNs of each scene do not have a relationship between one another. The radiometric correction of mosaicked imagery, where two or more scenes have been stitched together, calibrates and gives physical units to the underlying values for each pixel value across the whole merged data set. Although the previous work used a single Landsat scene, the radiometric correction was applied so as to maintain consistency in the workflow, although the step could have been omitted. Later in this chapter, multiple ASTER scenes are mosaicked and therefore radiometric normalization was required; it was therefore necessary to explain the procedure. Figures 4.8 and 4.9 show the workflow for converting Landsat-7 DN values to reflectance, where key parameters from the metadata file have been input into the utility. The red-boxed areas in Figure 4.8 show the parameters that are needed so that the utility can be executed. The utility shown in Figure 4.9 is accessed in a web browser (www.fourmilab.ch/cgi-bin/Solar) and calculates the Earth – Sun distance in astronomical units (AU). Annotations in the figure show the steps that are required.

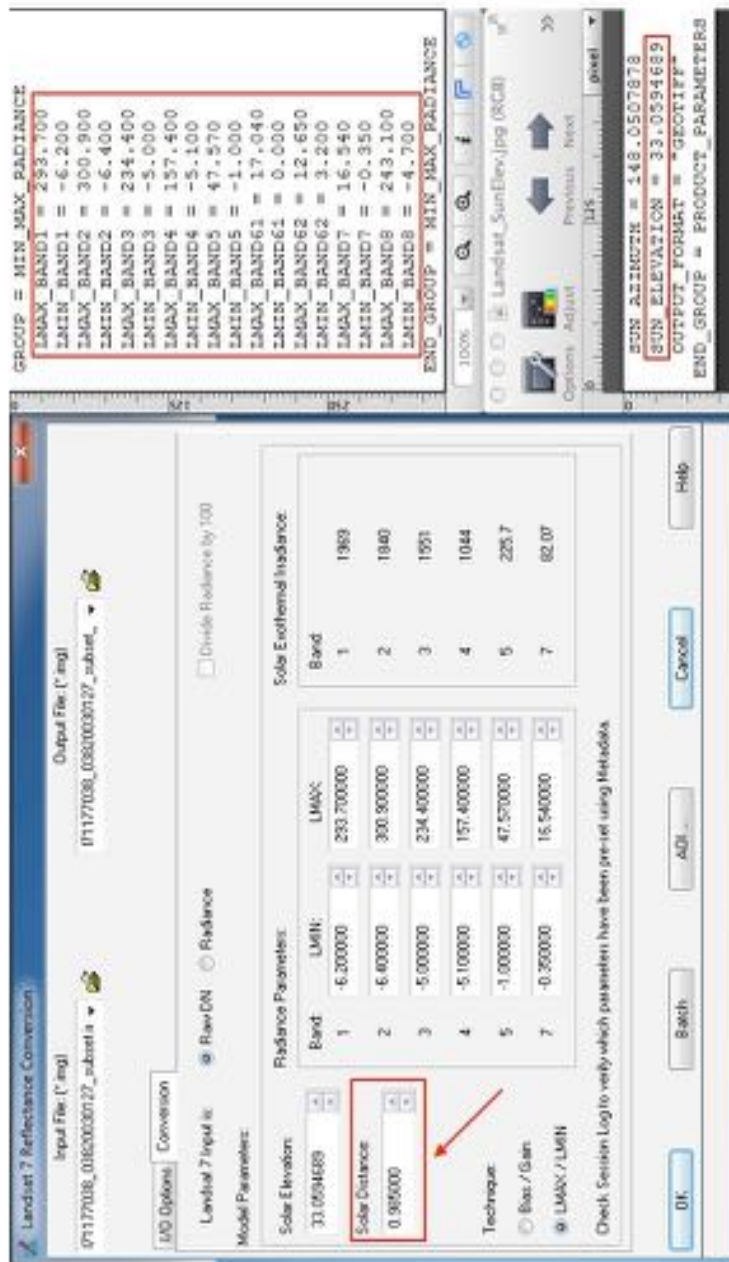
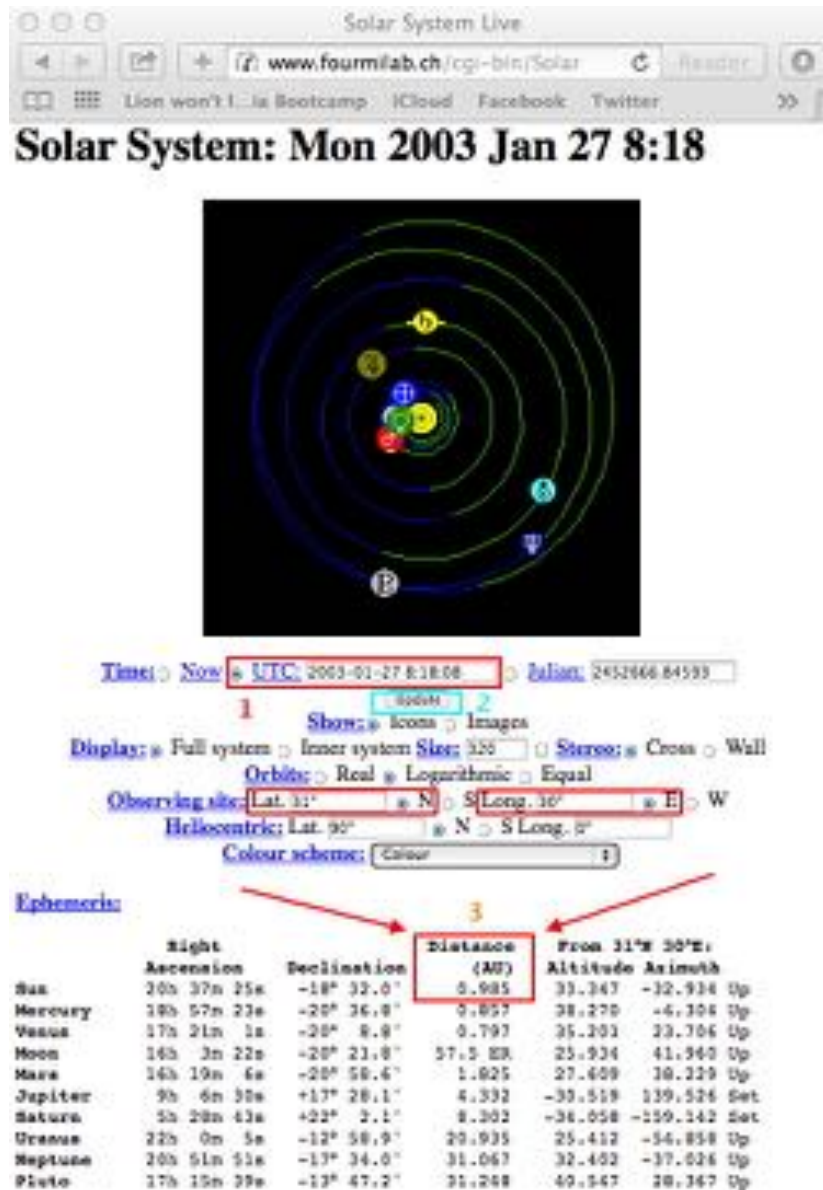


Fig. 4.8: Computing reflectance values from digital numbers (DNs) using ERDAS IMAGINE's conversion utility



1. Enter the MIN_MAX_RADIANCE values from MTL file into Reflectance Conversion dialog
2. Enter SUN_ELEVATION parameters from MTL file into Reflectance Conversion dialog
3. Enter orbital parameters into Solar System Live website (www.fourmilab.ch/cgi-bin/Solar)
4. Calculate Solar distance using Solar System Live update button and enter into Conversion dialog
5. Compute reflectance values from digital numbers

Fig. 4.9: Calculating the Earth-Sun distance (in AU) given the orbital parameters

The exoatmospheric reflectance, also known as top of atmosphere reflectance (ToA), does not consider the effects of the atmosphere on the signal. Atmospherically correcting an image can be complex and may not always offer much benefit, especially if a corrected image is to be used in further image processing operations, such as classification. Atmospheric correction changes the underlying digital numbers of the pixels that the satellite sensor measured. It should therefore be used with caution so as not to change the scene's radiometry. Furthermore, single scene studies usually don't require an atmospheric correction. Atmospheric correction should be performed in such situations as calculating ground reflectance, comparing radiance to ground reflectance measurements, and when conducting a change detection study.

Landsat ETM+ data processed using imagery analysis software appears to display greater contrast when compared to the rather washed-out appearance of Google Earth imagery (Figures 4.2 - 4.6). The subtle tonal and texture differences between the tell sites and the modern settlements are much clearer when viewed using the multispectral images. For

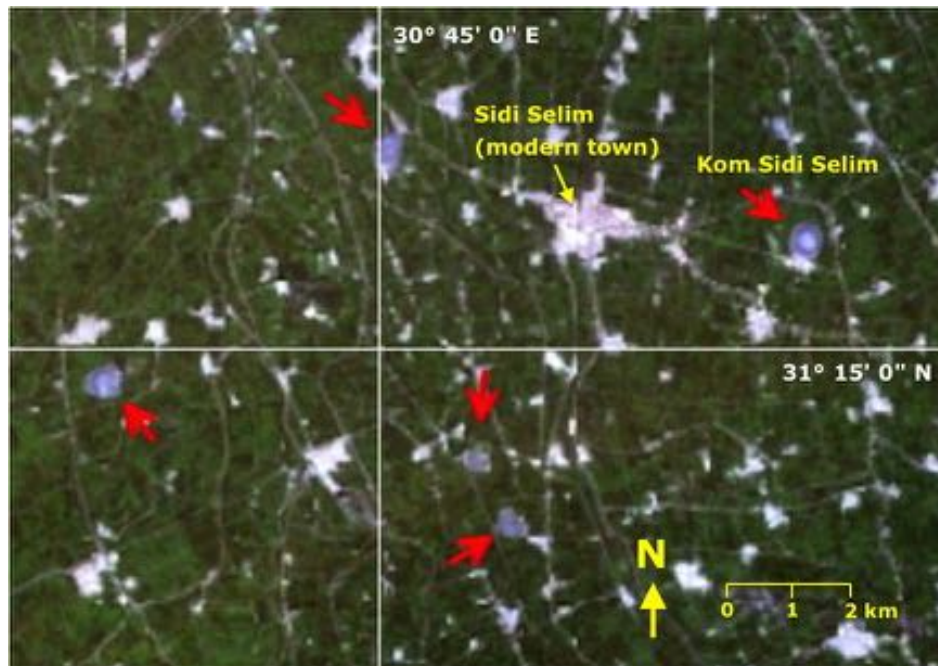


Fig. 4.10: Landsat ETM+ subset (3, 2, 1) from Fig. 4.7 showing colour and texture differences between tell sites and modern settlements. Several tell sites are indicated by red arrows.

example, in the processed ETM+ image shown in Figure 4.10, several tell sites are distinguishable by their marked contrast difference when compared to surrounding modern sites. Tells appear as a blue-grey colour (indicated by red arrows), whereas modern sites appear a much lighter white-grey colour. This may be due in part to the Google Earth compression algorithms that facilitate faster upload times by reducing resolution in the spectral domain.

An optional pre-processing step involves pan-sharpening the multispectral dataset (30 m) with the high-resolution panchromatic band (15 m), using a principal component algorithm with nearest neighbour resampling. Increasing the spatial resolution of a data set may not improve the ability to classify finer levels of spectral detail, but it does allow for the mapping of smaller features, thus helping to address the mixed-pixel problem. The benefits of pan-sharpening can be seen in Figure 4.11, where the city of Fuwa (31° 12' N, 30° 33' E) in Kafr el-Sheikh province is used as an example. The image is displayed using a band combination of 4, 3, 2 (NIR, Vis-Red, Vis-Green). The image on the right is visibly sharper than the one on the left, containing greater definition in the urban (grey), in addition to the vegetated (red) areas. This step was used only for visualization purposes and was not part of the methodology for site detection. This is because most tell sites are large enough not to warrant pan-sharpening, especially when higher resolution data in Google Earth can be used as a follow up ground-truthing tool (see Section 4.13). Furthermore, pan-sharpening changes the pixel values of the original image, which should be avoided when at all possible.

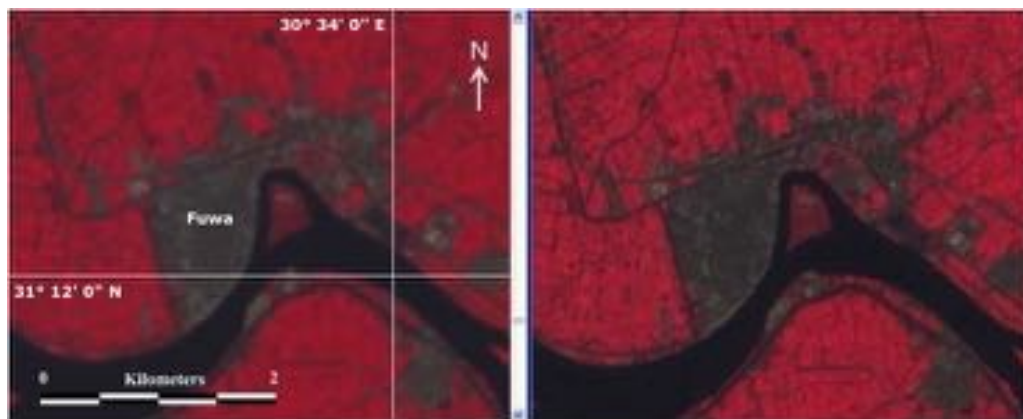


Fig. 4.11: Landsat ETM+ FCC image (4, 3, 2) at a 30 m spatial resolution prior to multi-resolution merge (left); same scene post 15 m PC merge (right)

4.6 Methodology 1: spectral profiling of tell sites; characteristics of “tell earth”

Tell sites are chiefly composed of mud brick, which was the principal building material used in ancient times. Covering the mud brick is usually a surface of silty soil (fine sand deposited as sediment). To better understand the spectral characteristics of tell sites a spectral profiling tool was utilized. This tool plots the distributions of DN_s (or reflectance values) of different land cover types against the different channels of the satellite sensor. The profiles produced are called spectral curves. Constructing a graph of spectral curves can assist in understanding how specific bands (i.e., wavelengths) may be used to identify specific materials or features. For example, Landsat-7 ETM+ band 4 (NIR) can assist in identifying highly vegetated regions due to their high reflectance values (when compared to other materials) at this wavelength (Figure 4.12).

Spectral profiles were collected from four different land cover classes, including water, modern urban settlements, agricultural land, and tell sites, making sure that the sample spectra were collected directly from single pixels (ensuring sample purity) by enlarging the imagery to pixel scale. To improve the accuracy of the measurements, ten samples were collected for

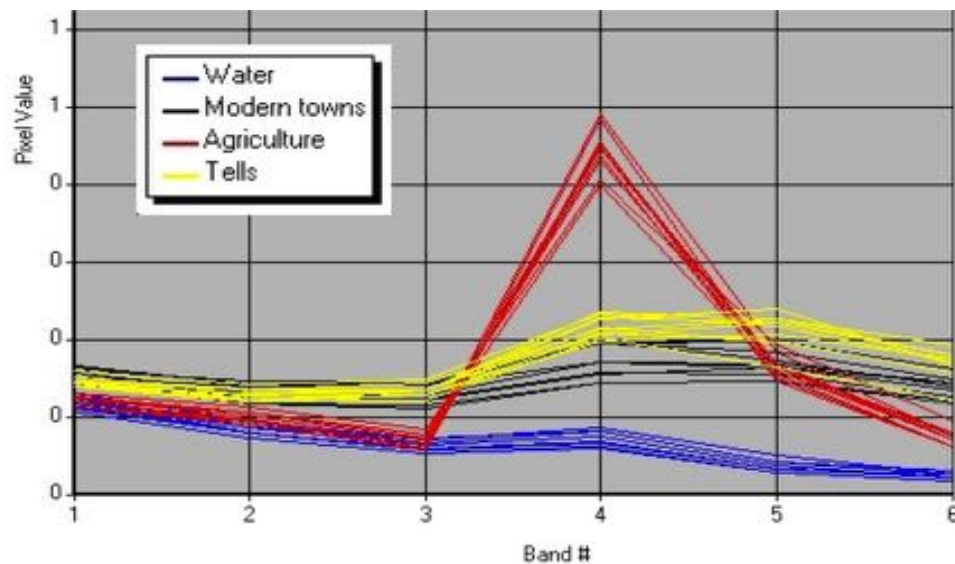


Fig. 4.12: Spectral profiles for several landscape cover types. Tell sites are displayed in yellow and modern settlements in black. Tell sites have consistently higher reflectance values when compared to modern sites in the NIR and SWIR regions of the spectrum.

each feature type; these were averaged together and displayed in graph format (Figure 4.12). Recall that Landsat ETM+ has 6 bands (not including the thermal or panchromatic channels), therefore the spectral curves extend across 6 channels. Band 6 in the figure refers to Landsat ETM+ channel 7 (SWIR).

Healthy vegetated regions, shown in red in the graph, display low reflectance in the visible (bands 1 - 3) and SWIR (bands 5 and 7), and high reflectance in the NIR (band 4). This peak in reflectance occurs because the pigments of the plant do not absorb the NIR energy but reflect about half of it, while the remaining half is transmitted through the leaf. Water (blue) exhibits high absorption throughout the spectrum, as would be expected, with the little reflectance it does exhibit, slowly decreasing with increasing wavelength, although showing a slight increase in the NIR. Modern towns and cities (black) and tell earth (yellow) share similar spectral characteristics, with a modest decrease in the visible, a slight increase in the NIR, and a decrease towards the end of the SWIR. Throughout the visible region of the spectrum, both tell sites and modern sites show similar reflectance values. However, in the NIR and the SWIR wavelengths, tell sites display modest increases in reflectance over modern sites and there may be potential for spectral separation in this region of the spectrum. This implies that channels from these subsystems may be important when formulating a strategy for tell site detection.

Difficulties in using spectral remote sensing as a detection tool are compounded by several factors. Firstly, modern developments are often found adjacent to tell sites or built over the top of them. Attempting to spectrally resolve an object that is in close proximity to a second spectrally different object brings into play the “mixed pixel” problem, which is when the signal from a single pixel contains more than one land cover type, so that several land cover classes contribute to the reflectivity. When mixed pixels are displayed at this resolution the signal received at the sensor is an average of the two different land cover classes. This problem in some ways can be resolved through the use of “sub pixel classifiers” or by using higher resolution imagery. A second difficulty that may be encountered is that tell mud bricks are often recycled from ancient sites and reused in the construction of modern developments, such as walls and buildings. Some modern sites may therefore exhibit spectral characteristics that are similar to those of tell sites and as a result be recorded as false positives.

4.7 Methodology 2: Band combinations and the Optimum Index Factor (OIF)

One difficulty often encountered in imagery analysis is deciding which band combinations are most appropriate to display, as each combination can enhance distinct features in the landscape. A sensor may provide hundreds of different channels covering many different portions of the EM spectrum. However, only three can be loaded in a display terminal at any one time, and therefore, a choice has to be made about which bands to include in the final output and which to leave out. For Landsat-7 data for example there are $6 * 5 * 4 = 120$ possible band combinations. Displaying each combination would be both time consuming and inefficient.

In an effort to determine the combination of bands that best enhance tell sites in the landscape a series of false colour composites (FCC) were constructed. In addition to displaying the usual band combinations, i.e., 3, 2, 1 (true colour) and 4, 3, 2 (false colour emphasizing the NIR in red), other combinations were tested with wavelength regions beyond the Visible and the NIR.

To help solve this problem, the Optimum Index Factor (OIF) was calculated to quantitatively assess the combination of bands that were best able to enhance the imagery. The OIF, first developed by Chavez, Berlin, and Sowers, 1982, was adopted to evaluate the data by examining all possible 3-band combinations, calculating the total variances within and between the bands, and ranking the combinations from highest to lowest on the basis of their spectral content. The highest score indicates the combination that displays the greatest amount of variance (i.e., the highest sum of standard deviations) with the least amount of duplication between bands (i.e., lowest correlation between band pairs). The OIF only indicates the choice of bands to display, leaving the analyst to decide the colour to which each band may be assigned.

Applied to the raw underlying DN values, the OIF is calculated by taking a ratio of the sum of the standard deviations and the sum of the absolute values of the correlation coefficients between two bands as shown in Equation 4.4.

$$OIF = \frac{\sum_{i=1}^3 \sigma_i}{\sum_{j=1}^3 |r_{ij}|} \quad (\text{Equation 4.4})$$

where σ_i = standard deviation of band i
 r_{ij} = correlation coefficient between bands i and j

This equation implies that the OIF will be high if the three-band combination contains a high degree of spectral information when compared to other combinations in the data set.

Both the standard deviations and the correlation coefficients were directly calculated from the image statistics (Table 4.2) and from the Correlation function utilized in the ERDAS IMAGINE Spatial Modeller (Figure 4.13), respectively. The correlation coefficients are displayed in a matrix, shown in Table 4.3, and indicate whether two bands of a dataset share any common information. A positive correlation exists when two variables increase together, whereas a negative correlation occurs when one variable increases and the other decreases. A perfect positive correlation is represented by the value +1.00, a perfect negative correlation by -1.00, while 0.00 indicates that no correlation exists between two variables. Note from the table how each band is perfectly correlated with itself (diagonal line of 1.00 values).

The correlation coefficients indicate the degree of redundancy between any two bands. Bands from the same subsystem occupy similar wavelength regions and tend to share much of the same spectral information. As a result, a large amount of redundancy often exists between these bands. In contrast, bands from different subsystems occupy distinct wavelength regions and tend to contain dissimilar, and therefore more unique, spectral content.

Examining the correlation matrix shows that the visible bands are highly correlated with each other, at 90% (0.90), meaning that 90% of the information is shared and only 10% unique between the bands. Both SWIR bands are correlated with each other at 75%. The NIR band has a negative correlation with the visible bands (correlations of -0.44, -0.27, and -0.57), and with the farthest SWIR band (-0.31). It has been suggested that band combinations should be constructed using a channel from each of the Visible, NIR, and SWIR wavelength regions as they can often result in more interpretable images (Jensen, 2004).

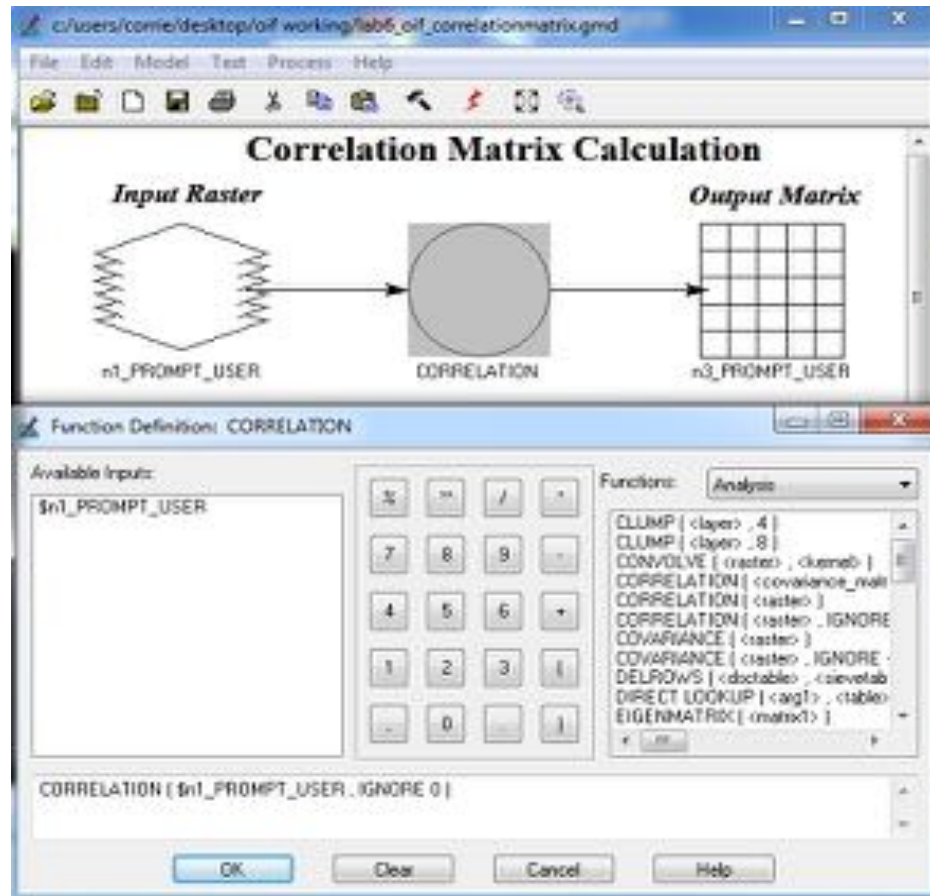


Fig. 4.13: Calculating the correlation matrix using IMAGINE's Spatial Modeler tool

Band	1	2	3	4	5	7
1	1.00					
2	0.90	1.00				
3	0.90	0.88	1.00			
4	-0.44	-0.27	-0.57	1.00		
5	0.43	0.64	0.46	0.33	1.00	
7	0.76	0.85	0.87	-0.31	0.75	1.00

Table 4.3: Correlation matrix for bands 1 – 5, and 7, for the image shown in Figure 4.7

The standard deviations from Table 4.2 and the correlation coefficients from Table 4.3 were entered into an Excel spreadsheet which had been pre-programmed with the OIF equation (Table 4.4). Running the OIF on the Landsat dataset produced a list of band combinations, sorted in numerical band order, the results of which appear in the lower left hand corner under 'Band Combo'. The data was sorted by OIF column and the ranked results presented, from highest to lowest, in the lower right hand corner under 'Ranked Band Combo'. Further details of the calculation and specifics of the OIF equation can be found in Chavez, Berlin, and Sowers (1982) and Chavez, Guptill, and Bowell (1984).

	A	B	C	D	E	F	G
1	Correlation Matrix						
2	TMband	1	2	3	4	5	7
3	1	1.00	0.90	0.90	0.44	0.43	0.78
4	2	0.90	1.00	0.88	0.27	0.64	0.85
5	3	0.90	0.88	1.00	0.57	0.46	0.87
6	4	0.44	0.27	0.57	1.00	0.33	0.31
7	5	0.43	0.64	0.46	0.33	1.00	0.75
8	7	0.78	0.85	0.87	0.31	0.75	1.00
9							
10							
11	Standard Deviation						
12	TMband	1	2	3	4	5	7
13		2.851	2.809	5.303	22.19	5.79	5.184
14							
15							
16							
17	Band Combo	OIF		Ranked Band Combo	OIF		
18	1,2,3	4.12		1,4,5	25.71		
19	1,2,4	17.41		2,4,5	25.02		
20	1,2,5	5.85		3,4,5	24.50		
21	1,2,7	4.37		4,5,7	23.94		
22	1,3,4	15.83		2,4,7	21.36		
23	1,3,5	7.80		1,4,7	20.06		
24	1,3,7	5.27		3,4,7	18.83		
25	1,4,5	25.71		2,3,4	17.64		
26	1,4,7	20.06		1,2,4	17.41		
27	1,5,7	7.11		1,3,4	15.83		
28	2,3,4	17.64		3,5,7	7.82		
29	2,3,5	7.08		1,3,5	7.80		
30	2,3,7	5.15		1,5,7	7.11		
31	2,4,5	25.02		2,3,5	7.08		
32	2,4,7	21.36		2,5,7	6.19		
33	2,5,7	6.19		1,2,5	5.85		
34	3,4,5	24.50		1,3,7	5.27		
35	3,4,7	18.83		2,3,7	5.15		
36	3,5,7	7.82		1,2,7	4.37		
37	4,5,7	23.94		1,2,3	4.12		
38							
39							
40	*Correlation matrix derived from Imagine using correlationmatrix_prompt.pmd						
41	*Standard deviation values for each band derived from Image Info, accessible from Imagine viewer						

Table 4.4: OIF worksheet showing correlation matrix and standard deviations for Landsat-7 ETM+ bands 1-5, 7 as inputs and computed OIF as output. All correlation matrix coefficients were entered as positive values into the spreadsheet due to the OIF formula expecting absolute values.

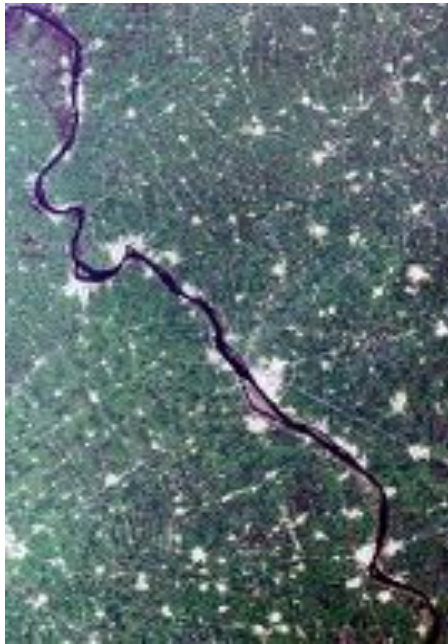
The four highest ranked band combinations are shown below.

1, 4, 5	2, 4, 5	3, 4, 5	4, 5, 7
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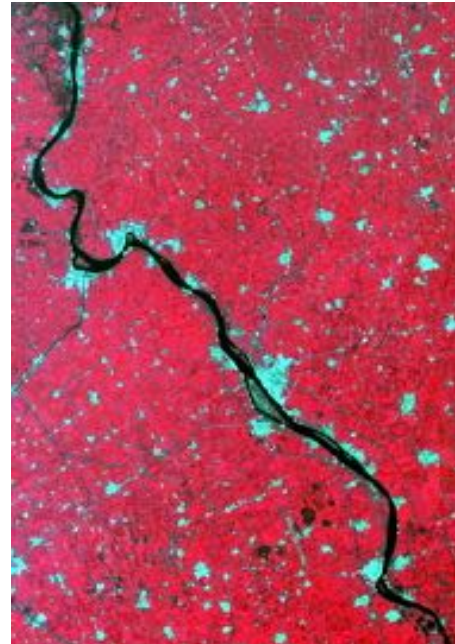
As expected three of the highest ranked combinations contain channels from all three subsystems (VIS, NIR, and SWIR wavelengths). Furthermore, out of the twenty possible Landsat ETM+ combinations, six of the highest-ranking seven all contained one band from each of the three subsystems. Viewing the imagery in true colour using only the visible region of the spectrum (combination 3, 2, 1) produced the lowest OIF ranking with a rating of just 4.12, whereas using channels from each of the three subsystems (combination 5, 4, 1) produced the highest ranking with a rating of 25.71. This confirms that viewing imagery using only the visible bands of the EM spectrum produces an image with the least amount of variation when compared to the original 6-band data set.

Four different band combinations are shown in Figure 4.14, including true colour (3, 2, 1) and false colour infrared (4, 3, 2), in addition to two of the highest OIF rated combinations: 1, 4, 5 and 4, 5, 7 – displayed as 5, 4, 1 and 7, 5, 4 respectively (the combinations are reversed here for aesthetic display purposes). Both the 5, 4, 1 and 3, 2, 1 band combinations were used throughout this case study for qualitative assessment of the imagery and for display purposes.

Figure 4.15 shows an enlarged region of the study area displayed using the OIF top ranked combination (5, 4, 1). Annotations identify the locations of three previously mapped tell sites - two from the EES and one from the UU survey catalogues (marked using the character ‘T’ with associated arrows). In this combination the tell sites and modern urban centres all map to the same light purple colour. Water features display as a dark blue-black colour, and agricultural fields appear as either green or yellow. Even when using the highest ranked OIF band combination tell sites cannot be visually differentiated from modern sites. Moreover, this was also true when displaying the imagery using all other band combinations. The results from the spectral profiling analysis (Section 4.6) suggested that tell sites show a modest increase in reflectivity in the NIR and SWIR wavelengths when compared to modern sites, however using simple band combinations at these wavelengths no single channel on its own was able to identify them. The next step was to apply various classification schemes – both unsupervised and supervised – to assist in the tell detection process.



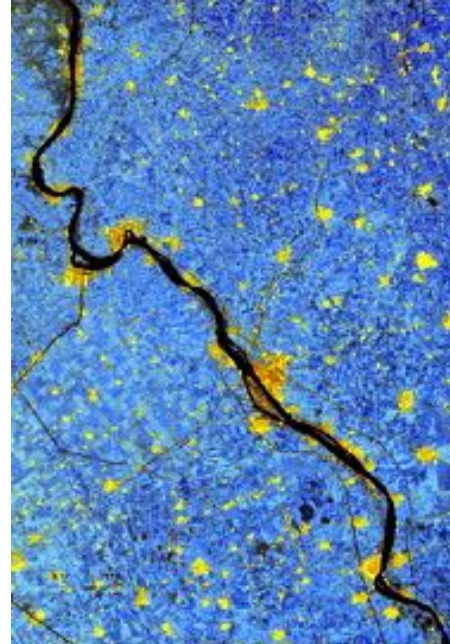
(a) true colour (3, 2, 1)



(b) false colour infrared (4, 3, 2)



(c) false colour composite (5, 4, 1)



(d) false colour composite (7, 5, 4)

Fig. 4.14: Using the OIF to determine the most appropriate band combinations to view Landsat-7 imagery

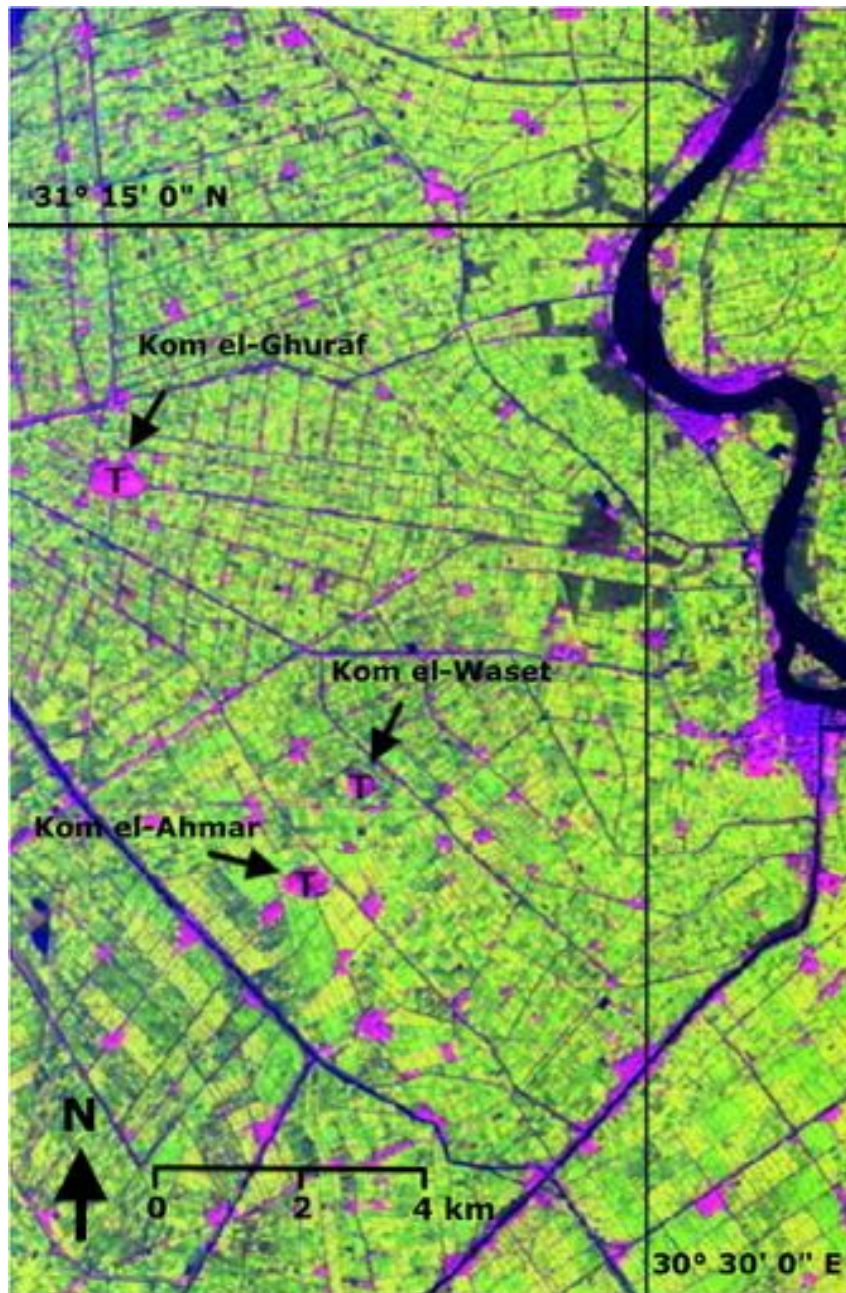


Fig. 4.15: Enlarged area, displayed using a band combination of 5, 4, 1, with added annotations. Three tell sites are indicated.

4.8 Approaches to imagery classification of sites: unsupervised and supervised

Classification was introduced in Chapter 3 as a means of simplifying a dataset by categorizing (classifying) pixels into a small number of classes usually based on their spectral characteristics. It was used here as a potential technique for tell site detection. It can also be seen as a way of reducing the size and complexity of a multiband data set.



Fig. 4.16: Performing an unsupervised classification using the ISODATA algorithm in ERDAS IMAGINE

Classifications were run on both the standard 30 m and the pan-sharpened 15 m Landsat data. The unsupervised classification was performed using the ISODATA algorithm (Figure 4.16), using the image statistics to generate clusters of pixels (in contrast to a supervised approach where training data is identified in the imagery which is then used to "train" the classifier). The number of classes was initially set to 10, which was later expanded to 30. Initializing options were set to seed the initial classes along the direction of majority image variance (principal axis) with a scaling range set at 2 standard deviations. The maximum number of iterations was set to 15, with a convergence threshold of 0.950.

Figure 4.17 shows an unsupervised classification of the Landsat data where 20 classes were merged into 4. These included agricultural (red), water (blue), modern and ancient settlement sites (black), and confused regions (white). The confused class consisted of a mixture of different land cover types, including agricultural fields and road networks that can be seen linking many of the urban sites. The classification was successful in identifying settlement sites, which stand out as black clusters in contrast to a sea of red agricultural fields. However, both modern and tell sites were represented as a single class and could not be separated.

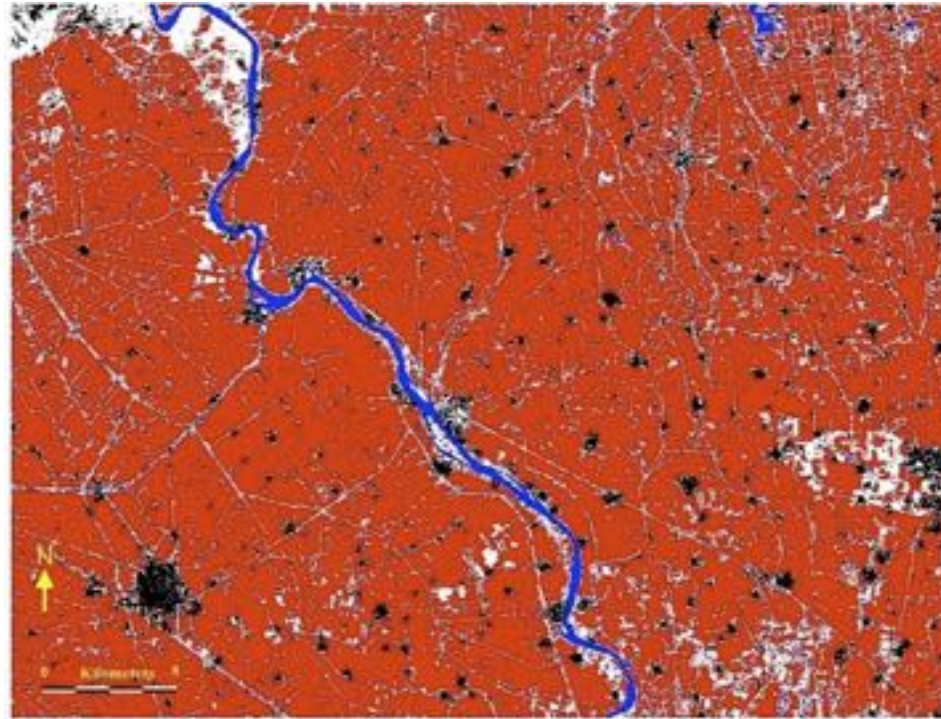


Fig. 4.17: An unsupervised classification produced four classes: agriculture (red), water (blue), settlement site (black), and confused (white). Both modern and ancient (tell) sites appeared as a single class and could not be distinguished regardless of the type of classification used.

The unsupervised classification therefore failed to detect tell sites, regardless of the parameters used, including the number of classes chosen, or whether the imagery had or had not been pan-sharpened.

A supervised classification was also performed. The supervised approach used a Maximum Likelihood classifier. Five classes were identified in the Landsat scene, including water, modern towns / cities, roads, tell sites, and vegetation / agriculture. Signatures were collected from training areas representative of each of the classes, including from 15 tell sites evenly distributed throughout the image. When collecting training data, imagery was zoomed to its maximum extent to ensure the collection of pure pixel values. The results from the classification were similar to the unsupervised approach showing that tell sites could not be spectrally separated from their modern counterparts. The increased spectral sensitivity of the ASTER sensor, with its 14 channels, including five in the TIR, may help to separate these classes in a future study.

4.9 Principal Components Analysis (PCA)

Section 3.7 described Principal Components Analysis (PCA) as a multivariate statistical technique for locating spectral patterns in data, for data reduction (reducing the dimensionality of a multiband dataset) and for decorrelating the channels within a highly correlated set of images. PCA is particularly important when performing an image classification, where many channels in the original data tend to be highly correlated, especially those that are spectrally close together. Because of the high degree of inter-band correlation, many channels end up sharing the same spectral content, and as a result large amounts of redundant information. PCA can be used to decorrelate the bands by rotating and transforming the original underlying digital values around a new set of axes, thereby defining a new coordinate space that is better able to display the underlying variance in the data.

In the present chapter PCA was used to transform a correlated multispectral set of images into a smaller number of linearly uncorrelated components with the objective of isolating the spectral signature for tell sites across a large swath of the western Nile Delta. Methodologies used in earlier sections of this chapter attempted to use band combinations and pixel-based classifications to spectrally separate tell sites. However, the information contained within the original bands may not have been arranged in the most effective manner and as a result the techniques proved unsuccessful.

PCA was applied to both a single 30 m Landsat ETM+ scene (6 bands) and a multiscene 15 m ASTER dataset (9 bands). The thermal bands from both data sets (Landsat ETM+ band 6 and ASTER bands 10-14) were not included. Unlike Landsat data which used a single scene, the ASTER data consisted of multiple scenes, and as a result the ASTER DNs were converted to reflectance values to radiometrically normalize the data prior to running the PCA. Figure 4.18 shows the dialog box and spatial modeller window for running PCA under ERDAS IMAGINE. IMAGINE does not automatically calculate the covariance matrix or the factor loadings, which are essential when conducting a PCA analysis. These were set up manually using the Spatial Modeler (see below) and an Excel spreadsheet respectively (Section 4.12). Applications, such as ENVI, output the calculations in one easy step, however in IMAGINE they need to be set up manually.

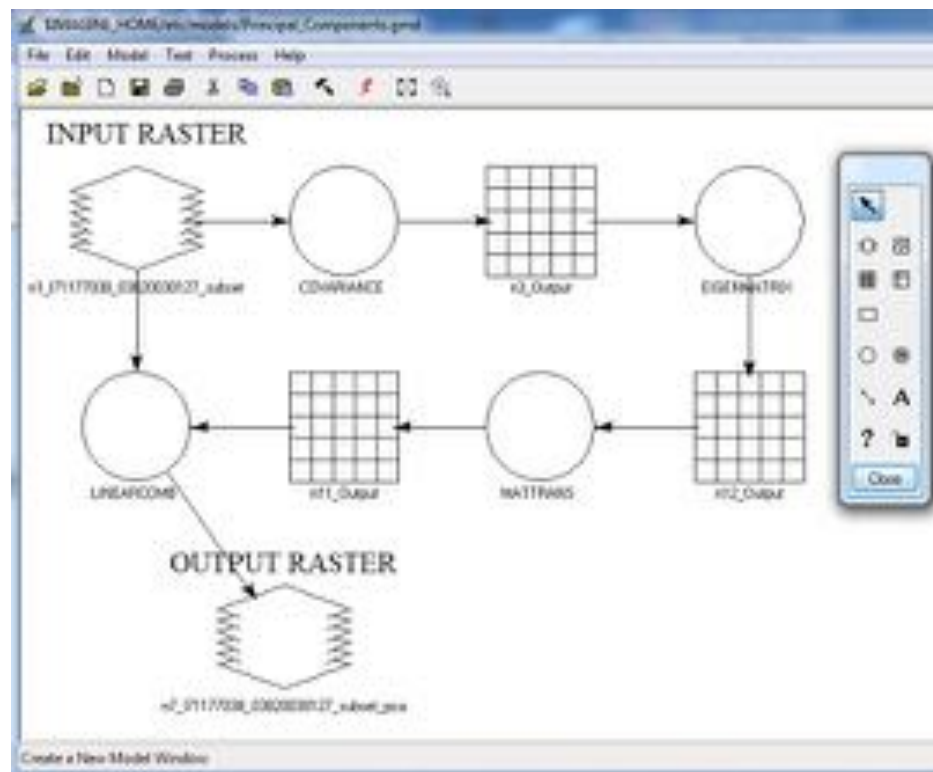
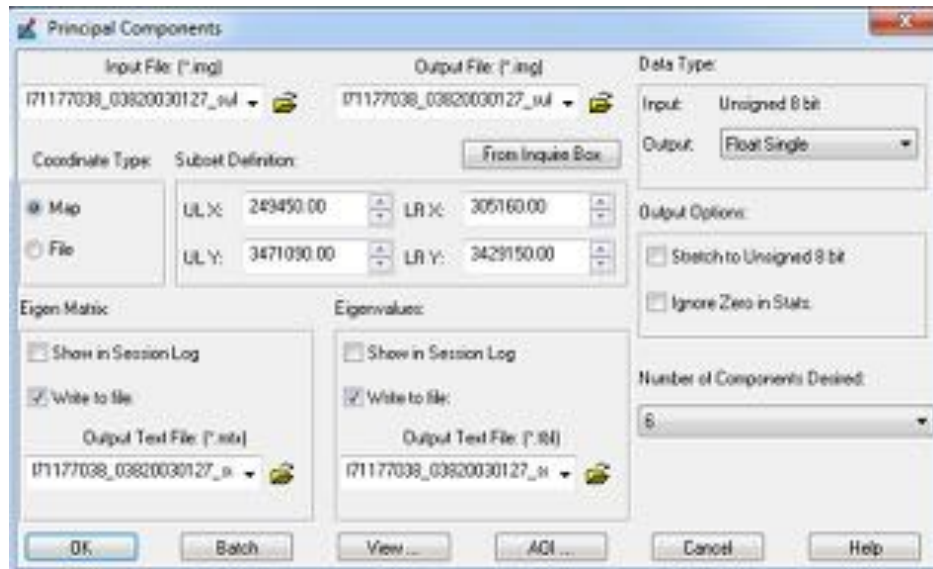


Fig. 4.18: ERDAS IMAGINE principal components dialog box and graphical model

As noted in Section 3.7, the maximum number of principal components (PCs) that can be created is equal to the maximum number of bands in the original dataset before the transformation. There were 6 channels in the Landsat ETM+ dataset, therefore 6 components were available in the output transformation.

Running PCA on a correlated set of images involves calculating the linear transformation coefficients from the spectral statistics and applying them to the original pixel values. The main steps can be summarized as follows:

1. Calculate either the correlation or covariance matrices;
2. Calculate the table of eigenvalues and the matrix of eigenvectors from the above;
3. Calculate the principal components images.

Depending on the choice of image processing software used, some of the steps can be set up using utilities built into the application, while others require the use of spatial modelling tools. In this work the covariance matrix was first calculated. The underlying statistics relating to covariance are best understood by first defining the variance. The definition of variance is the square of the standard deviation (s):

$$s^2 = \frac{\sum_{i=1}^n (X_i - \bar{X})^2}{(n-1)}, \text{ which can also be written: } \text{var}(X) = \frac{\sum_{i=1}^n (X_i - \bar{X})(X_i - \bar{X})}{(n-1)}$$

(Equation 4.5)

Both the standard deviation and the variance describe the “spread” of a single variable data set (i.e., a single band) with respect to the mean.

The covariance measures how two or more dimensions (bands) vary from the mean with respect to each other and is always measured between any two dimensions. The definition of covariance looks similar to the variance, except that instead of describing a single dimension (X), it describes a multidimensional data set ($X, Y, \dots$) and enables one to compare one channel to another. For instance, for 2 dimensions:

$$\text{cov}(X, Y) = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{(n-1)}$$

(Equation 4.6)

In an n dimensional data set, there are

$$\frac{N!}{(N-2)! \times 2} \text{ combinations of different covariance values.}$$

As a result, for the 6 band Landsat data, a total of 15 variance-covariance combinations is possible:

$$\text{i.e., } \frac{6!}{(6-2)! \times 2} = 15$$

For ease of readability, the combinations can best be presented in tabular format. The variance-covariance matrix for the Landsat data set is shown in Table 4.5. The matrix shows the variances and covariances between all the bands in the original data set, and is symmetrical about the main diagonal as well as having square dimensions (in this case producing a 6 x 6 matrix).

The main diagonal elements, highlighted in grey (also called the “trace”) show the variances for each individual spectral band, whereas, the remaining elements in the matrix show the covariances between two separate bands. A large variance indicates a large spread of pixel values and therefore a better chance for spectral separation. The total variance contained within the original bands is the sum of the trace, or the diagonal elements within the variance-covariance matrix, which amounts to a total of 597.49 (8.129 + 8.462 + 28.122 + 492.380 + 33.520 + 26.871).

ETM Band	1	2	3	4	5	7
1	8.129					
2	7.450	8.462				
3	13.612	13.635	28.122			
4	-27.960	-17.136	-67.572	492.380		
5	7.131	10.847	13.992	41.788	33.520	
7	11.205	12.747	23.994	-35.310	22.607	26.871

Table 4.5: Variance - covariance matrix of the Nile Delta subscene image shown in Fig. 4.7

The band containing the greatest information is ETM4 (NIR) with a variance of 492.380, which represents 82.41% of the total variance displayed in all six images ((492.38 / 597.49) * 100). The band containing the least information is ETM1 (VIS-Blue), with a variance of just 8.13, which accounts for just 1.36 % of the total variance.

From the variance-covariance matrix (Table 4.5) both the eigenvalues and eigenvectors are computed (Tables 4.6 and 4.7 respectively), using advanced matrix algebra. The mathematics used in the calculation is beyond the scope of this work; see Jensen (2004) for a more detailed discussion. The eigenvalues and eigenvectors represent the magnitude and direction of each component axis respectively. The eigenvalues describe the amount of the original variance explained by each of the new derived PC bands (highlighted elements in Table 4.6). After transforming the correlated data set into a set of uncorrelated components, the correlation between any two components should be 0. This implies that there is no shared information content between the PCs. This is why the eigenvalue matrix is usually written as a one-dimensional table, as the non-diagonal elements in the matrix will be 0.

The percentage of the total variance described by each of the PCs, %_p can be calculated using Equation 4.7.

$$\%_p = \frac{\text{eigenvalue } \lambda_p}{\sum_{p=1}^n \text{eigenvalue } \lambda_p} \times 100 \quad (\text{Equation 4.7})$$

The total variance contained within the original data set before transformation is conserved in the individual principal components after transformation. This can be shown by comparing the sum of the trace from the variance - covariance matrix in Table 4.5 with the sum of the eigenvalues in Table 4.6. The variances before and after transformation amount to the same value (597.49). This demonstrates that applying PCA to a set of correlated images does not create new variance but simply redistributes this information across a new set of uncorrelated components.

The contributions of each band to each component (the factor loadings) are computed from the eigenvectors, eigenvalues, and original band variances, which are discussed in Section 4.12. The principal component images, computed from the eigenvalues and eigenvectors, are shown in Figure 4.19 (displayed as greyscale images).

To transform the original data file values to PC values in the spatial domain, Equation 4.8 is

used: $P_e = \sum_{k=1}^n d_k \times E_{ke}$ (Equation 4.8)

where P_e = PC value for component e;
 d_k = data file value in band k;
 E_{ke} = Eigenvalue matrix at row k, column e.

	Component <i>p</i>					
	1	2	3	4	5	6
Eigenvalues, λ_p	510.562	78.098	6.079	1.476	0.719	0.551
Difference	432.464	72.019	4.603	0.757	0.168	--
Total variance	597.485					
% variance	85.45	13.07	1.02	0.25	0.12	0.09
Cumulative %	85.45	98.52	99.54	99.79	99.91	100.00
Table 4.6: Eigenvalues and cumulative eigenvalues for the image in Fig. 4.7						

	Component <i>p</i>					
	1	2	3	4	5	6
Band 1	0.060	0.231	-0.509	-0.374	0.536	-0.507
2	0.039	0.285	-0.372	-0.344	0.048	0.812
3	0.142	0.452	-0.486	0.359	-0.609	-0.199
4	-0.981	0.086	-0.138	0.102	0.007	-0.004
5	-0.076	0.602	0.538	-0.506	-0.245	-0.161
7	0.078	0.539	0.242	0.589	0.528	0.136
Table 4.7: Eigenvectors (factor scores) computed from the covariance matrix						

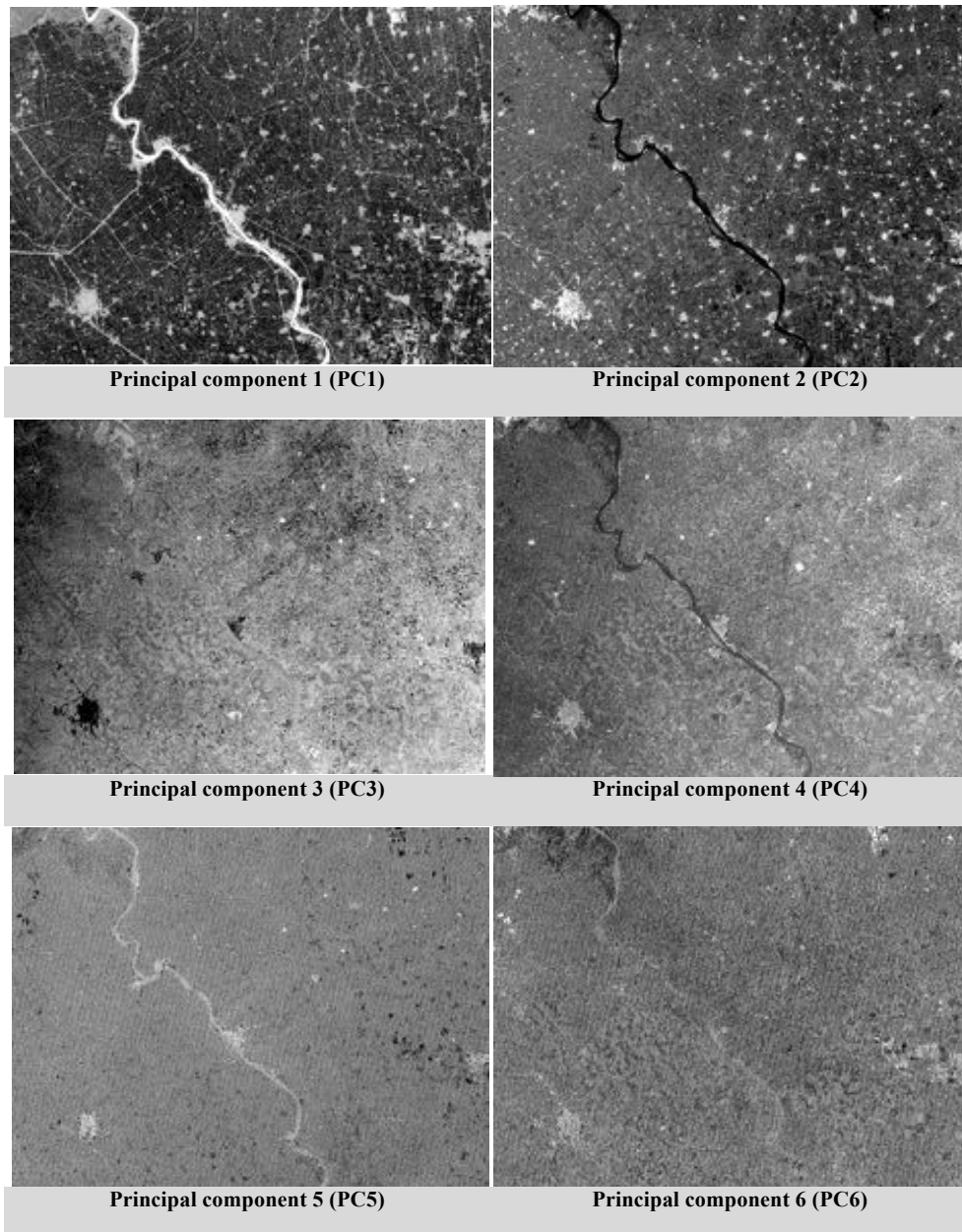


Fig. 4.19: Principal component images (PC 1 – 6) of the western Nile Delta area. Derived from six reflective spectral bands of Landsat ETM+ imagery obtained on January 27, 2003.

4.10 Discussion of results

The first principal component, PC1, contains the largest spread of data, accounting for approximately 85% $((511 / 597) * 100)$ of the variance of the entire multispectral data set (refer to Table 4.6). PC1 resembles a panchromatic image (Figure 4.20), with most variation attributed to changes in topography and albedo (overall brightness), and with little information associated with the spectral content. Therefore, in this component, it is impossible to differentiate tell sites from their modern counterparts. PC2 and PC3 account for a further 13% and 1% of the total variance respectively, and cumulatively the first three components account for over 99% of the original data. Therefore, in most instances, the last three components can be discarded with a loss of less than half a percent of information (0.46 %). This would result in a great improvement in both display and storage efficiency. However, often times, it is the last components that contain useful information and they should be visually checked before discarding them.

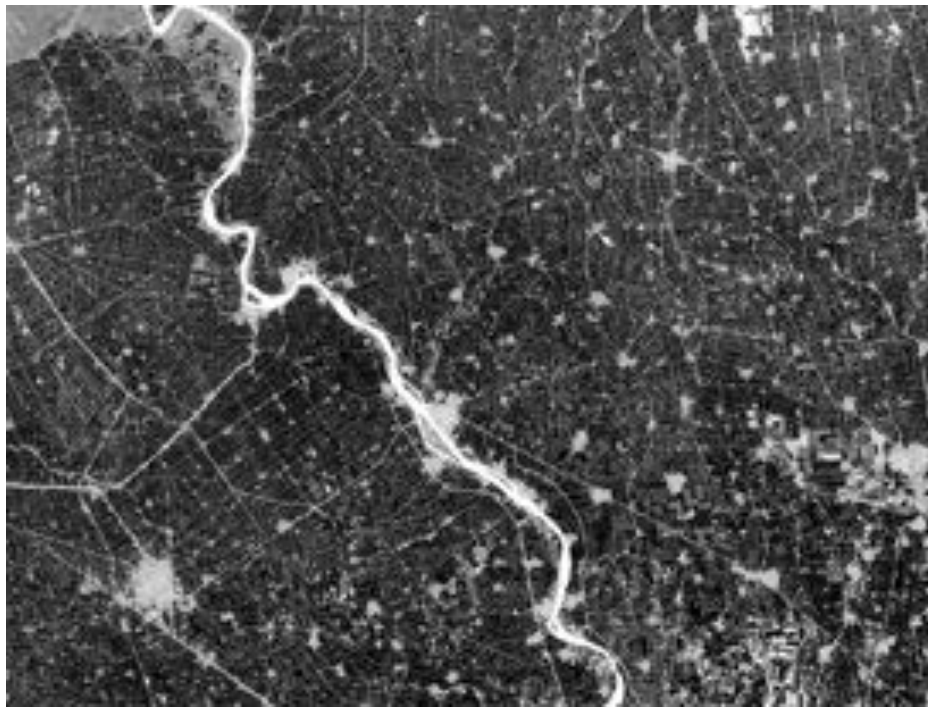


Fig. 4.20: PC1 image accounting for over 85% of the variance of original 6 ETM+ bands. In this component, both ancient and modern settlement sites cannot be distinguished.

Figure 4.21 shows a composite of the first three components, where PC1, PC2, and PC3, have been sent to the red, green, and blue colour guns of the display respectively. When viewing the higher-order components (lower numbered PCs) ancient and modern sites cannot be separated and appear identical to each other. Examination of the remaining components found that PC3 - 5 contained the variance required to detect tell sites (refer to Figure 4.19 for a side by side comparison of each PC image - the tell sites appear as bright regions in these images). More specifically, the fourth component, PC4, which accounted for only 0.25% of the total variance, was able to map all tell sites previously identified from the prior catalogues. These sites were confirmed using Google Earth imagery from the site location overlays. The results show that it is therefore important not to discount lower-order (higher numbered) components as they are often found to contain useful spectral content. PC4 is shown in Figure 4.22A after applying a two standard deviation stretch, where tell sites appear as high brightness greyscale values across the northern regions of the image. Applying a standard deviation (std) stretch is an enhancement technique that often improves the contrast in an image (see Section 4.9 for its formal definition). For a normal distribution of DN's, approximately 68%, 95%, and 99.7% of the values lie within 1, 2, and 3 standard deviations respectively. In a 2 std stretch, all values below 2.5% will be recoded to black and all values above 97.5% to white. This cuts off the tails of the data allowing for better contrast in the more commonly occurring values.

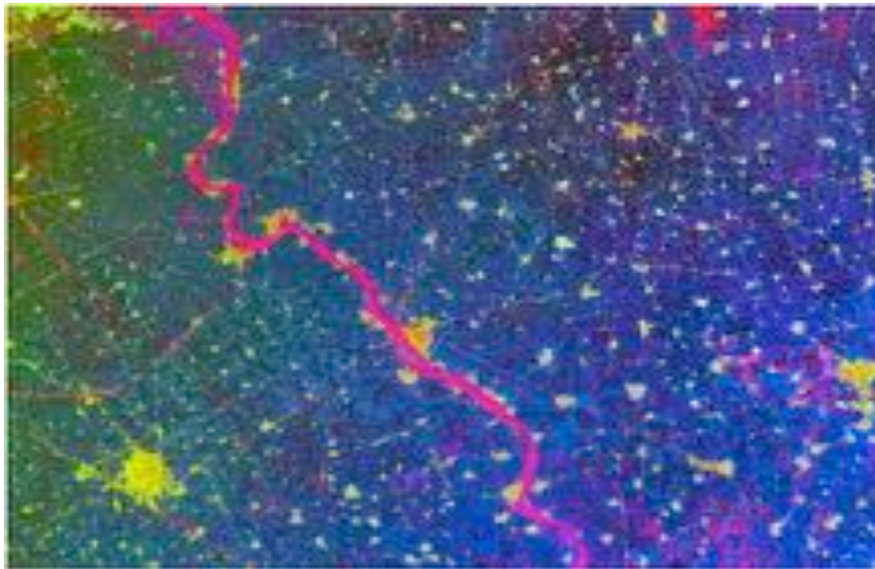


Fig. 4.21: PC FCC image derived from ETM+ subscene (PC1, PC2, PC3).
This image displays over 99% of the total variance shown in the original 6 reflective bands.

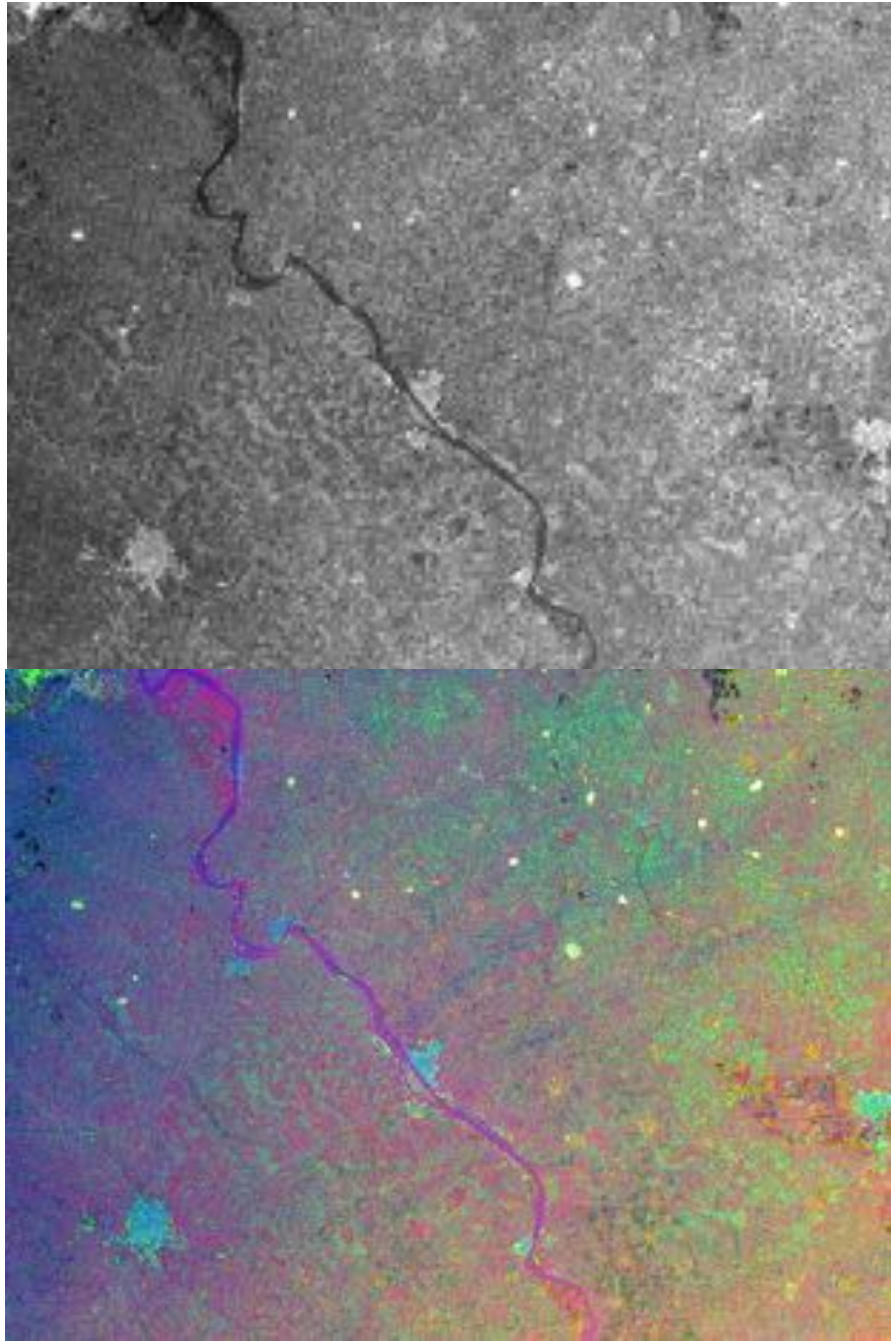


Fig. 4.22A (top): PC4 greyscale image derived from reflective spectral bands of ETM+ subscene; 4.22B (bottom): PC false colour composite derived from ETM+ subset image (PC3, PC4, PC5). In both images tell sites can be identified as high brightness values.

Figure 4.22B shows the same scene using a colour composite of RGB: PC3, PC4, PC5. Although these three components accounted for just 1.39% of the variance of the data set, they contributed the most spectral information for “tell earth”, making tell site detection possible. The last component, PC6, accounted for the remaining 0.09% of the variance, and could be safely discarded as it consisted of little spectral detail (it contained mostly systematic noise). Most of the spectral content for tell sites are attributed to PC4. Both PC3 and PC5 were unable to detect these sites, although these same components were able to detect many other tell sites on the eastern side of the Rosetta distributary. The images in Figures 4.22 - 4.23 appear pixilated due to their low spectral content.

Figure 4.23 shows an enlarged region taken from Figure 4.22B of an area west of the Rosetta branch of the Nile. In this image three tell sites are clearly visible when viewed using a colour combination of PC3, PC4, PC5. Tell site locations are shown with white arrows (labelled as sites 1 - 3 in Figure 4.24). These same tell sites could not be spectrally separated when using optical imagery before the transformation (compare with Figure 4.15).

The results of the PCA analysis and its comparison to known sites mapped from the two ground based surveys are shown in Fig. 4.24. Annotations on the image show some statistics derived from the results. Again, PC4 is a single component image displayed in greyscale. Generally, the locations of high brightness values correspond well with the recording of previously mapped sites using the EES Delta Survey and the UU Ancient Near Eastern databases. Previously mapped sites are circled in green and represent sites that have been previously surveyed and correctly detected using satellite imagery and PCA. Sites that are circled in red were found through PCA analysis but were not included in either Google Earth database (see the section on ‘Tell sites revisited’ in Chapter 7 for a further discussion of these sites). Figure 4.25A shows a more detailed view of the study area in true colour (ETM+ 3, 2, 1) with PC4 threshold overlay (see Section 4.11 for a description of the thresholding technique). Google Earth screenshots are displayed for a sample of the sites.

Tell sites (both known and unknown) were examined using high-resolution QuickBird imagery from Google Earth. Out of the 24 tell sites mapped from prior surveys, 19 were successfully detected with PCA, while 5 sites could not be detected using this technique. An

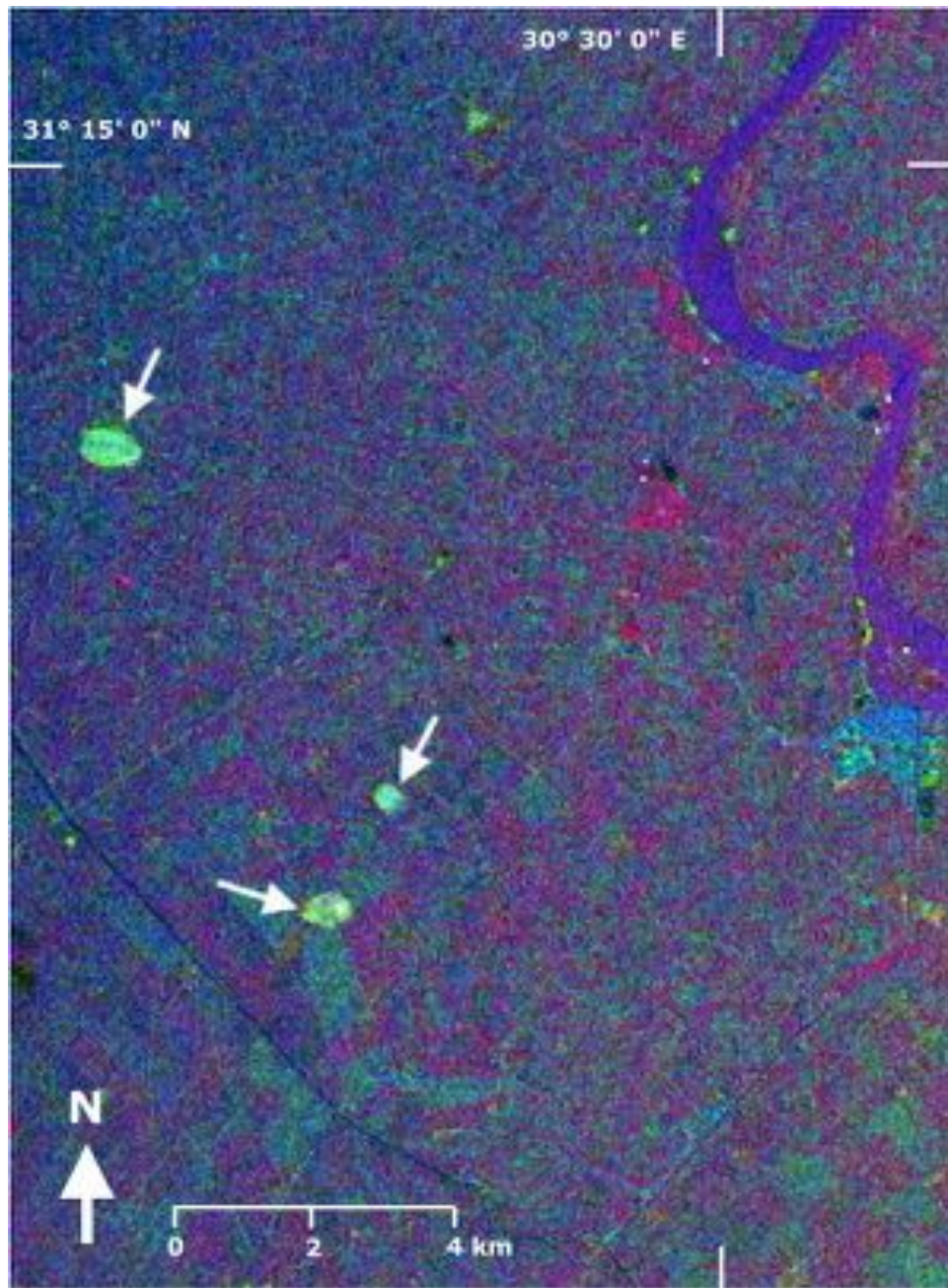


Fig. 4.23: PC false colour composite image of ETM+ subscene (RGB: PC3, PC4, PC5). Tell sites (indicated by arrows) are shown as a bright light green colour in this component combination. Compare this image to the optical image in Fig. 4.15.

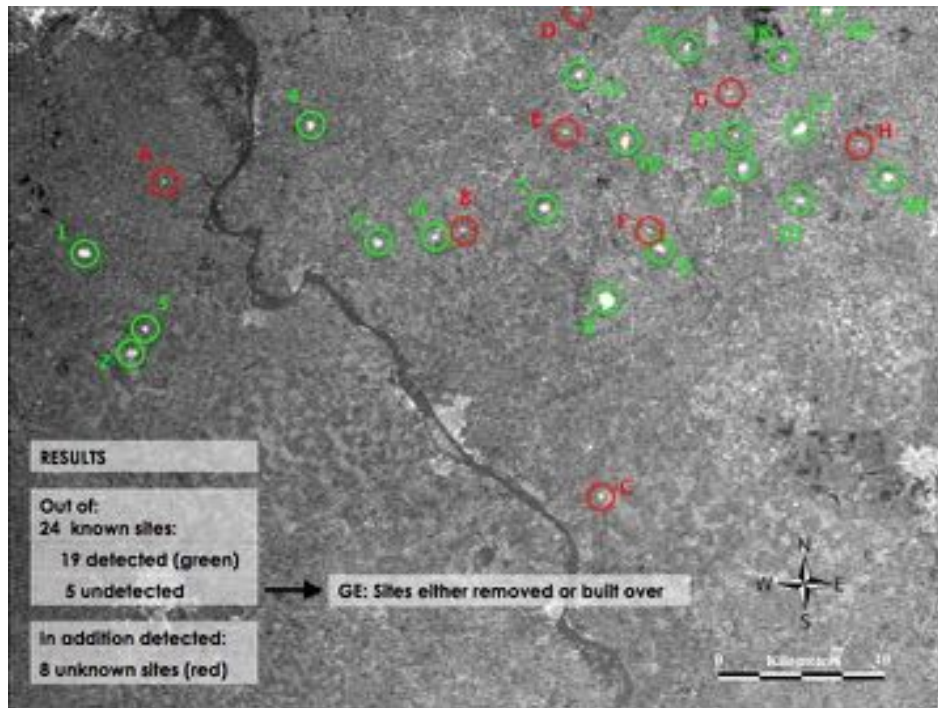


Fig. 4.24: Landsat ETM+ PC4 greyscale image after a 2 s.d. stretch showing tell sites as high brightness values. Sites known from earlier surveys and detected using this technique are circled in green, while sites that were detected but not included in either GE database are circled in red. Site identifications and descriptions are provided in Table 4.9.

examination of the locations of the five undetected sites in Google Earth showed that they had been levelled, or had been buried beneath the foundations of modern sites, before they had been visited. In either case too little tell earth remained on the surface to be detected using the spatial resolution of the satellite sensor.

In addition to confirming the locations of previously known tell sites, 8 further sites were identified, including one of circular shape with an approximate diameter of over 200 m (31° 18' 31" N, 30° 48' 58" E; Figure 4.25B). Tell sites adjacent to modern towns or cities are easy differentiated and identifiable using a thresholding approach (Section 4.11), such as kom el-Haddadi (31° 19' 58" N, 30° 47' 19" E; Figure 4.25C), and kom el-Khariba (31° 19' 42" N, 30° 50' 55" E; Figure 4.25D). This technique created a small number of what I term 'false positives', which can be seen in the southeast corner of Figures 4.25 and 4.26. Some of these locations may represent tell sites, but they have not been confirmed with any degree of

confidence. Imagery in Google Earth seems to suggest they are not tell sites as they do not possess a suitable topographical profile and their morphologies are not consistent with other tell sites (i.e., similar colour and texture). Future ground observations will be able to clarify their origins. Adjustment of the threshold levels used in the detection method will reduce false positives but this may also reduce the number of pixels representing real tell sites and so a suitable compromise has to be reached.

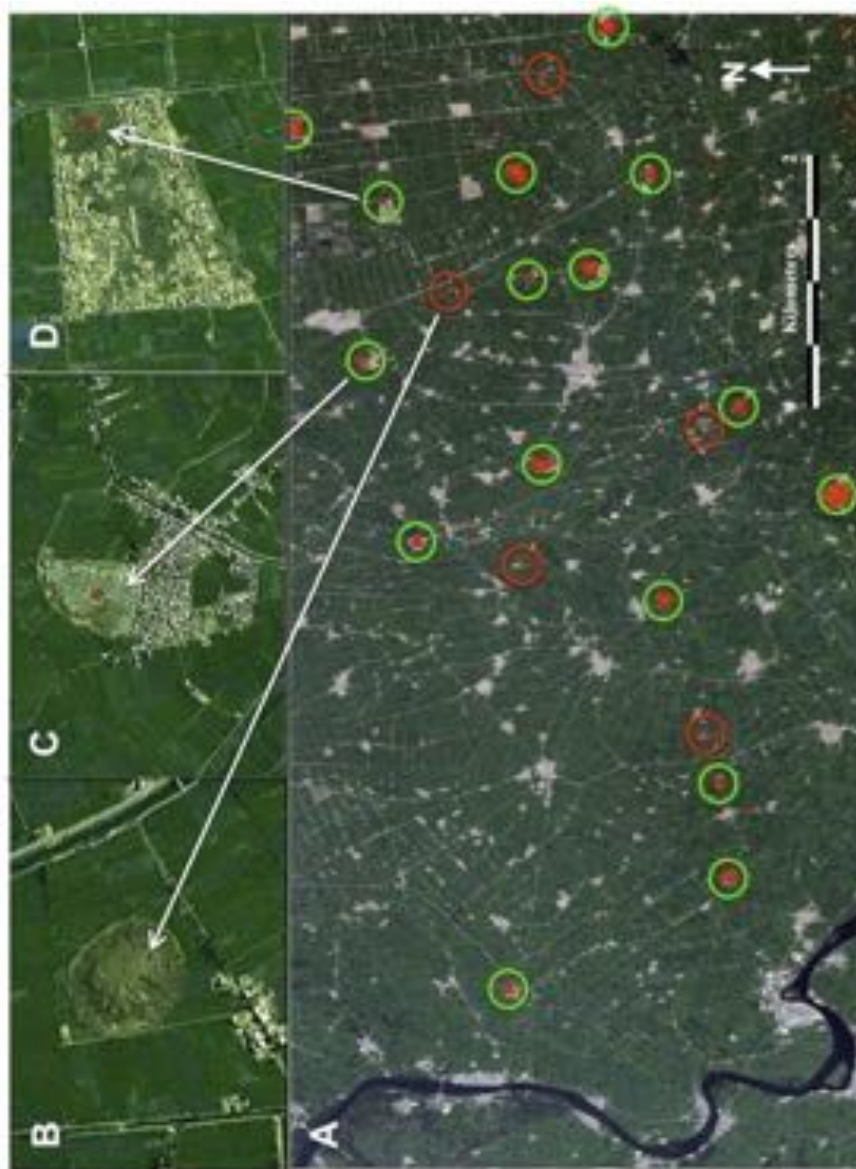


Fig. 4.25: Landsat ETM+ true colour composite (3, 2, 1) subset with PC4 threshold overlay in red. Previously known and newly detected tell sites are circled in green and red respectively (A); a newly detected tell site (B); the tell site of kom el-Haddadi (C), and tell site kom el-Khariba (D).

4.11 Thresholding techniques for tell site detection

Once the PC images had been calculated a thresholding approach was used to highlight pixel values greater than a predetermined value. Thresholding is used to segment an image into two classes based on some spectral region or feature of interest. The methodology used here was to paint tell sites above a specific threshold in red (255, 0, 0), leaving non-tell sites unchanged. This makes it possible to determine which pixels in the image most likely represent tell earth. Due to not being able to ground truth the results, the locations were checked using high-resolution satellite imagery in Google Earth.

Limits were set for detecting pixel values greater than a given threshold for the PC4 image, which was performed using the ERDAS IMAGINE model maker tool using an input raster (the ETM+ PC4 image), a process (function), and an output raster. The function consisted of the formula:

EITHER 0 IF (\$n1_PCAinputimage <= -0.020) OR 1 OTHERWISE

This function outputs a binary image (an image where the pixel values consist of only two values, i.e., 0 or 1), where values below the threshold are replaced with a 0, and values above the threshold are replaced with a 1. A threshold of -0.020 was found to be an optimal threshold after a process of trial and error. Performing this type of operation on raster data usually results in an image containing many small clusters of pixels. This is an unwanted side-effect of the operation which can often resemble a salt and pepper effect. The clusters were removed using the CLUMP and ELIMINATE GIS functions within the IMAGINE vector module. The CLUMP function works by using contiguity analysis on the thresholding raster (using 8 connecting neighbours), to identify clumps, or contiguous groups of pixels, which are recoded into a single class. The ELIMINATE function was applied to the output of the CLUMP function (analogous to the UNIX pipe command), to remove groups of pixels of a specified size. Figure 4.26 shows the Landsat raster image (RGB: 3, 2, 1) with the PC-4 overlay after thresholding and filtering has been applied. Modern settlements appear unchanged (light gray), whereas regions likely to contain tell sites are indicated in red. An assessment of the accuracy of these results using high-resolution imagery from Google Earth is presented in Section 4.13.

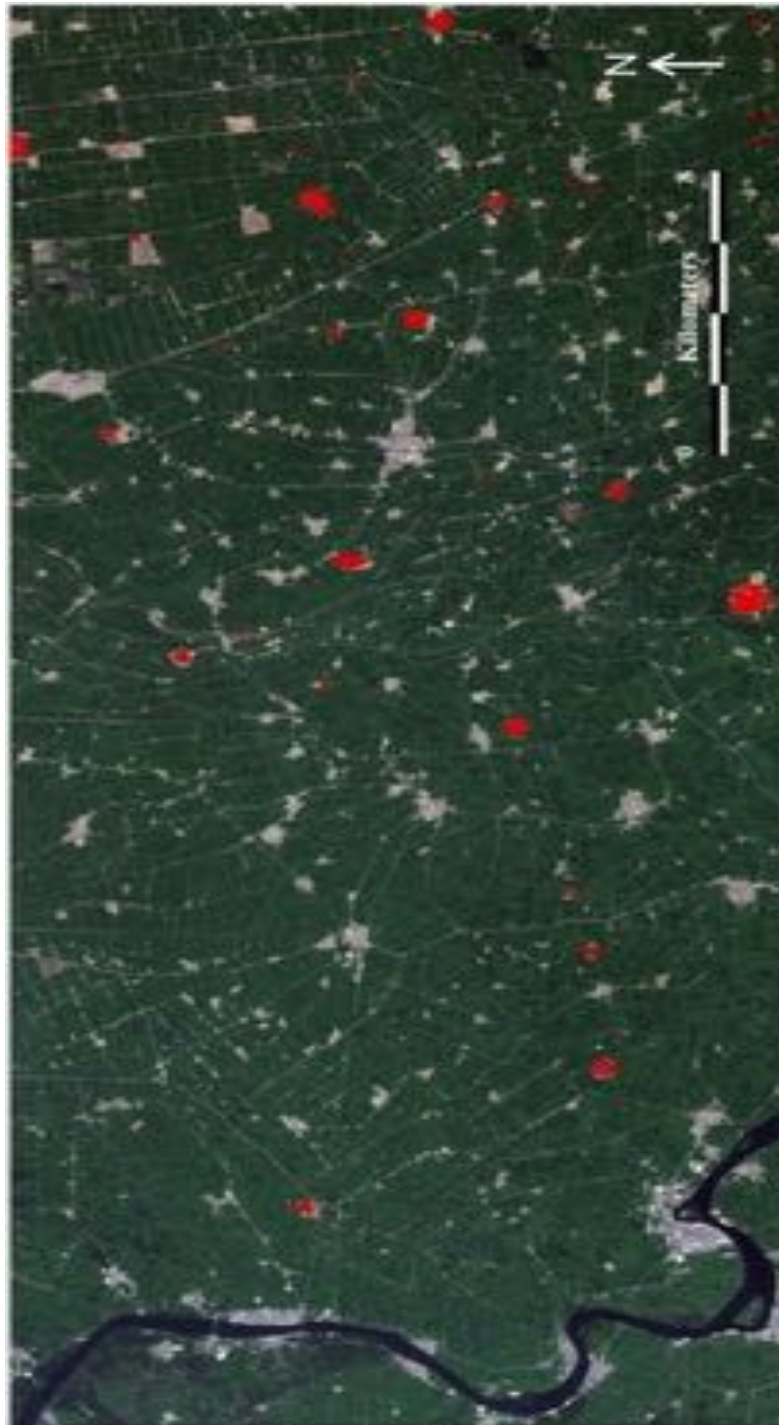


Fig. 4.26: Landsat ETM+ true colour image (3, 2, 1) with PC4 binary overlay displayed in red

4.12 Interpreting the PCA factor loadings

After displaying the PCs and identifying those best able to identify tell sites the next logical question is to ask which bands from the original Landsat data are contributing the most to the transformed images. This question can be answered by calculating the “factor loadings”. These can be calculated from the band variances contained in the variance - covariance matrix (Table 4.5), together with the eigenvalues and the eigenvectors calculated earlier (Tables 4.6 and 4.7 respectively). The factor loadings, R_{kp} , are calculated using Equation 4.9.

$$R_{kp} = \frac{a_{kp} \times \sqrt{\lambda_p}}{\sqrt{\text{var}_k}} \quad (\text{Equation 4.9})$$

where a_{kp} = eigenvector for band_k and component_p
 λ_p = p^{th} eigenvalue
 var_k = variance of band_k in the covariance matrix

The factor loadings are shown in Table 4.8. Elements shown in bold represent those loadings that are contributing significantly to each PC. For example, $\text{PC1} = (0.476 \times \text{band1}) + (0.303 \times \text{band2}) + (0.605 \times \text{band3}) - (0.999 \times \text{band4}) - (0.297 \times \text{band5}) + (0.340 \times \text{band7})$.

As seen from the factor loadings, PC1 had significant contributions from all bands in the original Landsat imagery (all band contributions are shown in bold), and as was mentioned in

	Component <i>p</i>					
	1	2	3	4	5	6
Band 1	0.476	0.716	-0.440	-0.159	0.159	-0.132
2	0.303	0.866	-0.315	-0.144	0.014	0.207
3	0.605	0.753	-0.226	0.082	-0.097	-0.028
4	-0.999	0.034	-0.015	0.006	0.000	0.000
5	-0.297	0.919	0.229	-0.106	-0.036	-0.021
7	0.340	0.919	0.115	0.138	0.086	0.020
Table 4.8: Degree of correlation, R_{kp} (factor loadings) between each band and each principal component. Bold face indicates significant band contributions of +/- 0.10.						

Section 4.10, represents the image's albedo (the albedo is the proportion of light reflected from a surface). PC2 was very highly correlated to Landsat bands 1, 2, 3 (VIS) and 5, 7 (SWIR), as was PC3. PC4, the component that was best able to detect tell sites, had significant negative correlations from Landsat bands 1 (VIS-Blue) and 2 (VIS-Green with loadings of -0.159 and -0.144 respectively and from band 5 (SWIR) with a loading of -0.106. A negative loading indicates inverse correlations between the band and the component, i.e., for a perfect negative correlation of -1.0 there exists a perfect mirror image where a bright tone in a component image corresponds to a dark tone in the spectral band and vice versa. PC4 also had a positive contribution from Landsat band 7 (SWIR) with a loading of 0.138. PC5 and PC6 displayed the least amount of spectral content (0.12% and 0.09% respectively as shown in Table 4.6) and were most correlated to either or both of the visible channels of the Landsat data (bands 1 and 2).

4.13 Identification and visualization of sites using Google Earth (GE)

Due to the political instability of many countries in northern Africa, including Egypt, and the fact that many sites were located on government land and therefore inaccessible by foot, it was impossible to visit the sites mentioned in this case study. Google Earth was used as an alternative for site identification / verification and for visualization, and as such can be described as a proxy for ground truthing purposes. As noted in Subsection 3.9.2, over 70% of Egypt has been mapped at a spatial resolution of 0.6 m (60 cm) using QuickBird imagery, and this product has been integrated into the Google Earth application. Tell sites due to their size, situation above ground level, and characteristic morphologies, are easy to identify from satellite imagery using Google Earth. However, because the sites described in this case study have not been visited on the ground they remain unconfirmed. Only a more extensive ground-based survey can provide further information as to their exact origins. Subsection 3.9.2 of Chapter 3 provides a more complete discussion of the benefits and pitfalls of using Google Earth (and similar applications, such as NASA's World Wind).

A complete listing of the tell sites that have been detected using the PCA approach described in this case study are shown in Table 4.9. The following key is used under 'Status (Catalogue / PCA)' in the table: *mapped* (previously mapped and catalogued in the EES or UU GE databases); *unmapped* (not included in either the EES or UU GE databases); *detected* (site detected using satellite imagery with PCA technique); *undetected* (site previously

Table 4.9: List of tell sites in the northwestern Nile Delta mapped using PCA

ID	Tell site name	Site location (centre latitude, longitude)	Catalogue	Status (Catalogue / PCA)
1	Kom el-Ghuraf	31° 12' 55" N, 30° 25' 04" E	EES / UU	Mapped / Detected
2	Kom el-Nuss el-Kebir	31° 09' 42" N, 30° 26' 56" E	EES / UU	Mapped / Detected
3	Kom el-Nuss el-Saghir	31° 10' 29" N, 30° 27' 24" E	EES / UU	Mapped / Detected
4	Kom Mutubis	31° 17' 11" N, 30° 33' 21" E	EES	Mapped / Detected
5	Tell Qabrit	31° 13' 26" N, 30° 35' 58" E	EES / UU	Mapped / Detected
6	Tell Amya	31° 13' 40" N, 30° 38' 07" E	EES	Mapped / Detected
7	Kom esh-Sheikh Ismail	31° 14' 42" E, 30° 42' 10" E	UU	Mapped / Detected
8	Tell el-Farain (Buto)	31° 11' 44" N, 30° 44' 34" E	EES / UU	Mapped / Detected
9	Tell el-Gir	31° 13' 27" N, 30° 46' 29" E	UU	Mapped / Detected
10	Kom Sheikh Ibrahim	31° 16' 53" N, 30° 45' 07" E	UU	Mapped / Detected
11	Kom el-Arab / Kafri	31° 18' 59" N, 30° 43' 19" E	UU	Mapped / Detected
12	Kom el-Haddadi	31° 19' 59" N, 30° 47' 20" E	UU	Mapped / Detected
13	Kom el-Mesk	31° 17' 10" N, 30° 49' 13" E	EES / UU	Mapped / Detected
14	Kom Sidi Salem	31° 16' 06" N, 30° 49' 33" E	EES / UU	Mapped / Detected
15	<Unknown name>	31° 15' 05" N, 30° 51' 40" E	UU	Mapped / Detected
16	Tell ed-Daba	31° 15' 54" N, 30° 54' 56" E	EES / UU	Mapped / Detected
17	Kom el-Khawaled	31° 17' 25" N,	EES / UU	Mapped /

		30° 51' 41" E		Detected
18	Kom el-Khariba	31° 19' 43" N, 30° 50' 56" E	UU	Mapped / Detected
19	Tell Nashwein	31° 21' 18" N, 30° 52' 35" E	UU	Mapped / Detected
-	Kom Deibi	31° 18' 47" N, 30° 30' 47" E	EES	Mapped / Undetected
-	Hermopolis Parva / Damanhur	31° 02' 07" N, 30° 28' 15" E	UU	Mapped / Undetected
-	Kom Abu Tahun	31° 12' 3" N, 30° 42' 22" E	UU	Mapped / Undetected
-	Kom el-Garad	31° 19' 42" N, 30° 54' 03" E	UU	Mapped / Undetected
-	Tell Mikheizin	31° 18' 49" N, 30° 57' 14" E	EES	Mapped / Undetected
A	Unknown site. Situated south of Ezbet Ghalab	31° 15' 15" N, 30° 27' 58" E	-	Unmapped / Detected
B	Unknown site. Situated northwest of El-Mandara	31° 13' 55" N, 30° 39' 08" E	-	Unmapped / Detected
C	Unknown site. Situated west of Shabas Ash Shuhadaa	31° 05' 25" N, 30° 44' 29" E	-	Unmapped / Detected
D	Unknown site. Situated southeast of Izbat Al Ghabayshah	31° 21' 08" N, 30° 43' 11" E	-	Unmapped / Detected
E	Unknown site. Situated south of Al Abbasi	31° 17' 10" N, 30° 42' 52" E	-	Unmapped / Detected
F	Unknown site. Situated east of Izbat Faramund	31° 14' 01" N, 30° 46' 06" E	-	Unmapped / Detected
G	Unknown site. Situated southeast of Izbat Sayyid Al Ballasi	31° 18' 31" N, 30° 48' 58" E	-	Unmapped / Detected
H	Unknown site. Situated south of El-Mansheya El-Gadeeda	31° 16' 56" N, 30° 53' 51" E	-	Unmapped / Detected



Fig. 4.27: Eight tell sites detected but not included in either GE database, A - H (from left to right moving down). Letter designations can be found under the 'ID' column in Table 4.9.

mapped (EES or UU) but not detected using this PCA technique). Screenshots of the sites that were detected using this technique (*unmapped, detected*) are shown in Figure 4.27). Metadata for each site, including the latitude and longitude, can be found in Table 4.9.

4.14 Increasing spectral resolution: ASTER imagery PCA

To exploit the increased spectral resolution of ASTER in the SWIR (five bands versus Landsat's two), two ASTER scenes were downloaded from NASA's LP DAAC, and subset to the same study area as the previous Landsat study. ASTER data was acquired under a license agreement with NASA for educational research approval. However, unlike the Landsat data which had a fixed spatial resolution of 30 m for its 6 bands in the VNIR / SWIR, the ASTER data had different spatial resolutions for its VNIR (15 m) and SWIR (30 m) subsystems. As a result, the SWIR bands were re-sampled to 15 m to match the resolution of its VNIR subsystem. Once again, similar to the Landsat data, the TIR bands were discarded as they were incompatible with this study. Once the data had been re-sampled, the individual bands for the two scenes were layer stacked to produce a single multispectral image file. A similar methodology was followed for the pre-processing and radiometric correction of the imagery as was performed on the Landsat data, using metadata included with the imagery, and using procedures employed in the literature (Milder, 2008; Smith, 2007; Abrams, Hook, and Ramachandran, 2000). It was important to convert the ASTER DN values to reflectances for each satellite scene prior to mosaicking the imagery due to the data set consisting of more than 1 scene and where each scene had a different acquisition date and therefore different radiometric attributes (a problem not encountered with the single Landsat scene).

After mosaicking and subsetting the imagery to the western Nile Delta, PCA was calculated and the individual PCs examined to ascertain which components were best able to detect tell sites. It was found that PC5 was the most appropriate component, as shown in Figure 4.28, which shows ASTER PC5 after a two standard deviation stretch has been applied. High brightness values indicate the location of tell sites and these were later confirmed through the examination of high resolution Google Earth imagery in a similar way that was carried out in the prior Landsat study. PCA applied to ASTER imagery provides a cleaner looking result with tell sites showing higher contrast compared to processed Landsat imagery. Results from the ASTER data also produced less false positives, unlike the Landsat imagery. This is most likely due to ASTER's increased spectral resolution in the SWIR.

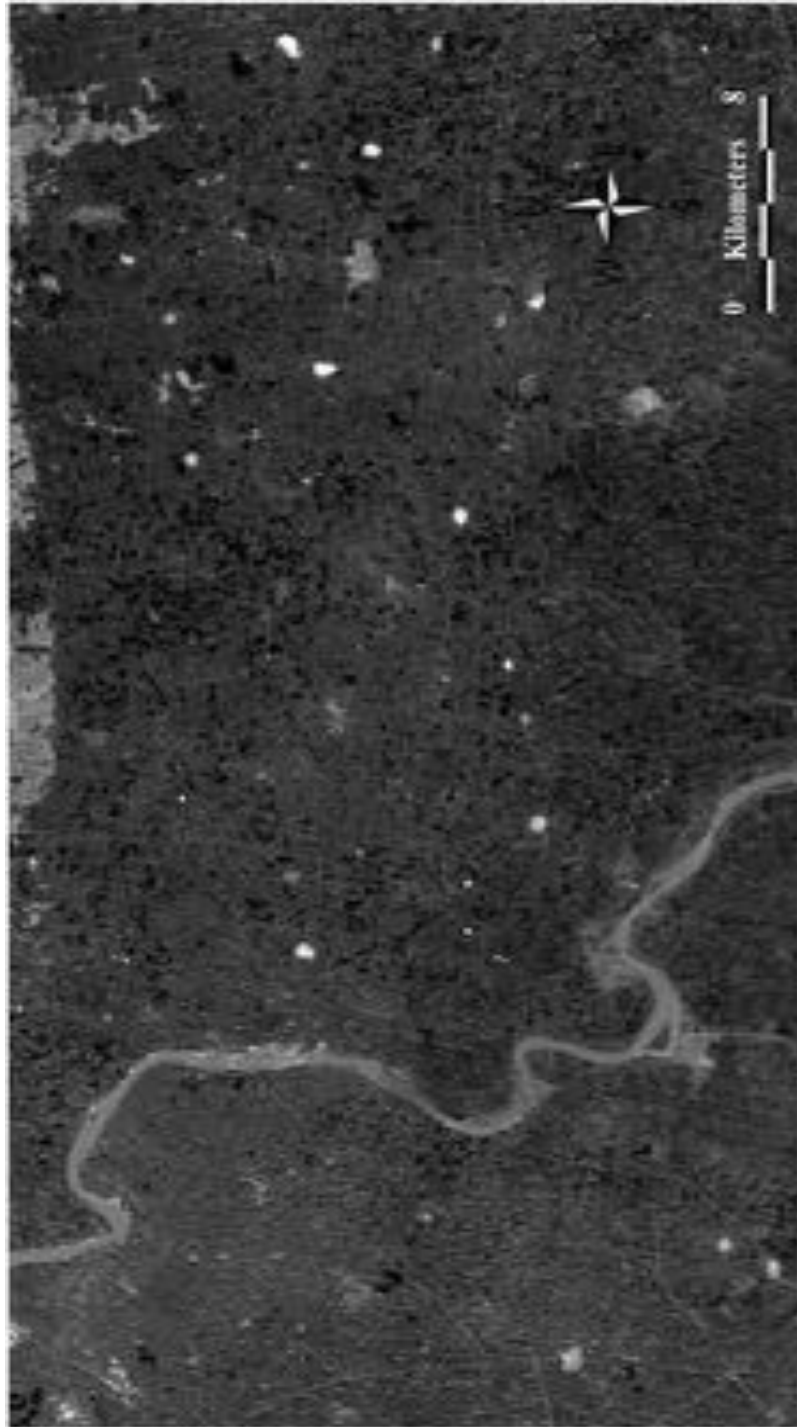


Fig. 4.28: ASTER PC5 greyscale image after a two standard deviation stretch.
Tell sites appear as high brightness values.

4.15 Conclusions

The practical component of this chapter set out a strategy for detecting ancient settlement mounds, or “tell” sites, in Egypt’s northwestern Nile Delta, using satellite imagery analysis. The case study principally used Landsat data which has been made freely available and in the public domain since 2008. As an alternative, ASTER data can be acquired free of charge through a NASA academic research grant. PCA was applied to both the VNIR and SWIR channels of Landsat ETM+ and ASTER imagery. The results indicate that PCA can be a valuable tool for detecting tell sites when applied using a semi-automated approach. It was found that the lower-order components (higher numbered), more specifically Landsat PC4, contained the necessary variance that was needed to separate the spectral characteristics of tell earth. These features were not directly visible in any other lower-order component or when viewed using different band combinations of the original data. PCA was also applied to the higher-resolution ASTER data. Whereas PC4 was best able to separate tell sites in the Landsat data, in the ASTER dataset, PC5 provided the most appropriate component. The increased spectral resolution in the SWIR bands provided by ASTER yielded clearer results through a marked increase in contrast, and producing fewer false positives than when compared to the Landsat data. Although no additional sites were readily apparent in the ASTER PC image compared to the Landsat, the clearer imagery nevertheless made the tell sites easier to observe.

After applying PCA, the results showed that Landsat PC4 was best able to separate tell sites spectrally from other landscape features. Out of 24 sites included in both the EES and UU Google Earth .kml databases, 19 were found using PCA and a thresholding approach, representing a 79% success rate. The 5 sites that could not be detected had either been destroyed and removed or had been built over by subsequent settlements. Therefore the success rate of the technique itself could arguably be considered 100% as long as there remains some tell earth for the satellite sensor to detect. In addition to the previously recorded sites, 8 further sites were also mapped using this technique (ID A – H in Table 4.9 and Figure 4.27). These 8 sites were not included in the database provided by the Google Earth .kml file but were known from prior EES surveys (Wilson and Grigoropoulos, 2009). These sites from A through H are Sidi Uqba, Matiur, Shabas Umayyir, Alawi, Quleia, Tell el Daba, Bunduq, and Ineizi.

Five tell sites were not detected by means of PCA but had been previously mapped by one of the earlier ground-based surveys. A review of high-resolution Google Earth imagery of these locations revealed that the sites no longer existed and had either been completely removed or had been buried beneath the foundations of modern developments. All five had been visited by the EES (and four by the UU). The EES database provides comprehensive metadata for each visited site. Table 4.10 shows the EES Delta survey notes made for these sites, and these confirm in most cases that the sites had indeed been removed or that not enough tell earth survived for them to be detectable in a satellite image at a scale of 30 m per pixel cell.

Site / Survey	Latitude / Longitude	Survey notes*
Kom Deibi (EES)	31° 18' 47" N, 30° 30' 47" E	Visited in 2004 by Penny Wilson, who found the site completely overbuilt but still quite elevated.
Hermopolis Parva / Damanhur (EES/UU)	31° 02' 07" N, 30° 28' 15" E	No trace found by Steven Snape during a visit to the area in 1996. Satellite imagery (2006) shows a cultivated area between built-up suburbs of Damanhur, the possible location of the site.
Kom Abu Tahun (EES/UU)	31° 12' 3" N, 30° 42' 22" E	Archaeological site overbuilt by a village, with a small cemetery on the southeastern edge.
Kom el-Garad (EES/UU)	31° 19' 42" N, 30° 54' 03" E	Satellite imagery (2007) shows a small mound surrounded by cultivation.
Tell Mikheizin (EES/UU)	31° 18' 49" N, 30° 57' 14" E	Visited in 1990 by Jeffrey and Patricia Spencer. Highest parts rise a maximum of 2m, with a few modern graves on top. The rest is very low and prone to flooding. The main part lies south of the tarmac road, but a small portion is present on the northwest side. A large walled compound has been built on the edge of the mound.
Table 4.10: EES Delta survey notes of previously mapped tell sites undetected in this study using principal components analysis		

*EES Delta Survey notes published online (Spencer, 2007).

The survey notes for the sites Kom el-Garad and Tell Mikheizin seem to suggest portions of them were intact at the time they were visited. Tell Mikheizin was visited in 1990, and significant development may have taken place since the Landsat image was recorded in 2003. When these site locations are viewed using recent imagery from Google Earth, no trace of

them seem to remain. This is also true for the other three sites shown in the table. The ‘historical imagery’ feature in Google Earth was invaluable for displaying imagery of suspected tell sites using data that was acquired at approximately the same time that the sites were visited in the surveys. However, high-resolution data has only been available since early 2000, so that Google Earth is not able to display imagery at a high enough resolution for tell sites visited in the surveys at an earlier date. Historical imagery from the Corona satellite (1960s–1980s) may also prove useful in showing how tell sites have changed over time. Corona photography was relatively high resolution (~1.8 m) and can provide good archaeological information. In any event, the majority of the sites had been visited on the ground between 11 and 25 years ago, and much change could have resulted during that time.

The PCA procedure transformed the original data values onto a new set of uncorrelated principal components using the variance-covariance matrix. An alternative method is to use the correlation matrix, which by definition standardizes the measurement scale of each band. If the covariance matrix is selected, more weight is given to variables with higher standard deviations. With the correlation matrix all variables are given equal weight (they are said to be standardized). The two techniques can produce different results and therefore different sets of principal components. Generally, the correlation matrix should be used when the range of data values differs greatly between the bands and therefore normalization is needed. The differences between the two resulting transformations and the advantages and disadvantages of the different approaches have not yet been fully explored. However, this study has shown that using the variance - covariance matrix works well for this particular study area. A study to compare the two techniques would be a valuable endeavour.

The failure of classification techniques to spectrally resolve tell sites was due to working within the coordinate system of the original bands, many of which shared similar spectral information – that is, they were highly correlated – and as a result the spectral variance could not be displayed in the most effective way. The use of PCA to decorrelate the bands, by re-projecting the data onto a new set of uncorrelated components, provided the means to analyze the variance in new ways.

The work in this study was confined to a large part of the northwestern Nile Delta. Although the results from these findings seem to suggest the technique works well, it does not imply

that the same approach will work in other regions of the Delta, the Nile floodplains of Middle Egypt, or indeed further afield in other parts of the world where tell sites may be found. Much work has already been carried out using digital elevation models to map sites in the Middle East, for example, but a full PCA analysis has not been published. Further testing and refinement of the approach is needed for its full potential to be realized. If successfully applied to regions beyond Egypt, the technique will be established as a digital image-processing tool for archaeological exploration of tell sites.

This work constitutes an important first step for mapping the spatial distribution of these important monuments. This will help to provide a window into urban land distribution and settlement patterns at a time of the first emerging communities. Many of these sites are at risk from modern urban, industrial, and agricultural expansion, in addition to looting and vandalism. It is important to document them before they completely disappear from the archaeological record. However, the results from the investigations reported here have not yet been independently verified from the ground, and therefore any newly detected sites should be considered with prejudice and continue to be classified as anomalies until a ground campaign can prove otherwise. This first case study has discussed the detection of tell sites in Egypt's Nile Delta.

In the next chapter the second case study is presented where the search for water in the eastern Sahara Desert becomes the main focus.

Chapter 5

Case study 2: The palaeohydrology of the eastern Sahara: the search for water

5.1 Introduction

The Sahara of North Africa is one of the hottest and driest places on Earth. It is the third largest desert in the world with sand dunes covering vast regions, some of which can reach heights of up to 180 m (Strahler and Strahler, 1987). Some areas in Egypt's Western Desert receive rainfall as little as once every 30 to 50 years (Elachi, Roth, and Schaber, 1984). As a result, large swaths of the region are largely devoid of vegetation and unable to support human life on any appreciable scale. Figure 5.1 shows the Sahara Desert dominating much of northern Africa. This image was acquired by the Moderate Resolution Imaging Spectroradiometer (MODIS) on board the Terra satellite, which records electromagnetic energy at the optical wavelengths with a range of spatial resolutions from 250 m to 1 km. The Sahel can be seen extending horizontally across the whole of Africa at a latitude of approximately 10° to 15° demarcating the zone of transition between the Sahara Desert to the north and green Sub-Saharan to the south. The bright and dark regions to the north represent extensive sand seas and the remains of ancient lava flows respectively.

The Sahara's climate, however, has not always been as harsh and unforgiving, having undergone a series of extreme climate shifts that has seen its environment change significantly over the last few hundred thousand years (Kuper and Kröpelin, 2006). Today the Sahara reveals little indication of its volatile past, but buried beneath the perennial sand sheet lies another landscape indicative of a very different environment to what we know today. This hidden world attests to a time when today's deserts once held broad flowing rivers, lush grasslands, inland deltas, and diverse habitats. Many of the rivers would have terminated in large inland lakes, four of which may have been larger than the size of Belgium (Drake, 2012a). These inland water bodies would have provided reliable sources of water to support abundant animal and human populations. Such was the past biodiversity of the region that it is often referred to as "The Green Sahara" (Blom et al., 2009).



Fig. 5.1. The Great Sahara desert of north Africa. The bright areas, dominant across much of the region, are the locations of major sand seas. The Sahel transitional zone divides the dry Sahara to the north and the green savanna to the south (MODIS image, NASA).

Since that time the climate has become gradually hotter, drier, and less hospitable. The water sources dried up and eventually disappeared. This in turn had a dramatic impact on the survival of plant, animal, and human life. Settlement sites were abandoned and alternative trading and travel routes were sought. It is thought that the onset of the last drying phase (around 3,400 B.C.) prompted a move by Saharan people towards coastal and other accessible regions in an effort to find more permanent sources of water (Blom et al., 2009; Blom, 1988). One such route was towards the Egyptian Nile valley, where it has been suggested the water-rich environment (amongst other factors) provided the ideal conditions for the genesis and development of the ancient Egyptian civilization (El-Baz, 2003).

It is now known that the Sahara has experienced many such cycles of climate change, seeing the alternation between wetter more humid phases (pluvials), to hotter, drier and more arid regimes. The last wet phase (the Neolithic Subpluvial) lasted from as recently as the late Pleistocene until the middle Holocene, approximately 14,500–5,500 years ago (Foley et al., 2003). Causes for the climate shifts are not well understood, but variations in solar output (irradiance) due to slow shifts in the Earth's orbital parameters – the so-called Milankovitch variations – have been proposed (Berger, 1978).

The evidence for climatic cycling comes from a wealth of data, including both geological and archaeological sources: 1) buried dry river channels (McCauley et al., 1982; McCauley, Breed, and Schaber, 1986); 2) surface lake deposits and their associated shoreline features (Gaber et al., 2008; Maxwell, Issawi, and Haynes, 2010); 3) fossilized remains of plants and animals, and rock art showing animal species that are no longer indigenous to the region today, including the ostrich, elephant, and giraffe (El-Baz, 1998); and 4) prehistoric human occupation sites and artifacts found alongside the edges and shorelines of relict water sources (e.g., Wendorf, Close, and Schild, 1987; McHugh et al., 1988a; Kuper and Kröpelin, 2006).

Over time, the water that once flowed in surface rivers and lakes dried up, but the remains of their river valleys and some shoreline features remain today. Moreover, many of the regions are still associated with water sources such as oases and springs due to moisture locked up as groundwater in underground aquifers. These features are now invisible to the human eye on the ground and to optical remote sensing instruments from above due to a mantling of fluvial and eolian deposits of sand.

The arrival of new imaging sensor technology from spaceborne and airborne Synthetic Aperture Radar (SAR) systems (see Section 5.2) has made it possible to locate where water once flowed across the surface. SAR systems achieve this by removing the top few metres of sand deposits using long wavelength penetrating radar, thereby revealing the remains of the fluvial-borne landscape below.

The location of water played a key role in determining the placement of many ancient settlement sites, desert pathways, trading routes, trading centres (caravansaries), and their protective installations. Identifying relict water sources is therefore key to locating the archaeological sites that developed in proximity to them and depended upon them for their existence. In arid regions the presence of water would have meant the difference between life and death. Therefore, the search for water is key to locating where people would have gathered.

The focus of this second case study is the search for present and past sources of water (located both on the surface and in the subsurface) using a range of optical, long wavelength SAR, and digital elevation model data. Investigations focused on regions of the eastern Sahara: Egypt, eastern Libya, northwestern Sudan, and northeastern Chad. This is an ideal area for study given the large number of palaeochannels first observed by Shuttle Imaging Radar in the early 1980s (McCauley et al., 1982), in addition to being dotted by large numbers of former lake systems. Ancient drainage features of the Sahara provide a record of its past hydrological activity and palaeoenvironmental conditions. The integration of this data with archaeological work should help in our understanding of how human occupation has adapted to changes in climate. The case study mapped 1) surface vegetation patterns (indicators for the presence of subsurface water, i.e., oases and springs) using a variety of vegetation indices (band ratios), such as the Normalized Difference Vegetation Index (NDVI); 2) subsurface river valleys (also known as palaeochannels or "radar rivers"), using long wavelength C and L-band SAR; and 3) former lake systems (palaeolakes) from their lacustrine limestone deposits using spectral band ratios in the SWIR and TIR. In addition to using spectral techniques for locating palaeolakes, SRTM DEMs are used to search for lake depressions and accompanying palaeoshoreline features. These three investigations are described in greater detail in Subsections 5.4.1–5.4.3 of this case study.

The maps produced from the above work are used as inputs into a Geographical Information System (GIS) for spatial analysis and used in Case study 3 to predict locations where new archaeological sites potentially may be found.

5.2 Subsurface imaging in arid regions

The principles of radar imaging (SAR) were introduced in Chapter 2. This section continues the discussion with a focus on its application in arid regions, where it can be used to penetrate several metres beneath the desert sand. This technology is relevant to the mapping of buried palaeofluvial features, such as palaeochannels, which are discussed at length in this chapter.

The mapping of palaeochannels usually presents a problem, as they tend to be invisible either from ground level or from airborne or spaceborne optical sensors. An advantage of using radar imaging is that, under certain conditions, it can produce images of subsurface features. This unique capability to look beneath the surface of desert regions and make visible what is invisible to the human eye, is due in part to the long wavelength characteristics of microwave energy. Generally, the longer the wavelength of the signal used, the greater the depth of penetration.

Observations from NASA's first Shuttle Imaging Radar mission (SIR-A), onboard the Space Shuttle Columbia in 1981, revealed hidden subsurface features, including a network of previously unknown valleys and palaeochannels buried under the desert sand sheets of Egypt and Sudan (McCauley et al., 1982). This was the first time that imaging radar had shown its potential for mapping buried hydrological features in desert regions, although its use had first been proposed, almost a decade earlier, in the 1970s (Roth and Elachi, 1975). Figure 5.2 shows a Landsat MultiSpectral Scanner (MSS) image (left) with a radar SIR-A filmstrip superimposed (right) of the Darfur region in western Sudan. The radar data clearly shows a hidden network of previously unknown river valleys, which are invisible in the Landsat image. To get an idea of scale, the largest of the river channels in the upper right part of the strip is 20 km in width.

Subsurface imaging using orbital radar in arid environments can only occur under a limited set of optimal conditions: (1) an extremely dry (hyperarid) environment with less than 1% moisture content to reduce electrical conductivity and maximize penetration depth (Hoekstra and Delaney, 1974); (2) a relatively thin, fine-grained (relative to the radar wavelength), and

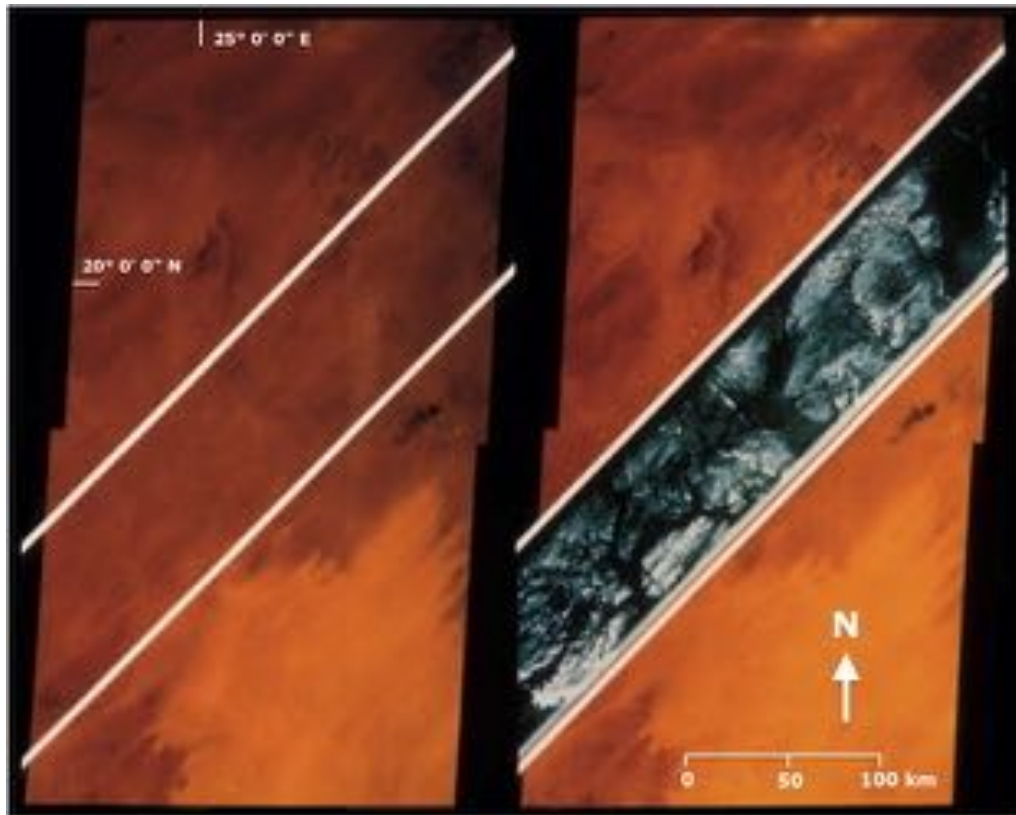


Fig. 5.2. Landsat MSS mosaic (left) with SIR-A radar filmstrip superimposed (right); (after Farr, Blom, and Paillou, 2010)

homogeneous layer that presents itself to the sensor as radar-smooth, i.e., little attenuation of the signal for grain sizes one-fifth of the radar wavelength (Elachi and Granger, 1982; Roth and Elachi, 1975); (3) the interface at the subsurface (between sand and bedrock interface) should produce strong backscatter, i.e., radar-bright return (Elachi, Roth, and Schaber, 1984); (4) a long EM wavelength resulting in a deeper signal penetration, as noted above (Elachi and Granger, 1982; Schaber, McCauley, and Breed, 1997); (5) a high look angle (greater than 30 degrees) which is more likely to reveal subsurface features (Elachi, Roth, and Schaber, 1984); and (6) cross-polarization of the radar signal, i.e., VH or HV (see Subsection 2.8.1), which tends to enhance signal penetration depth (Schaber, McCauley, and Breed, 1997). All these conditions need to be met for maximum subsurface imaging to occur.

The aridity of the eastern Sahara, with the low moisture content of the surface sands, presents ideal radar imaging conditions. A range of skin depths (the depth at which radar energy is

attenuated) has been recorded for several radar antenna wavelengths, including up to 50 cm for C-band (Schaber, McCauley, and Breed, 1997), and up to 2 m for L-band (Paillou et al., 2009). Theoretically the depth of penetration can be greater – up to 5 m using L-band instruments, but this largely remains unproven (Elachi, Roth, and Schaber, 1984). Longer wavelength P-band sensors are capable of greater depths, but they are currently operational only on airborne systems. Table 5.1 shows several commonly used radar wavebands and their range of skin depths given ideal environmental conditions. Increased penetration depth at longer wavelengths has an inverse relationship to the spatial resolution that can be acquired. Therefore, in order to achieve deeper penetration depths, spatial resolution may need to be sacrificed.

Band / Wavelength	Depth of penetration	Spatial resolution
C / ~ 5.6 cm	Low (0.5 m)	High
L / ~ 22.5 cm	↑ ↓ (1–5 m)	↑ ↓
P / ~ 68.5	High (5+ m)	Low
Table 5.1: Penetration capabilities for various radar wavelengths		

Figure 5.3 illustrates the advantages of using radar compared to optical imagery when searching for subsurface features. Each image shows an identical region in the Nile Valley, northern Sudan, where the dimensions of the image are approximately 80 km wide by 30 km high. Geographic North lies in a northeasterly direction in the image. The fourth cataract (currently flooded by the Merowe Dam) is located to the west and the Bayuda volcanic field to the southwest. The upper frame displays a colour infrared photograph taken by the Space Shuttle Columbia in 1995, whereas the bottom frame shows the same region acquired by the Shuttle Imaging Radar-C instrument aboard the Shuttle Endeavour in 1994. Even after image enhancement, very little geological information can be obtained from the Shuttle photograph due to the extensive covering of windblown sand, so that the shorter optical wavelengths are unable to detect features in the near or subsurface. The SAR image, on the other hand, shows the region using longer microwave wavelengths. Smooth alluvium-filled deposits at the surface or near-surface appear dark in the radar image due to specular reflectors, whereas rough deposits appear bright due to backscattering from diffuse reflectors. In the upper right of the radar image an abandoned earlier Nile channel can be seen, which is invisible in the

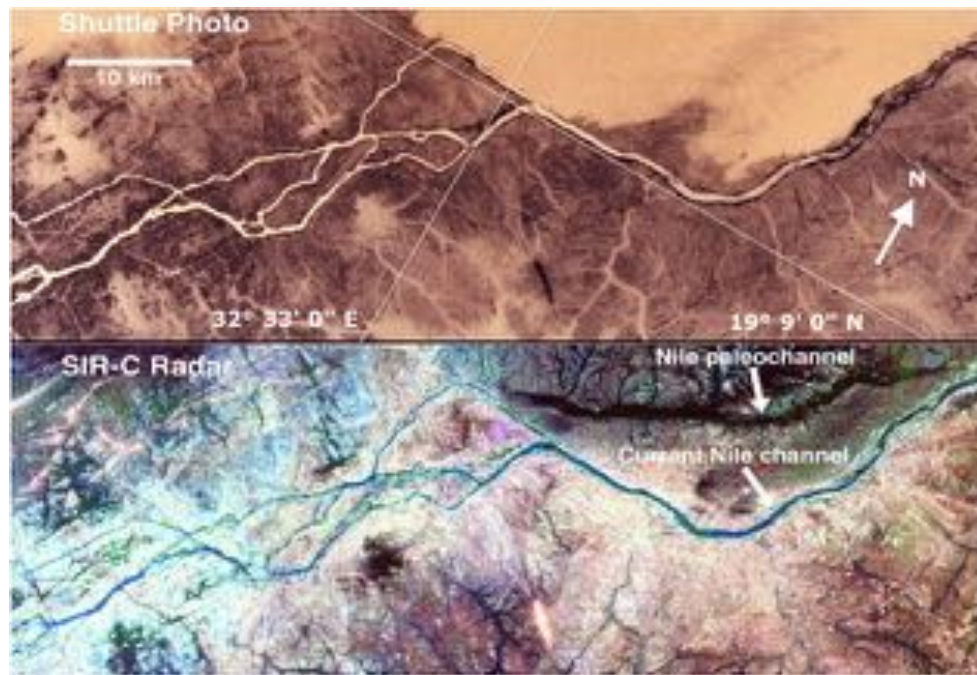


Fig. 5.3. Shuttle photograph (top) and SIR-C image (bottom) of an 80 x 30 km region of the Nile, close to the Fourth Cataract in Sudan, taken in the 1990s. A palaeochannel is visible in the northeastern region of the radar image which is invisible in the optical frame due to widespread mantling by sand deposits (after Wiseman and El-Baz, 2007).

optical frame. Further information on radar imaging in desert regions can be found in Roth and Elachi, 1975; Elachi, 1983; Elachi, Roth, Schaber, 1984; Robinson, 1998; and Abdelsalam et al., 2000.

5.3 Data used

Five complimentary sources of remotely sensed data were employed in this case study: topographic data from the Shuttle Radar Topography Mission (SRTM), radar reflection data from SRTM and ALOS PALSAR, and Landsat ETM+ and ASTER optical imagery. All imagery was displayed in a Geographic projection using a WGS84 datum.

5.3.1 Topographic data: Shuttle Radar Topography Mission (SRTM)

SRTM was a joint project developed by the National Aeronautics and Space Administration (NASA), the National Geospatial-Intelligence Agency (NGA), the German Aerospace Centre (DLR) and the Italian Space Agency (ASI). Flown on the Space Shuttle Endeavour in

February 2000, SRTM used dual radar antennas to acquire interferometric data to produce the most complete, seamless, highest resolution digital elevation model of the Earth (Farr et al., 2007). The hardware consisted of two SIR-C antennas, one mounted in the orbiter's payload bay and the other at the end of a 60-metre mast. Within the United States, data is provided at 1 arc-second or 30 m horizontal resolution (SRTM1), whereas for regions outside of the United States, the data is re-sampled to a resolution of 3 arc-seconds or 90 m (SRTM3). Vertical resolution for all data varies by geographic region but for Africa it is considered better than 10 m, with a 90% confidence level (Rodriguez, Morris, and Belz, 2006). All SRTM data (reflectance and topographic) is divided into tiles extending over $1^{\circ} \times 1^{\circ}$ of latitude and longitude using a geographic projection (plate Carree).

Because SRTM collected data using interferometric SAR, SRTM was able to image in all weather conditions, including through cloud, and was therefore able to collect a complete data set (between 56° south and 60° north latitude) in a relatively short period of time (11 days). However, SRTM suffers from areas of missing data (voids), most often due to imaging in steep terrain where radar shadowing occurs (this is due to the nature of the side looking design of SAR). This is not a problem for optically derived digital elevation models (DEMs), such as ASTER GDEM, which collect elevation data using stereo observation by nadir and backwards looking sensors.

The SRTM data used in this dissertation consisted of a restricted distribution (SRTM1), provided by special permission from JPL that was otherwise not publicly available. The spatial resolution of 30 m provides significant improvement in detail when compared to SRTM3 (90 m). Both SRTM1 elevation and reflection data were used for mapping and hydrological modelling of palaeodrainage features, for determining flow directions, and for mapping surface depressions and shoreline lineaments of palaeolakes (see Subsections 5.4.2 and 5.4.3).

SRTM3 and the coarser resolution data set, SRTM30 (~ 1 km), for Africa and the rest of the world are freely available either from JPL (www2.jpl.nasa.gov/srtm/) or from The Consortium for Spatial Information (CGIAR-CSI, srtm.csi.cgiar.org/). CGIAR data (current release is version 4.1) can be downloaded in blocks of $5^{\circ} \times 5^{\circ}$ tiles. The availability of the data in a block tile size makes it convenient for downloading and assembly. Version 4.1 uses

an improved algorithm over previous versions to ensure all holes in the data have been filled (void-filled). Void filling replaces missing elevation points in the data by interpolating from the surrounding pixels and is essential when performing any kind of hydrological study. However, for regions in the eastern Sahara where there is a large amount of missing data, the interpolation algorithm is unable to provide an accurate result.

5.3.2 Radar imagery: C-band SRTM and L-band PALSAR

As previously mentioned, at the heart of the SRTM instrument were two modified Shuttle Imaging Radar (SIR-C) C-band antennas. When used as a pair in interferometric mode, digital elevation model (DEM) data can be acquired in a single pass. The process is termed single pass interferometry. In addition to collecting elevation data it is also possible to acquire radar reflection imagery using a single antenna. The SRTM image (amplitude) data does not show topographic data but the strength of the radar signal reflected from the ground, i.e., radar backscatter. The SRTM image data was acquired at 5.6 cm wavelength (C-band), consisting of a mixture of C-HH and C-VV polarizations, acquired using a ScanSAR collection mode. ScanSAR enables an unusually large swath width when compared to conventional SAR systems, and in the case of the SRTM instrument it is achieved by scanning 4 different sub-swaths on the fly while varying the sensor look angle between 30° and 62°. The sub-swath number (SS1–4) is key to the type of polarization of the radar signal, with polarizations progressing from HH, VV, VV, and HH, increasing outward from the spacecraft nadir point (i.e., SS1 uses HH polarization, SS2 VV, SS3 VV, and SS4 HH). A "datatake" is comprised of four sub-swaths of ScanSAR data, producing a 225 km swath width, which starts from the time the spacecraft crosses from ocean to land and finishes when it crosses back to ocean from land. The radar reflectance data is sampled at 1 arc second (30 metres at the equator) with pixel dimensions of 3601 samples and 3601 lines.

SRTM amplitude data has been made available as two different releases: Swath Image Data (SID) and Combined Image Data (CID). In SID each data take that crossed a tile is stored in a separate file (no mosaicking or averaging was done). SID files are composed of radar magnitude data (.mag) and local incidence angle (.inc) files for each sub-swath. As a result this data set includes 4 sub-swaths as individual files. On the other hand, in CID format, all sub-swaths for each data take for the 1° x 1° tile were averaged, similar to the DEM and produced a smoother, albeit uncalibrated image. Each tile directory includes only two files: a

single image mosaic (.img) and a second file containing the number of pixels averaged for each output pixel (.num). The SRTM image mosaics produced in this work were derived from the SRTM CID data set.

In addition to SRTM image data, PALSAR scenes were acquired at various resolutions. PALSAR was briefly discussed earlier in Subsection 2.8.4 (i.e., L-band, 23.6 cm wavelength, quad polarization etc.). The longer wavelength capabilities of the PALSAR scenes (compared to C-band SRTM) provided improved depth of penetration when needed.

Data from the original Shuttle Imaging Radar missions (SIR-C), flown on two Space Shuttle flights in 1994, were also available. However SIR-C was only able to provide discontinuous strips of coverage of the study area and was therefore not utilized (SIR-C imaged only 10% of the Earth's surface). In contrast to SIR-C data, SRTM, and PALSAR provide almost full geographic coverage of the Earth's surface (80–90 %).

Although operating at a shorter wavelength in comparison to PALSAR and therefore providing decreased penetration depths (about 50 cm), SRTM image data has the advantage of being accurately registered to the underlying SRTM elevation data set (Ghoneim, Robinson, and El-Baz, 2007). This makes it very useful for performing spatial analysis when the separate layers are imported into a GIS. Further information on SRTM, PALSAR, and SIR-C can be found in Farr et al., 2007, Rosenqvist et al., 2007, and Evans, Plaut, and Stofan, 1997 respectively.

5.3.3 Multispectral optical imagery: Landsat ETM+ and ASTER

In addition to elevation and SAR data, multispectral optical imagery was also utilized. Landsat ETM+ and ASTER data were downloaded from the Global Land Cover Facility (GLCF) and from the United States Geological Survey's (USGS) Land Processes Distributed Archive Centre (LP DAAC) respectively (GLCF: <http://glcf.umiacs.umd.edu/>; USGS: <https://lpdaac.usgs.gov/>). Landsat data is freely available to download, but ASTER was acquired under a NASA-supported research grant.

Landsat data at a 30 m pixel resolution was used to 1) map the distribution of oases using vegetation indices; 2) map carbonate deposits of palaeolake systems with a band combination of 7, 4, 2 (commonly used in geological mapping); 3) visually interpret palaeochannels from

modern surface fluvial features; and 4) act as a base image for display purposes.

Using radar imagery alone it is not always possible to determine whether palaeodrainage features are located on the surface or in the near-surface. Therefore, pan-sharpened (15 m) Landsat ETM+ imagery and 60 cm QuickBird imagery (streamed through Google Earth), were used alongside radar data to assist in palaeofeature identification (Ghoneim, Benedetti, and El-Baz, 2012). If the features cannot be observed in optical imagery but were visible in radar, this is a good indication that they are located in the near surface. Additionally, ASTER band ratios were used to identify spectral signatures of calcium carbonate, which are often indicative of former lake deposits, using the TIR (90 m) sensor subsystem.

5.4 Methodology

Understanding the palaeohydrology of a region is especially relevant to archaeology. Reconstructing past sources of water can assist in determining where ancient peoples would have gathered. People living in or travelling through the desert would have been aware of the locations of both surface and subsurface water, and this awareness would have influenced the locations of settlement sites. Furthermore, large contiguous areas of land connected by water would have made possible travel ways for large-scale human and animal migrations using the so-called “green corridors” during key humid phases. By constructing detailed maps of relict water sources, archaeologists can begin to narrow down regions where evidence of past material remains may be found. Thus, the search for water becomes key to identifying the locations of archaeological remains in hyperarid environments. The search for water is also a modern concern as populations increase and are forced to move farther into the desert to utilize more land. However, groundwater is easily exhausted and it is unknown how long these resources may last. The mapping of water trapped in underground reservoirs can therefore aid ongoing ground water exploration efforts for humanitarian purposes.

The next three subsections discuss various strategies that use satellite remote sensing to detect both surface and subsurface water. These include detecting present-day oases by means of VNIR spectral ratios, such as the NDVI (Subsection 5.4.1); uncovering buried remains of palaeorivers with long wavelength penetrating radar (Subsection 5.4.2); and mapping the remnants of palaeolakes and their shoreline features, using SWIR / TIR band ratios and digital elevation models (Subsection 5.4.3). This methodology forms the basis for generating data

sets for the final case study (Chapter 6), where several raster and vector coverages will be input into a GIS to predict the most likely locations for archaeological sites.

5.4.1 Detection of oases in Egypt's Western Desert: Mapping surface water using the Improved Vegetation Index (IPVI)

Ancient Egyptian civilization was centred around the “Black Land” – the Nile Valley to the south and the Delta to the north – so named for the colour of its rich fertile alluvial deposits. The River Nile was the only source of water in this otherwise dry and barren region, and without it ancient Egyptian culture and civilization is unlikely to have developed. For millennia, intense rains over the Ethiopian Highlands in Central Africa allowed the Nile to flow northwards and out to the Mediterranean Sea, annually flooding its banks between July and October. When the waters receded, the nutrient-rich silt remained and the soil became naturally fertile and ready for cultivation. This process was cyclical, predictable, and the water was usually plentiful (Butzer, 1976).

In stark contrast, beyond the influence of the Nile lay the “Red Land” – an endless expanse of desert. The Eastern, or Arabian Desert, lay to the east of the Nile, with its routes to the Red Sea coast, whereas the Western, or Libyan Desert, lay to the west. Both make up a small portion of the Great Sahara, which extends across much of northern Africa.

Scattered throughout the desert landscape are the oases – naturally forming moisture-rich islands existing in sharp contrast to the vast oceans of surrounding sand (Figure 5.4). They provide a life-support for both animal and human populations in what is otherwise a dead zone.

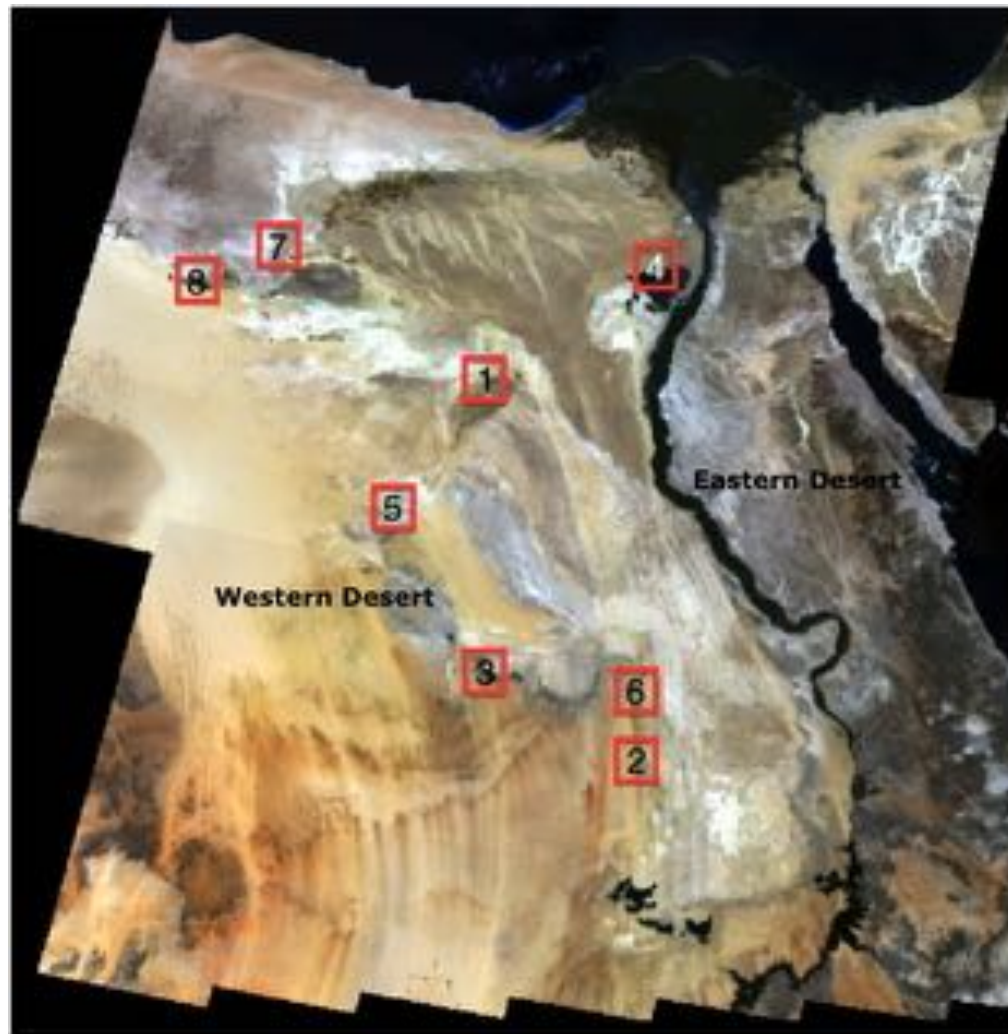
Oases are formed when water from underground aquifers rises to the surface, forming natural springs. Aquifers hold vast quantities of water that were locked up during earlier pluvial cycles. In addition to supplying an important source of water for travellers, oases also provide land for the development of agriculture, food for the cultivation of animals, and supply significant quantities of mineral resources.



**Fig. 5.4: A typical oasis setting: Ubari Oasis in the Fazzan region of southwestern Libya;
Source: Sfivat (released into public domain)**

Even though the Sahara contains a large number of oases of varying sizes, their exact number and location are not well known (there are literally hundreds of varying sizes in the eastern Sahara alone). Observing an area at a regional scale using spaceborne imagery and applying digital image processing techniques allows for an accurate determination of both their distribution and location. Figure 5.5 shows a simplified map of Egypt and northern Sudan, identifying some of the major oases located in the Egyptian Western Desert.

Forty-eight Landsat-7 ETM+ scenes with a spatial resolution of 28.5 m were downloaded from the GLCF (Table 5.2). Acquisition dates for the imagery varied between 1999 and 2003, with the months constrained to December through March, which are considered the wettest months of the year. All imagery were acquired before May 31, 2003, which is when the scan line corrector failed on the sensor.



1	Bahriya	5	Farafra
2	Baris	6	Kharga
3	Dakhla	7	Qara
4	Faiyum	8	Siwa

Fig. 5.6: The major oases located in Egypt's Western Desert. Base imagery is composed of a 48 scene Landsat ETM+ mosaic (RGB: 3, 2, 1)

To derive oasis locations, spectral indices (ratios) were calculated using channels sensitive to vegetation content. Healthy green vegetation tends to absorb red light but strongly reflects the NIR. Indices exploit these properties, one of the most frequently employed being the Normalized Difference Vegetation Index (NDVI), first introduced in Section 3.5 (Rouse et al., 1973; Tucker, 1979). The NDVI is defined as the normalized ratio of the difference between the NIR and VIS-red bands to their sum, where the red channel is located in the strong chlorophyll absorption region and the NIR channel is located in the high reflectance region (Equation 5.1):

$$NDVI = \frac{NIR - R}{NIR + R} \quad (\text{Equation 5.1})$$

The inputs can be in units of either radiance or reflectance, where the calculation outputs greyscale values with a dynamic range of between -1 and +1. Generally, extremely negative values (black) represent water, values around 0 indicate bare soil, and values between 0.6 and 1.0 (white) represent healthy green vegetation.

The Infrared Percentage Vegetation Index (IPVI), first proposed by Crippen (1990), was an improvement in the efficiency of the NDVI, where it was noticed that the subtraction of the red in the numerator was irrelevant and the operation could be eliminated with no effect on the overall result. The advantages of using the IPVI are that it is computationally faster and never negative (gives a range between 0 to +1). The IPVI can be calculated using Equation 5.2:

$$IPVI = \frac{NIR}{NIR + R} \quad (\text{Equation 5.2})$$

The IPVI is often used as a more efficient alternative to the NDVI. However, such indices may not be as effective in identifying vegetation in arid regions due to a component of the signal arising from the soil background, to which both the NDVI and the IPVI are susceptible. Because of this, several other vegetation indices have been proposed to correct for the effect of the soil background, and to enhance sensitivity to vegetation. These include the Soil Adjusted Vegetation Index (SAVI) and the Modified Soil Adjusted Vegetation Index (MSAVI). They are calculated using Equations 5.3 and 5.4 respectively:

$$SAVI = (1 + L) \times \frac{NIR - R}{NIR + R + L} \quad (\text{Equation 5.3})$$

$$MSAVI = \frac{NIR - R}{NIR + R + L} (1 + L) \quad (\text{Equation 5.4})$$

SAVI, introduced by Huete (1988), uses a factor, L , the soil adjustment factor, which is assumed to be 0.5 for general soils with intermediate vegetation densities (the values can vary between 0.0 and 1.0) and adjusts the position of the soil line for better vegetation sensitivity. The range of output values varies between -1 and +1. MSAVI, developed by Qi et al. (1994), provides a variable correction factor, L , which also varies between -1 and +1. Many of the indices that correct for soil background generally require atmospherically corrected reflectance values for the Red and NIR bands, otherwise they are known to perform poorly. Both NDVI and IPVI provide qualitative assessments of vegetation cover and do not require an atmospheric correction. Therefore, the IPVI was applied to the Landsat ETM+ dataset for the purposes of deriving oases locations.

The workflow presented here for detecting vegetation patterns parallels an approach first introduced by Luedling and Buerkert (2008), but with modifications. It has been reduced to six simple steps (summarized in Figure 5.7): 1) Acquire, download, and pre-process imagery: Landsat-7 ETM+ multispectral data covering the whole of Egypt, including its Western Desert region was downloaded (48 scenes). All scenes were pre-processed and mosaicked (no colour balance applied) to create a single seamless image data set (Fig. 5.6); 2) Calculate IVI: Bands 3 (VIS-red) and 4 (NIR) were subset and the IPVI calculated; the bright pixels correspond to regions of high vegetation (oases); 3) Correct for seasonal variations / altitude: If radiometric normalization has not been applied in step 1 to correct for seasonal and altitude effects of multi-temporal imagery (by converting DNs to reflectance values), a moving filter using focal statistics can be applied to the IPVI image as an alternative. This is achieved by subtracting an average NDVI value from each pixel of the NDVI image using a moving kernel window size of 300 x 300 pixels; 4) Remove natural vegetation: A second filter was applied to remove small patches of natural vegetation from the imagery. Small cluster removal was achieved by replacing each pixel with an average of a 3 x 3 moving window;

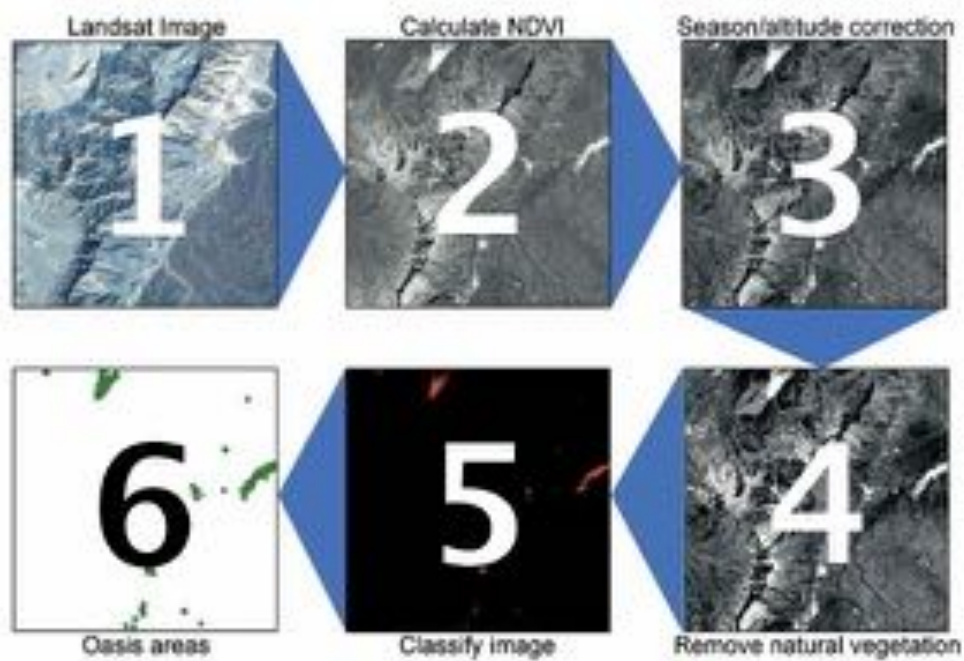


Fig. 5.7: Oases detection methodology (after Luedeling and Buerkert, 2008)

5) Classification: The enhanced IPVI image was classified using a thresholding approach, where pixels above a specified value were highlighted. Ground truthing (validation) was provided by high-resolution imagery from Google Earth to confirm oasis pixel classes. A majority filter was used to eliminate small clusters of pixels that may have been incorrectly labelled and to generally tidy up the classification; 6) Create binary image: Finally, a binary image (pixel values of 0 and 1) was calculated, where a value of 1 represents an oasis pixel, and 0 represented some other land cover type. This final product was ready for input into a GIS after conversion to a vector coverage.

Figure 5.8 shows the Faiyum Oasis, south of Cairo (refer to Figure 5.6 for context). The ETM+ true colour image (3, 2, 1) is shown on the left, and the derived IPVI image on the right. Highly vegetated regions (oases and Nile floodplain) are displayed in green and the water bodies are displayed in black in the true colour image. Water bodies include Lake Moeris (Birket Qarun) in the northern part of the Faiyum. Further lakes can be seen to the southwest, which are artificial in origin. These were created in the 1970s from saline water run-off during irrigation processes.

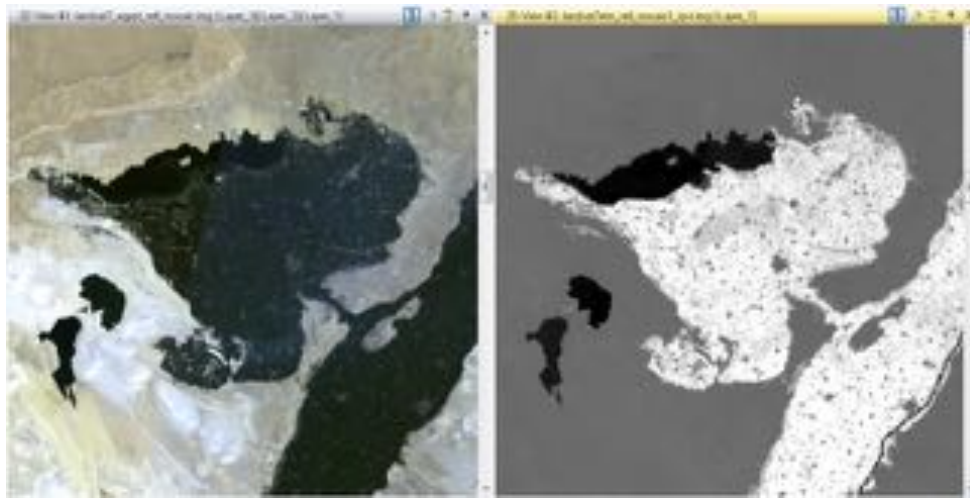


Fig. 5.8: Faiyum Oasis: L7 ETM+ true colour image (left); IPVI L7 derived image (right).

Single channel data is usually displayed in greyscale, such as the IPVI derived image in Figure 5.8 (right). Landsat data, for example, has an 8-bit radiometric resolution and can therefore display images using 256 discrete shades of gray (Subsection 2.4.4). Vegetated areas are displayed as high brightness values, indicating high moisture content. Note the location of the River Nile on the eastern side of the floodplain clearly stands out, and is seen trending in a northeasterly direction.

To enhance vegetated regions a greyscale image may also be displayed in pseudocolour. A pseudocolour image allows a range of brightness values to be assigned different colours, where each intensity value is mapped to a colour according to a function, such as a look-up table. A pseudocolour image can therefore serve as a simple classification (Subsection 3.8).

In Figure 5.9 the central part of Egypt's Western Desert is shown. The Nile floodplain can be seen in the extreme upper right in this image. Again, high brightness values correspond to moisture-rich vegetated regions, whereas darker values correspond to more arid and moisture-free regions (compare with Fig. 5.6). Three oases are identified in this region including the Kharga, Dakhla, and Farafra.

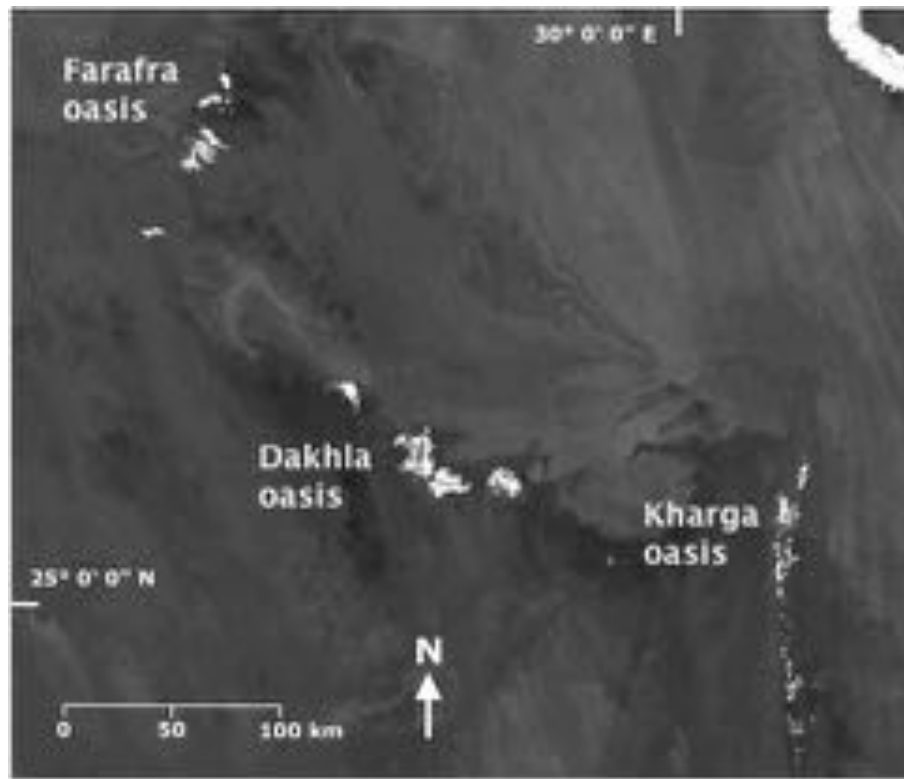


Fig. 5.9: Oases located in the Egyptian Western Desert detected as high brightness values; IPVI image derived from Landsat ETM+ imagery

Using a thresholding approach, pixel values greater than an IPVI value of 0.58, corresponding to vegetation, were painted in red. This value was attained through a process of trial and error by finding the optimum value that had a good correlation between the derived IPVI image and the same scene viewed using Google Earth. The surrounding pixel values were left unchanged. Results indicate that the methodology is robust in identifying regions with high moisture content. Figures 5.10 and 5.11 show enlarged regions where a number of different oases are highlighted using this technique.

As stated above, the locations for each oasis were validated using high-resolution imagery from Google Earth. The spatial resolution provided by Landsat ETM+ was high enough for the identification of individual pivot watering systems. However, the spatial resolution prevented detailed mapping at the administrative boundary level. The complete IPVI dataset for the Western Desert is shown in Figure 5.12, where it has been saved in a vector format ready for input into a GIS.

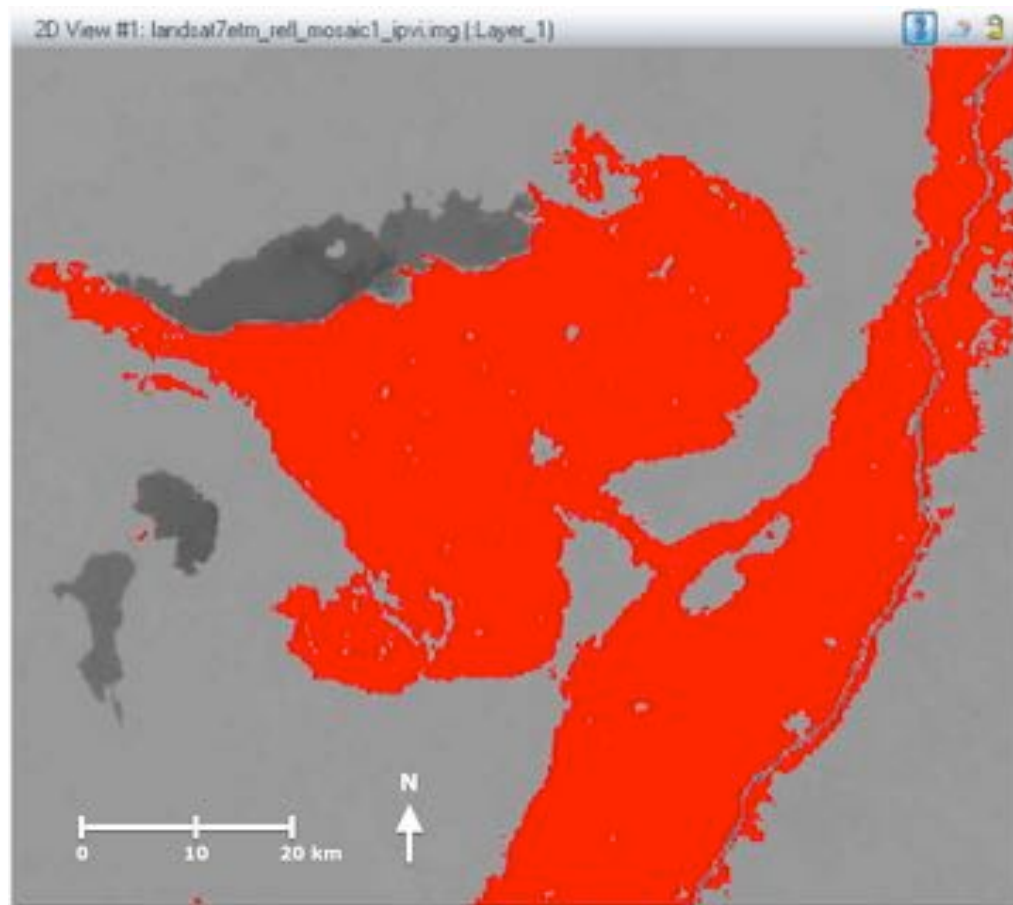


Fig. 5.10: The Faiyum Oasis displayed using a thresholding approach in pseudocolor. Nile floodplain and oasis all displayed in red. Landsat ETM+ IPVI derived image.

There are many different approaches to classifying an image. The approach used here was to apply the vegetation index to Landsat imagery and categorize each transformed pixel using a threshold value. A binary file was then created from that image. Another approach is to apply an unsupervised classification using an ISODATA clustering algorithm, merging selected pixels into different classes, such as an oasis class. Given sufficient training data for oasis sites, a supervised classification may also have been a reasonable alternative.

The next subsection discusses the use of spaceborne radar to map buried ancient river channels and how they may be relevant when searching for archaeological sites.

ETM+ VIS-R, G, B

ETM+ derived IPVI

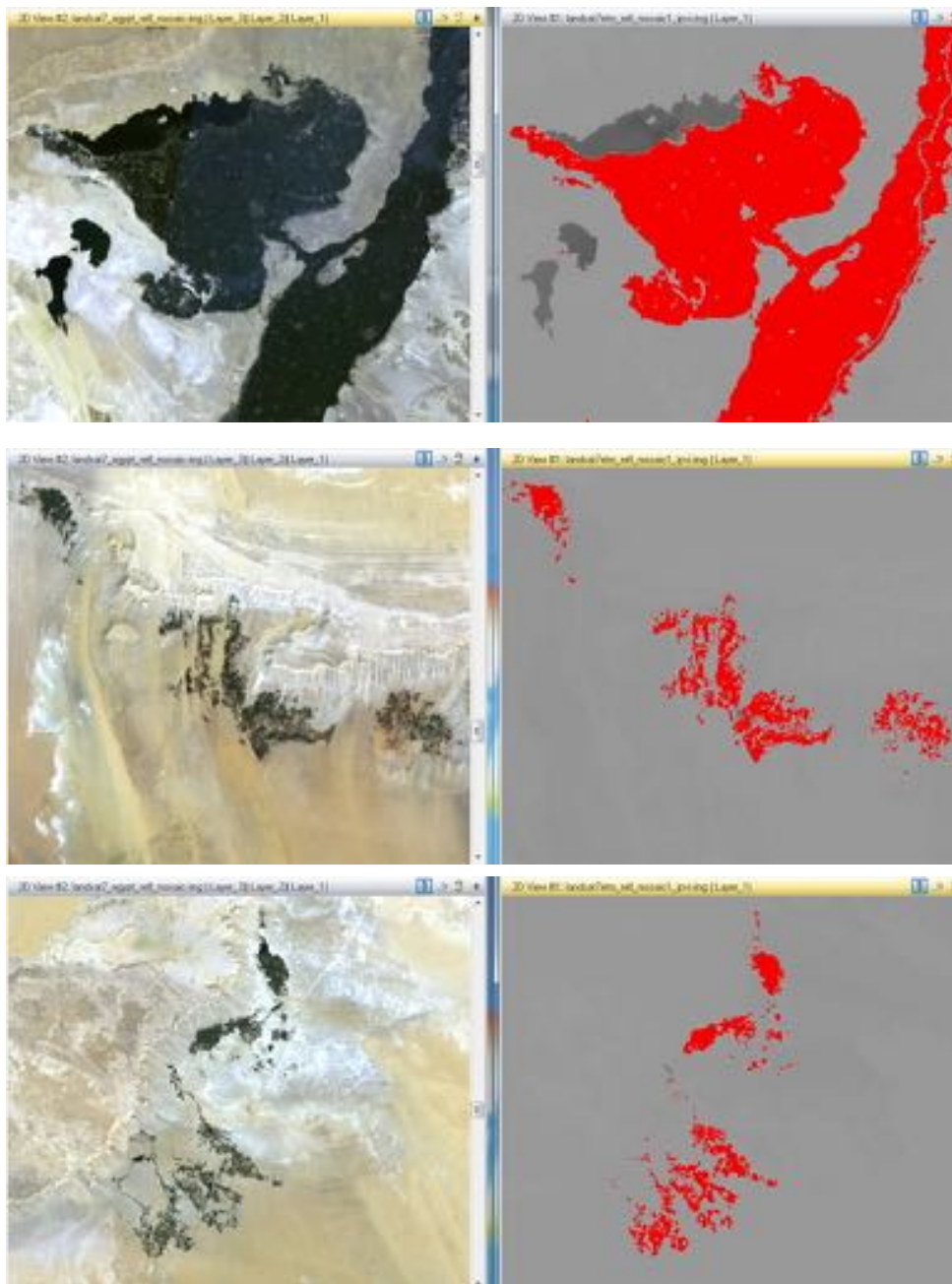


Fig. 5.11: IPVI Faiyum Oasis (top row), Dakhla Oasis (middle row), and Farafra Oasis (bottom row). Refer to Fig. 5.6 for map locations.

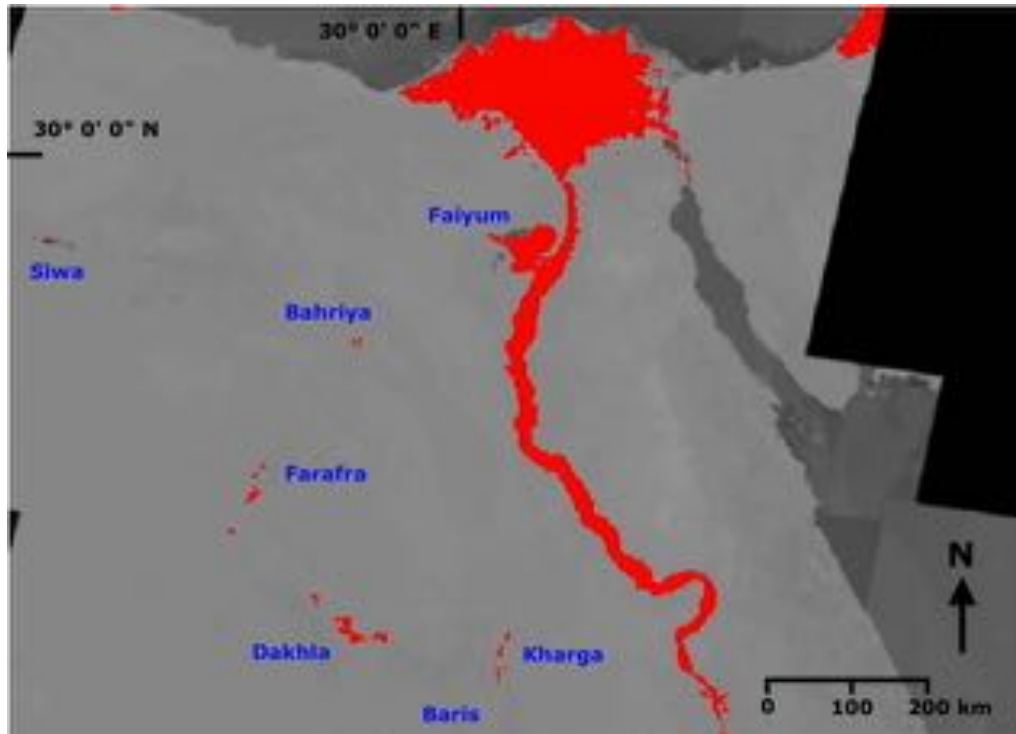


Fig. 5.12: IPVI threshold data set for the Egyptian Western Desert region. This image is rendered at a very small scale and as a result only the major oases are visible.

5.4.2 Mapping near-surface palaeohydrology using long wavelength SAR: The radar revealed palaeochannels of the eastern Sahara

An orbital imaging radar system for land observations was not developed until the 1980s. As a result, near-surface investigations of the world's desert regions continued to be impeded by the masking of widespread Quaternary deposits. Seasat, developed by NASA/JPL and launched in 1978, was the first orbital SAR system, but it was designed for use over the ocean and was short lived (105 days) due to a critical system failure. The follow-on missions – SIR-A, B, and C, launched during the 1980s and 1990s – although very capable in design, provided very limited geographic coverage of the planet. SIR-C, for example, imaged only about 10% of the Earth's surface. As a result, there were large gaps in the imagery collected over the eastern Sahara, and the full picture of the palaeohydrology of the region remained elusive. Nevertheless, the first images obtained by SIR-A and its immediate follow-on missions provided the first glimpses of the Sahara's water-rich past (Figs. 5.2 and 5.3). The launch of SRTM (2000), PALSAR (2006), and most recently, PALSAR-2 (2014), extends the

capabilities of previous radar systems, by providing near-global coverage of the planet, using fully polarimetric data, and at much higher spatial resolutions. For the first time it is now possible to use radar to fully map the distributions of ancient water flows beneath the desert sand sheet and observe what had been an uncharted terrain.

As discussed in Section 5.2, long wavelength (low frequency) SAR has the capability to penetrate several metres beneath the ground surface in sufficiently arid conditions. As such, SAR images acquired over the eastern Sahara desert reveal a network of buried river channels, termed palaeorivers or palaeochannels, which flowed across the region during more temperate times. Their discovery provides further evidence for cyclical, dramatic palaeoenvironmental shifts in the climate of the Sahara during Cenozoic time scales, i.e., the last 66 Ma (Issawi and McCauley, 1992). Some of these rivers may have been comparable in length and were certainly as wide as the present day Nile (Paillou et al., 2009). Using radar to map these features provides a better appreciation of their size, extent, and evolution over time.

Modern springs and oases draw their water from the remains of ancient water sources trapped in underground reservoirs. Studies using exploration wells have shown that there are vast resources buried under depressions where water collected during past humid phases. One study from the 1990s focused on the Great Selima Sand Sheet southwest of the Kharga Oasis. Based on results from remote sensing imagery analysis, over 1,000 wells were dug beneath the sand of what is believed to be a former lake. Large sources of fresh water were found trapped under high pressure buried at a depth of 100 metres. From this one source it has been estimated that the water can supply 250,000 acres (100,000 hectares) of agricultural farms for more than 100 years (El-Baz, 2012). Locating desert water sources can also avert long-standing humanitarian crises. The competition over scarce clean water in such regions as Darfur in northwestern Sudan can be shown to be directly responsible for much of the regional political and social instability. Therefore, locating fresh water sources for increasing desert populations is of vital importance.

Early SIR-A studies in the 1980s, carried out by workers at the USGS, sought to gain a better understanding of the hydrological history and morphological characteristics of the observed palaeoriver features (McCauley et al., 1997, 1986, 1982). Three types of buried river channel were identified, which they referred to as “radar rivers” (The term “radar river” is used when

microwaves are used to detect them): 1) broad alluvial valleys or basins (RR-1), 2) groups of braided channels inset within the broader valleys (RR-2), and 3) isolated, narrow, but long channels incised into bedrock (RR-3). Table 5.3 summarizes each type with typical characteristics and examples noted.

Several theories have been proposed to explain the distribution of the drainage channels. McCauley et al. (1986) suggested that they were first active from about 40 Ma through to the last Holocene pluvial, about 6 ka, and were part of a ‘Trans-Africa Drainage System’ (TADS), that originated in the Red Sea Hills in eastern Egypt, and extended across eastern Africa in a southwesterly direction, through the Chad Basin, before terminating on the western side of the continent at the Atlantic Ocean. Burke and Welles (1989) challenged the westward-flow theory, attributing the channels to an ancestral Nile. Issawi and McCauley (1992) proposed a further hypothesis, suggesting that the palaeochannels are the remains of three former drainage systems: the Nile, the Qena, and the Gilf rivers, and that the Nile is composed of surviving remnants from these former river systems. Investigations into palaeoflow directions have since showed that a southwesterly direction towards the Chad Basin seems unlikely. Robinson et al. (2000) has proposed that palaeochannels of the Selima Sand Sheet do not flow in a southwesterly direction but northeastward towards the Kharga Oasis, suggesting an interior drainage system under the Selima Sand Sheet. These flow directions are opposite to those proposed by the TADS. Due to the large timescales involved and the complicated geological history of the region, including episodes of tectonic uplift and volcanism, a full understanding of palaeochannel evolution, age, and flow direction has not yet been achieved.

Type	Description	Example
RR-1	Broad alluvial valleys or basins (10–30 km wide)	Wadi Arid
RR-2	Braided channels inset in the RR-1 valleys	Wadi Safsaf
RR-3	Isolated, narrow and long, bedrock-controlled channels; usually visible to optical sensors	Wadi Metareg
Table 5.3: Radar river types and their characteristics		

The second part of this case study constructed a regional map of the palaeohydrology by using SAR data and a digital elevation model derived from radar interferometry. The Libyan Desert was used as a focus in these investigations, which covers an area of over 1 million km², including eastern Libya, western Egypt, northwestern Sudan, and northeastern Chad. This region was considered ideal due to the widespread palaeofluvial features underlying much of the surface made clear from earlier SIR and PALSAR studies (McCauley et al., 1997; Paillou et al., 2010). The SAR data made visible the remains of subsurface features and provided a qualitative imagery assessment, while the DEM and derived contour models supplied a more quantitative evaluation of the topography. A combination of microwave (SRTM) and optical imagery (Landsat) was used to determine whether the palaeofeatures are located in the near surface or at ground level. This is because it is not always possible to identify near- or subsurface features using radar imagery alone. Subsurface features do not have a surface expression and are therefore invisible to the optical satellite sensor. Wadis (valleys or sometimes dry ephemeral riverbeds), however, may be visible on both types of imagery and can appear quite similar to palaeochannels.

The pre-processing of the SRTM1 radar reflection data (CID format) involved 1) geo-referencing each tile to its latitude / longitude coordinates, 2) mosaicking to enable synoptic observation, 3) contrast stretching to enhance palaeohydrological features, and finally 4) subsetting to focus on specific regions of interest. The mosaicking was carried out in stages by first stitching together 5 x 5 tiles to produce larger blocks of 25 (5 degrees of latitude and longitude), where each block consisted of 18001 x 18001 pixels. This was found to be a suitable dimension to manage in view of the large file sizes involved. Each block was saved at the highest resolution for image processing work (1 arc-second (0.0002777 decimal degrees), or approximately 30 m). All blocks were subsequently mosaicked together to create a 'super-mosaic' covering a geographical extent from approximately 10°–35° N latitude, 10°–35° E longitude. The super-mosaic covered the eastern Sahara in its entirety and consisted of a total of 447 tiles with a combined file size of 8 GB. Lastly, the individual blocks were exported to Google Earth, where they were saved at a reduced resolution of 8,000 x 8,000 pixels, which is the largest texture size that the program supports. Figure 5.13 displays the SAR super-mosaic registered to Landsat data in Google Earth. The red rectangle shows an area that was subset so as to focus on a more manageable region (Figure 5.14).

Examination of the SRTM image mosaics (Figures 5.13–5.14) shows that in contrast to the Landsat data, which displays only surface features of the desert landscape (see Figure 5.6), the SAR image reveals evidence of a period when the Sahara was much wetter than it is today. The subsurface is dominated by a complex drainage network that has since been covered by wind-blown sand deposits – clear evidence that the climate of the eastern Sahara has changed significantly in its past. The majority of the relict fluvial features are found in a central drainage region that today converges on the international borders of southwestern Egypt, northwestern Sudan, southeastern Libya, and northeastern Chad. The most prominent of the palaeochannels are located near the Gilf Kebir Plateau in southwestern Egypt ('A' in Figure 5.14), the Kufra palaeoriver system in southeastern Libya (B), and the Great Selima Sand Sheet, which extends across the border between south-central Egypt and Sudan (C).

As discussed in Chapter 2 (Section 2.8), the conditions that affect the intensity of brightness or darkness in a SAR image are primarily a function of the characteristics of the radar system (wavelength, depression angle, and polarization), in addition to the physical properties of the terrain (surface roughness, dielectric constant, and the aspect with respect to the look direction). Regions appear dark due to reflection of the radar signal away from the sensor (specular reflection); these surfaces tend to be flat and smooth. This is in contrast to brighter areas that are due to diffuse backscattering of the signal from rough surfaces towards the sensor, such as from exposed bedrock or from rocky outcrops. Palaeochannels appear dark in a SAR image due to the thickness of sand above being greater than the radar skin depth (which for L-band SAR is approximately 5 m). If the signal penetrates the sand and encounters bedrock, scattering will occur, and some of signal will travel back to the radar sensor, so that those regions will appear brighter. However, not all dark regions in the radar image can be attributed to past fluvial processes. Regions where the radar signal is fully attenuated (absorbed) due to thicknesses much greater than the radar skin depth appear dark and mask any underlying palaeofeatures that may be present, such as in the Calanscio Sand Sea, north of the Kufra Basin in northeastern Libya (D in Figure 5.14). As a result, these features conceal any fluvial channels that may pass beneath them.

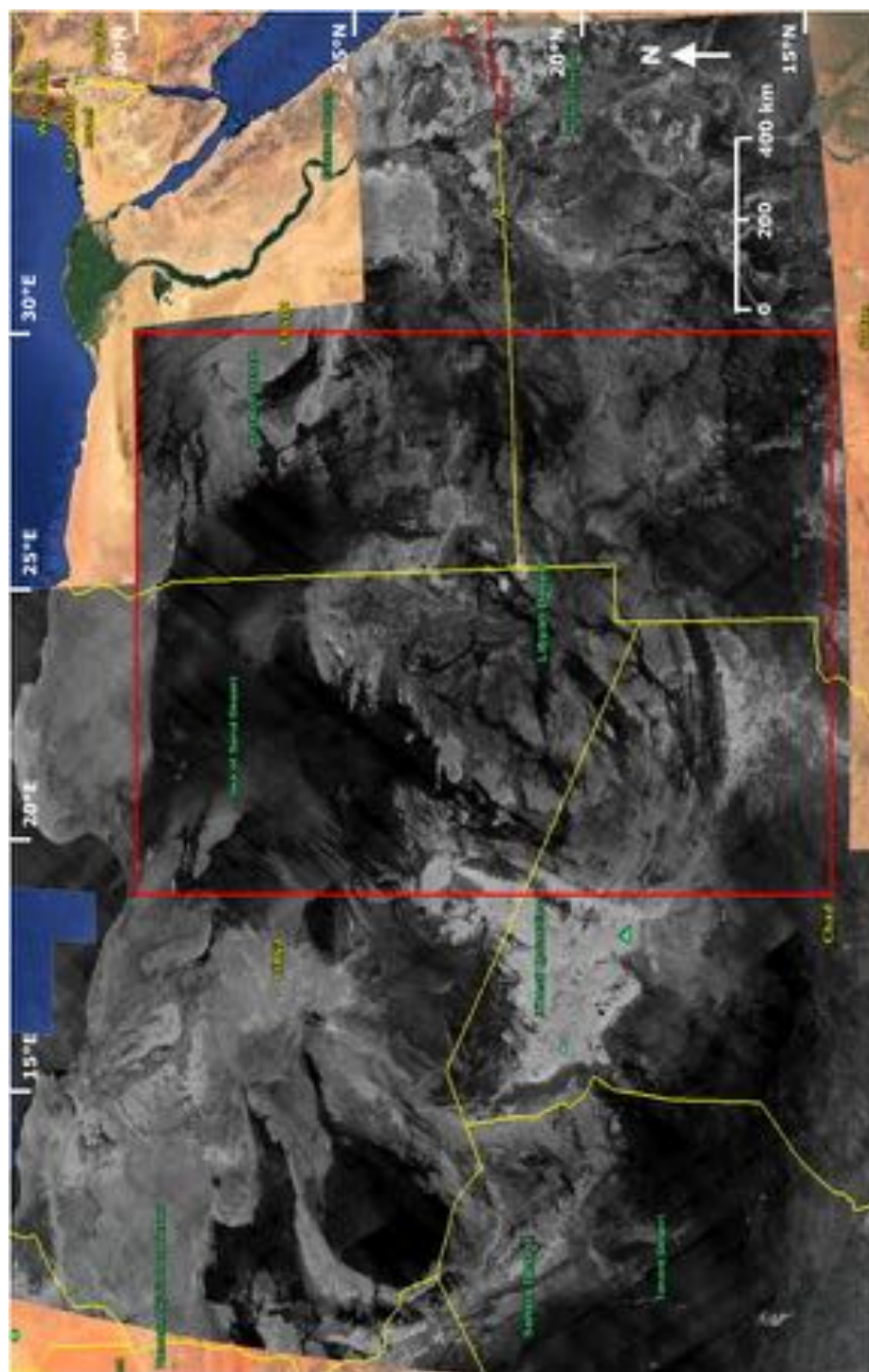


Fig. 5.13: SRTM1 amplitude mosaic (~30 m) superimposed over Google Earth. Red box indicates study focus.
Refer to Fig 5.1 for true-colour image of the Sahara desert for comparison purposes.

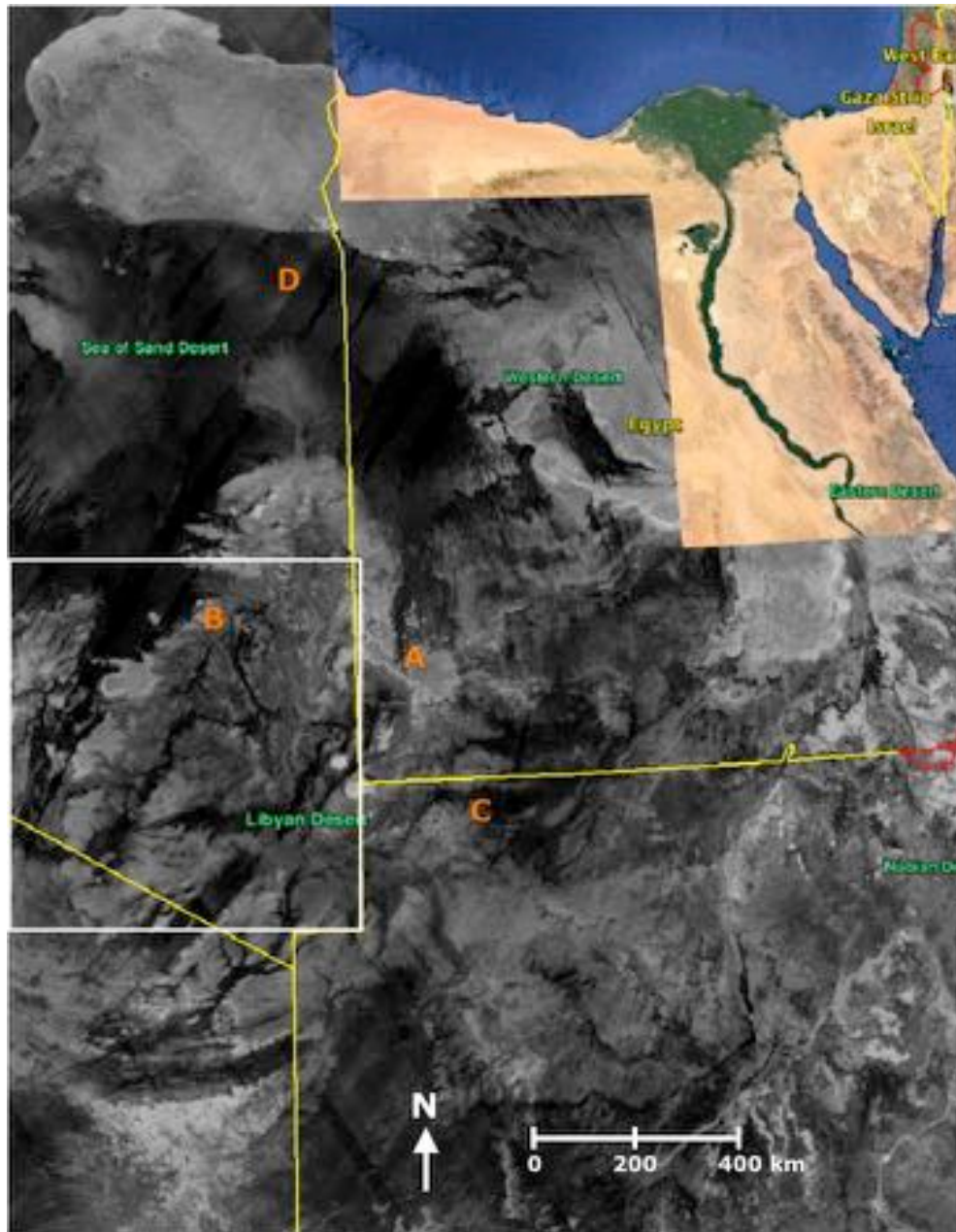


Fig. 5.14: SRTM1 amplitude subset (~30 m) registered to Google Earth imagery. Former river and lake systems can be seen dominating much of the region centred on the intersecting borders of Egypt, Libya, Chad, and Sudan. Landsat ETM+ optical imagery is shown as base imagery (RGB: 3, 2, 1), where these same palaeofeatures remain invisible (16°–33° N, 21°–36° E). Refer to Fig. 5.6 for true-colour image of Egypt for comparison purposes.

Figure 5.15 shows an SRTM amplitude image of the Kufra River system located in Libya (white box in Figure 5.14), first mapped using RADARSAT by Robinson et al. (2006). It is a major northward flowing palaeoriver system believed to have linked the southern Kufra Basin to the Mediterranean Sea through the Gulf of Sirte. The Kufra is one of three major palaeochannels in the eastern Sahara. The two further systems include the Sahabi River further to the west, and the Gilf Kebir River in Egypt to the east (Ghoneim, Benedetti, and El-Baz, 2012). The SAR image clearly shows two major channels of the river converging at the Kufra Oasis (white boxed area in Figure 5.15, 24° 11' N, 23° 26' E).

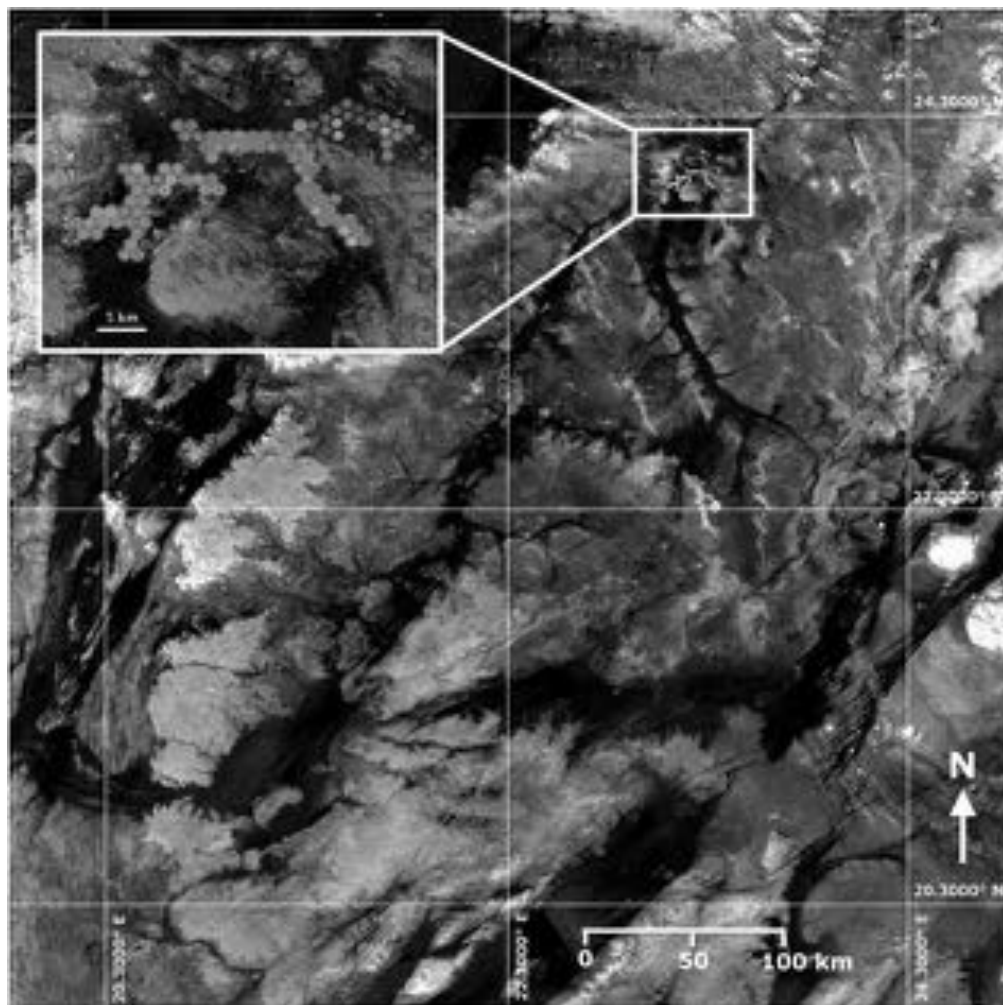


Fig. 5.15: SRTM1 amplitude image of the Kufra river system converging at the Kufra Oasis in SE Libya. If a route is found to the Mediterranean Sea, this river system will be comparable in length to the Egyptian Nile. Contrast stretch applied.

The magnified view identifies a number of circular pivot irrigation systems. The distribution of irrigation wells seem to follow the dendritic pattern of the subsurface palaeochannels, suggesting that there are still large quantities of water locked up in these channels. In Figure 5.16 a Google Earth screenshot of the same pivot well system using optical Landsat data is shown, where indications of subsurface river channels are obscured. PALSAR was later used to map a continuous 900 km section of the palaeoriver, although from the radar data it was unclear if a route existed out to the Mediterranean Sea (Paillou, Tooth, and Lopez, 2012). As the river continues to flow north through the Jebel Dalmah, its path terminates at an inland palaeodelta (just southwest of the 'Sea of Sand Desert' annotation in Figure 5.14). Thick sand deposits of the Calanscio Sand Sea prevent further mapping of the river system as it travels northwards. If an outlet is found through to the Mediterranean Sea, the river system will be comparable in length to the River Nile (Paillou et al., 2009).

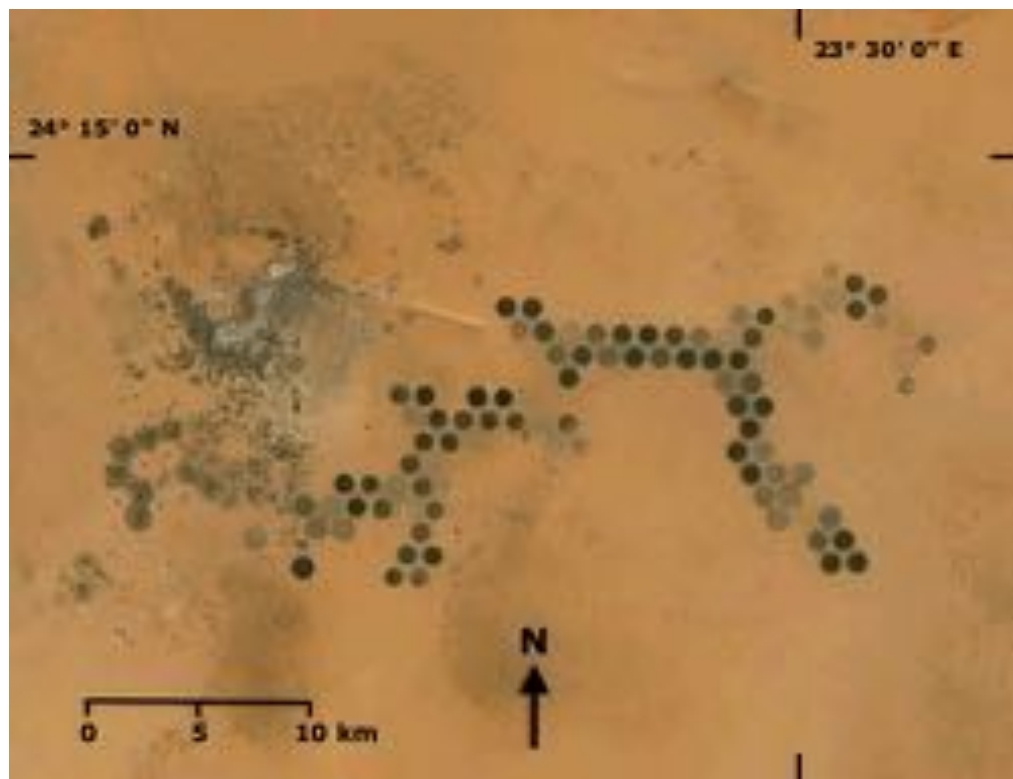


Fig. 5.16: Dendritic pattern of irrigation fields located in the Kufra Oasis. The well distributions follow closely the tributaries of the palaeoriver (refer to Fig. 5.15).

The use of radar amplitude data provides one strategy for mapping buried river channels. However this technique relies on a somewhat subjective and qualitative approach, based on visual characteristics only, and can often be time-consuming when identifying some of the smaller channels. A second strategy uses a SAR derived digital elevation model, such as from SRTM, by delineating drainage networks from the underlying elevation data, providing a more automated approach.

As previously discussed, SRTM acquires elevation data using interferometric synthetic aperture radar (InSAR). This technique generates elevation data points by recording two images of the same location from different vantage points. SRTM used single-pass interferometry where data was acquired by two antennas on board the same instrument located at a fixed distance apart (in contrast to repeat-pass interferometry where conventional SAR images are collected from different overflights of an area on slightly different paths). An advantage of using SRTM is that in addition to providing elevation data, the C-band radar allows the signal to penetrate into the subsurface. In effect, this technique allows for the elevation data to be collected for near-surface palaeodrainage networks. Palaeohydrological investigations by several workers have demonstrated the effectiveness of this technique (Ghoneim, Robinson, and El-Baz, 2007; Ghoneim and El-Baz, 2007a, 2007b). Digital elevation models (DEMs) applied to the eastern Sahara Desert have been instrumental in mapping fluvial pathways, calculating palaeoflow directions, and searching for internal lake systems based on elevation data from palaeoshoreline features (Robinson et al., 2000; El-Baz, Robinson, and Al-Saud, 2007; Ghoneim and El-Baz, 2007a; Ghoneim, Robinson, and El-Baz, 2007).

For topographical and hydrological analysis, both SRTM1 (30 m) and SRTM3 (90 m) elevation data were used for investigations at a local to regional scale, whereas SRTM30 (~ 1 km) was used for broader scale mapping when working with higher spatial resolutions was less important. Contouring and modelling of the drainage networks was derived from the underlying SRTM DEM at various resolutions. Additionally, PALSAR imagery (L-band) was used as a secondary radar source, mainly consisting of 100 m ScanSAR data. As such it proved useful for deeper penetration work (L-band vs. C-band) or when a secondary radar source was needed to address ambiguities in palaeochannel morphologies.

SRTM30 is comprised of SRTM and the U.S. Geological Survey's GTOPO30 datasets, of which the latter derives its topographic information from several raster and vector sources, including Digital Terrain Elevation Data (DTED) and the Digital Chart of the World (DCW). SRTM30 is formatted to the same specifications as GTOPO30, with elevations regularly spaced at 30-arc seconds (approximately 1 km spatial resolution at the Equator), and delivered in 33 tiles, each tile covering 50 degrees of latitude and 40 degrees of longitude. SRTM30 Version 2.1 was used in this case study which was a substantial rework of the original (version 1), incorporating enhancements including improved coastline definitions and a zero elevation for oceans and other water bodies (in earlier versions these regions were flagged using a -9999 value). Spikes and wells in the data (single pixel errors) had also been eliminated, as had detector errors, including banding. Large voids in the data (first discussed in Subsection 5.3.1), which are found in both the amplitude and elevation data of SRTM, and which are considerable throughout the desert regions of North Africa, have been filled and replaced with data from GTOPO30. As a result, SRTM30 contains SRTM data where the radar elevation data were valid and GTOPO30 data where SRTM data was void. Figure 5.17 shows substantial voids (black pixels) in SRTM1 amplitude data for a region corresponding approximately to the red box in Figure 5.13.

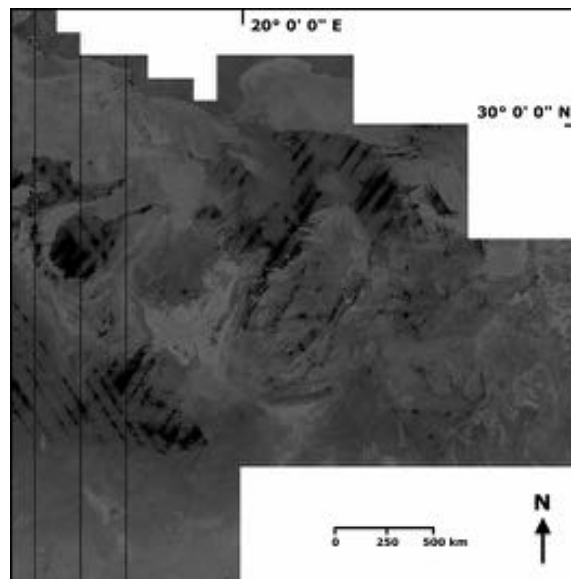


**Fig 5.17: SRTM1 amplitude data (30 m) showing voided data regions (voids shown in black).
 Voided data should be corrected for (filled) prior to computing fluvial networks.
 Vertical lines to the west are guidelines from the mosaicking process.**

Two SRTM30 tiles were downloaded from the USGS Earth Resources Observation and Science (EROS) Centre (<http://dds.cr.usgs.gov/srtm/>) covering the whole of north and central Africa, between 10° S–40° N latitude, 20° W–60° E longitude. The tiles were mosaicked into a single image, applying minimal enhancements so as to preserve the original pixel values (Figure 5.18). The elevation attributes, including the minimum, maximum, mean, and standard deviation for each tile are displayed in the table above the figure. Resolution at this scale, although coarse (~1 km), is good enough to provide a general overview of the topography. Bright areas in the image indicate regions of high elevation, while darker areas are of lower elevation. The low-lying regions are topographic depressions and are associated with large volumes of sand accumulation. Many of these depressions may have once hosted large lakes (see Subsection 5.4.3).

Tile	Latitude		Longitude		Elevation			
	Min	Max	Min	Max	Min (m)	Max (m)	Mean (m)	Std. dev.
w020n40	-10	40	-20	20	-139	3958	256	314
e020n40	-10	40	20	60	-415	5778	516	573

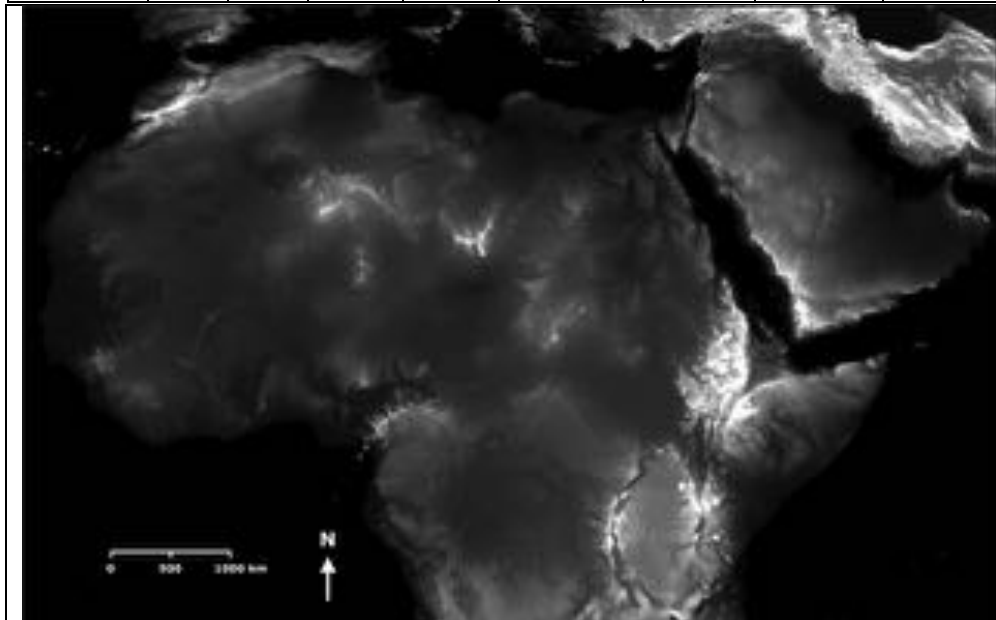


Fig. 5.18: SRTM30 DEM (~1 km) covering northern and central Africa (2 tiles)

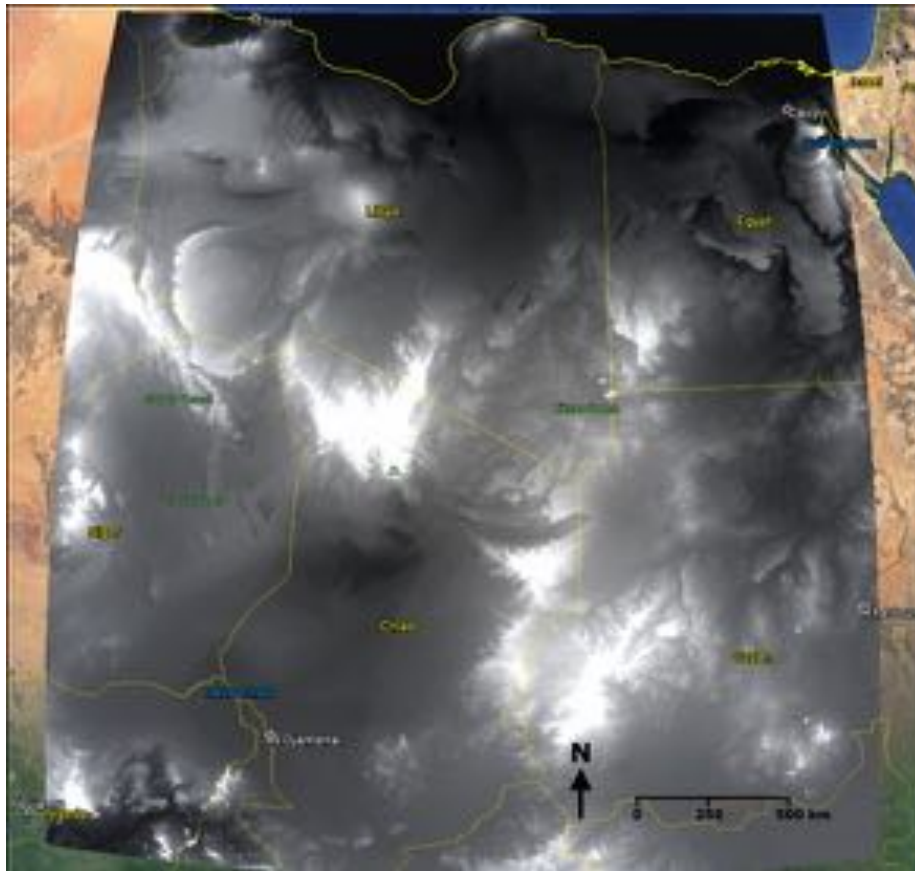


Fig. 5.19: SRTM30 DEM subset of the eastern Sahara with annotations from Google Earth showing country boundaries

After mosaicking, the tiles were subset to the eastern Sahara and superimposed over Google Earth imagery (Figure 5.19). Notable areas of higher elevation include the Gilf Kebir in southwestern Egypt, the Tibesti Mountains in northern Chad, and the Jebel Marra (Marra Mountains) located in southwestern Sudan.

Figure 5.20 shows a mosaic of two PALSAR scenes (ScanSAR mode) of the Kufra palaeoriver system described earlier (Figures 5.14 and 5.15). Contour lines (shown in white) and a vector map, represented by red arrows, were added as overlays, both being derived from SRTM3 data. Minimum and maximum elevations were set at 125 m and 725 m respectively with a contour interval of 75 m. The vector map shows areas of steepest slope at a particular location and was used to determine the direction water would take if it were poured over the

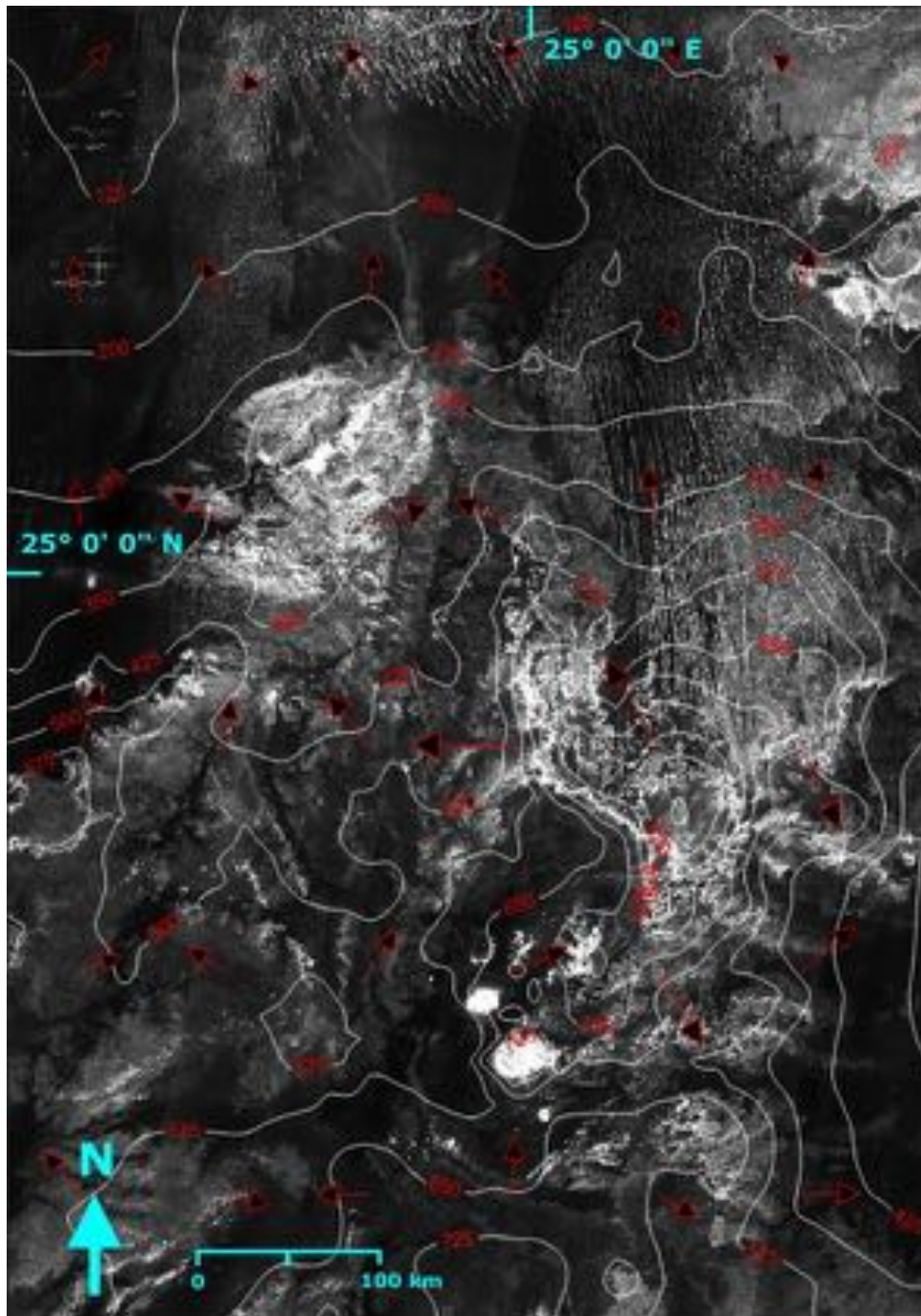


Fig. 5.20: The Kufra Basin with contour and vector map overlays indicates flow direction if water were poured over the palaeosurface. Contour levels and vector map derived from SRTM3 DEM (90 m), overlaid on PALSAR (100 m ScanSAR) imagery.

surface. It therefore gives a basic estimation of palaeoflow direction. The direction of the arrows indicate the downhill orientation while the length represents the magnitude. Effectively the arrows point in the direction of maximum potential water flow.

As shown from the elevation data, there is a general trend of decreasing elevation the further northward one proceeds. Without taking into account any major tectonic events since mantling by Quaternary deposits, it can be assumed that the direction of water flow was north towards the Mediterranean. The grid file used for the contouring was created from the x, y, and z data points using a kriging technique with a linear variogram so as to produce an accurate grid of the source data.

Topographic data from SRTM mosaics were used with a GIS surface flow algorithm to model subsurface palaeochannels. This involved creating watershed maps that divided regions into drainage basins and streams. A watershed is defined as an upslope area that drains water into a stream, stream system, or body of water. The mapping of the drainage features involved several steps: 1) Data voids were filled by interpolation of surrounding pixels (SRTM1 and SRTM3 data sets only). This was carried out using the SRTMFill utility by 3DNature (<https://3dnature.com/srtmfill.html>); 2) Additionally, all sinks (pits, or undrained depressions) were removed to allow the modelled water to flow easily across the surface. A sink occurs when a cell in the DEM is lower than its surrounding grid cells. Sinks can occur naturally due to inland depressions or sink holes, but they can also be due to detector errors; 3) Flow directions at each grid node were determined using an eight-direction surface runoff algorithm (D8), which is the one most widely used in the literature (Jenson and Domingue, 1988). The D8 algorithm determines the direction of steepest descent from a central cell to one of 8 neighbouring cells; 4) Flow accumulation, which is the total number of cells that drain into a given cell, is calculated from the flow direction. Stream networks and basins are calculated based on a “threshold” of accumulation. This is the number of upstream cells (flowing into a specific grid cell) that are required to create a stream network. A higher threshold creates fewer streams and basins, whereas a lower value creates a greater number. This value can be set within the modelling software. A more detailed treatment of modelling hydrological networks is covered in Subsection 6.4.6.

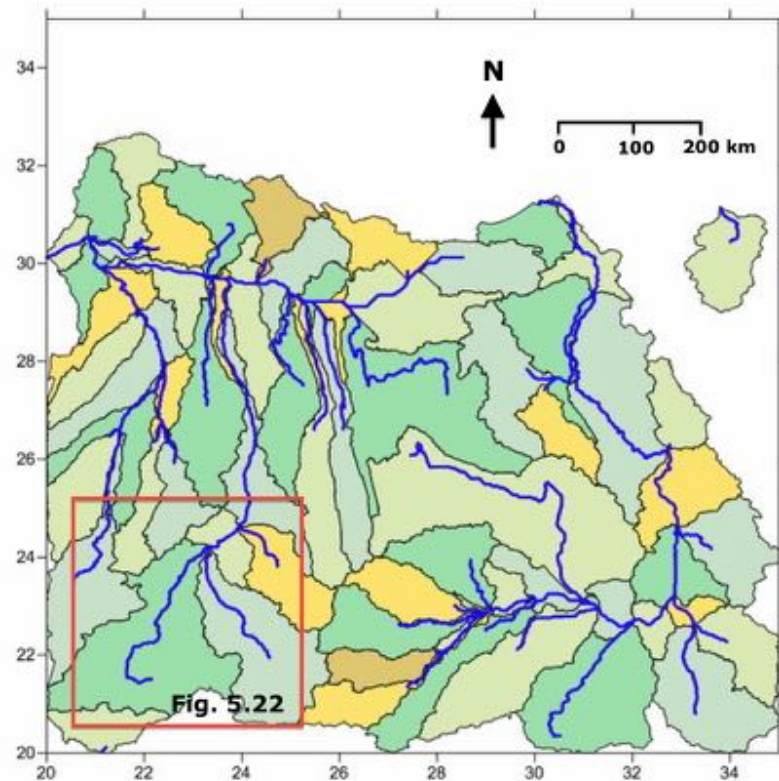


Fig. 5.21: Major palaeochannels of Egypt's Western Desert derived from SRTM3 (90 m). Colour ranges indicate river catchment basins. Latitude and longitude grid displayed in degrees.

All hydrologic analysis including modelling of the drainage networks and the calculation of palaeoflow directions was carried out using the Watershed module in Golden Software Surfer v.11 (www.goldensoftware.com). A watershed map for the eastern Sahara derived from SRTM3 data is shown in Figure 5.21, where the major palaeochannels have been delineated. Colour ranges indicate the catchment basins and their drainage contributions to each stream.

Part of the Kufra palaeoriver system is shown in Figure 5.22, with the drainage network superimposed over SRTM image data. The DEM was derived from SRTM30 data. Three branches of the river system are mapped and are annotated on the image as the western, eastern, and northern channels. All channels can be identified from both the radar amplitude and elevation data, except for the northern channel, which is invisible to SAR data. The western channel is oriented northeast-southwest, originating from Chad to the south and the

Tibesti Mountains to the west and flowing northward through the Kufra Oasis (the oasis is marked in magenta in the figure). The eastern channel has a northeast-southwest orientation through the Kufra Oasis, appearing to originate from the direction of the Gilf Kebir–Uweinat region to the east. Although the third branch (the northern channel) is invisible to radar, it can be identified by means of the elevation data and appears to originate from the southwest in the direction of the Gilf Kebir Plateau before connecting to the Kufra River north of the oasis, where it continues northbound. All three tributaries connect and flow northwards where they discharge into a large inland delta (seen clearly in Figure 5.14). Further mapping of the channels is not possible due to the depth of sand cover of the Calanscio Sand Seas to the

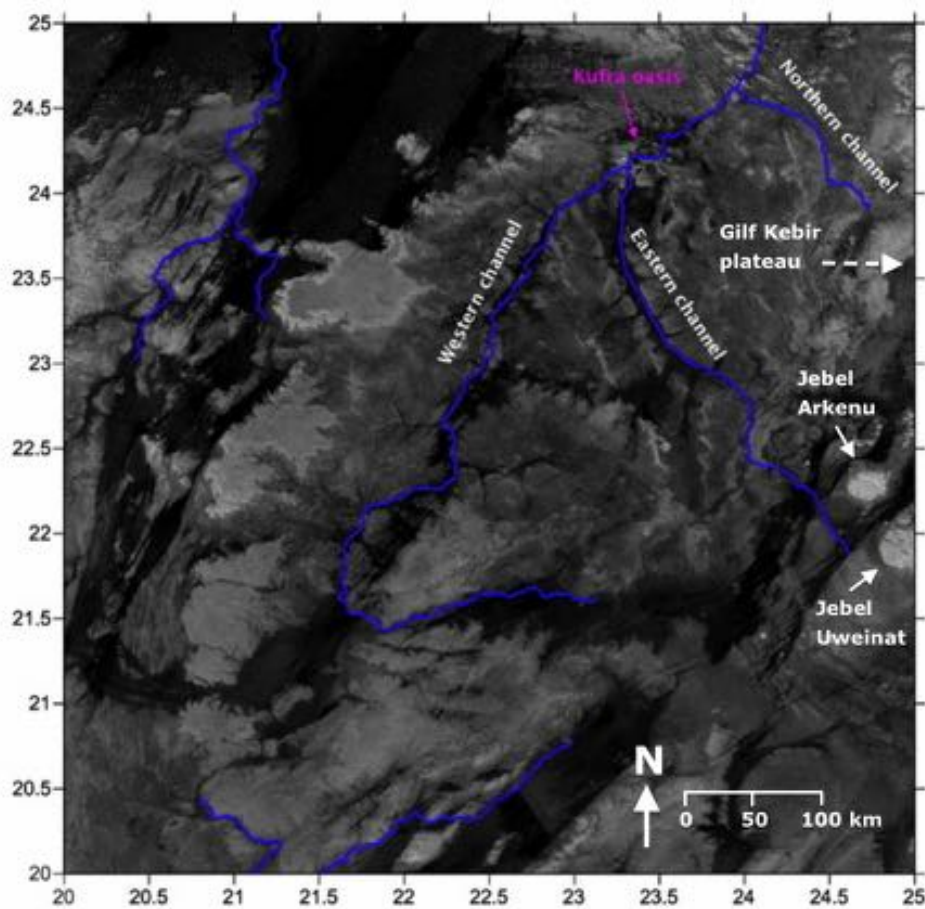


Fig. 5.22: Palaeodrainage of the Kufra River system (enlarged from red box in Fig. 5.21) as derived from SRTM30 (~1 km) superimposed over SRTM image data. Latitude and longitude grid displayed in degrees.

north, but a connection through the Gulf of Sirte and out to the Mediterranean Sea seems likely (Paillou, Tooth, and Lopez, 2012). The development of new spaceborne sensors using longer wavelengths (such as the P-band) may offer a means to examine the drainage channels in greater detail and find a route out to the Mediterranean.

As noted earlier, the SRTM DEM does not model the elevation of the present surface but records the subsurface, due to the penetration characteristics of the C-band radar. For instance, if the USGS HYDRO1k streams database (derived from GTOPO30) and the radar-interpreted palaeodrainage (from SRTM DEM) were superimposed, their drainage features would not coincide.

Maps derived from SRTM elevation data were produced at various scales for the eastern Sahara and northern Africa and are shown in Figures 5.23 and 5.24. The data sets will help constrain search locations for archaeological remains, of which the methodology is described in the next chapter. First, this case study concludes by examining a third means of locating water sources: the detection of former lakes and their palaeoshoreline features.

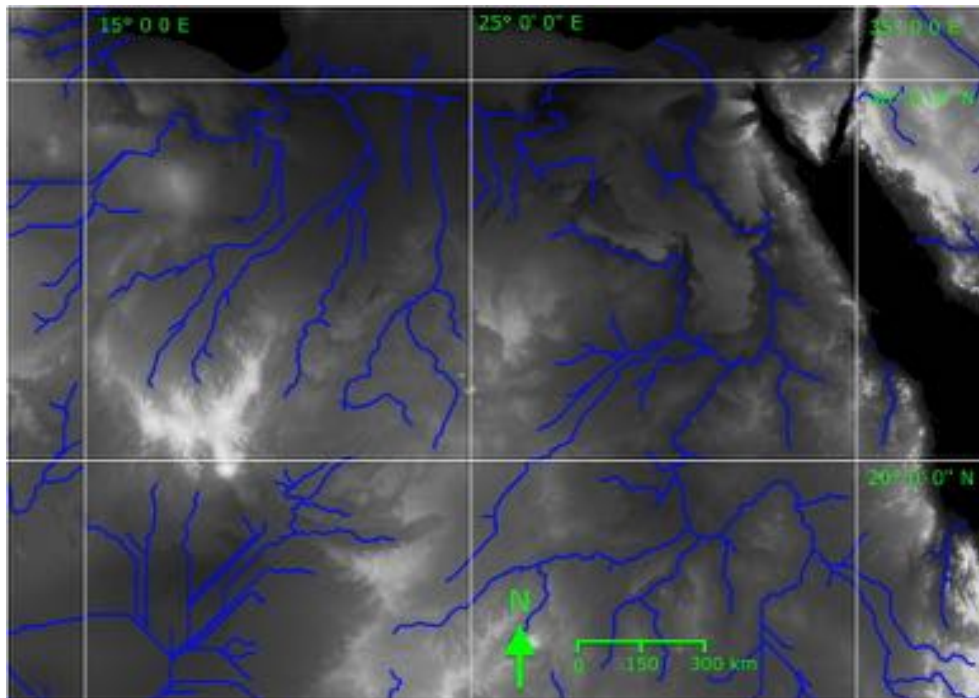


Fig. 5.23: SRTM30 DEM of the eastern Sahara with drainage network superimposed.
Refer to Fig. 5.24 for geographical context.

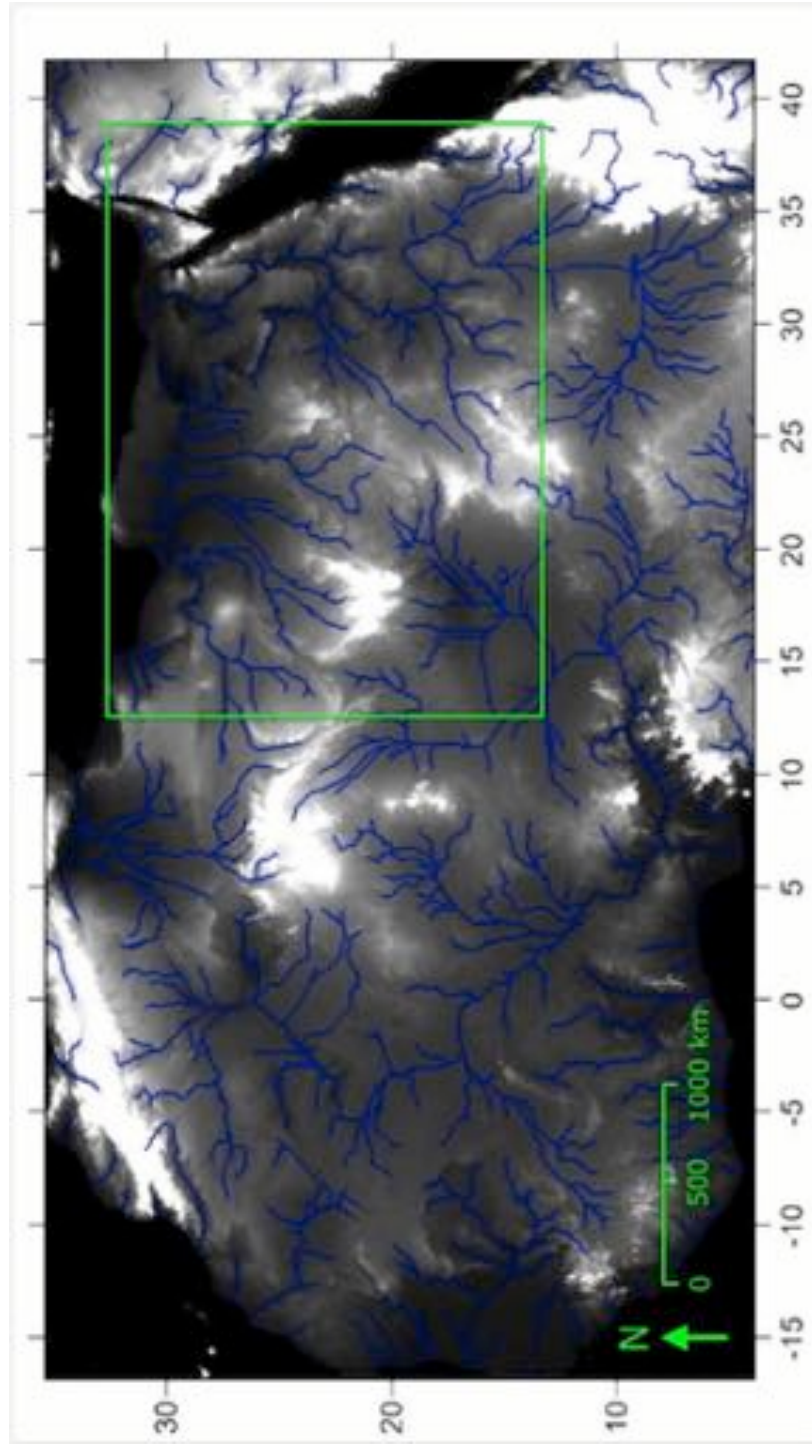


Fig. 5.24: Major palaeochannel distributions across northern Africa derived from SRTM30 (~1 km) data.
Boxed region enlarged in Fig. 5.23.

5.4.3 Mapping palaeolakes and their shoreline features using ASTER SWIR / TIR and SRTM DEM

Previous studies have identified a number of former lake systems that were active during the pluvial episodes of the Sahara's history. These systems, identified through satellite remote sensing coupled with ground-based investigations, are known to have formed during the Pleistocene (2.5 Ma–11.7 Ka) and Holocene epochs (11.7 Ka–present) and are termed “megallakes”. Three of the largest are found in adjacent closed basins (Figure 5.25) and had surface areas greater than 30,000 km², which is equivalent in size to modern day Belgium (Drake, 2012b). They include the Lake Megachad catchment, situated on the modern borders of Chad, Nigeria, and Niger (Ghienne et al., 2002; Schuster et al., 2005; Drake and Bristow, 2006); Lake Megafazzan in western Libya (Thiedig et al., 2000; Drake et al., 2008); and the Chotts Megalake on the borders of Tunisia and Algeria, south of the Atlas Mountains (Causse et al., 2003). In the eastern Sahara several smaller lakes have been mapped, either from their lake deposits or from digital elevation models, including the Tushka Lakes in southern Egypt, the Rahib palaeolake in Sudan, and the West Nubian and Northern Darfur palaeolakes in northwestern Sudan.

Mapping the distributions of historical lakes is important for several reasons. First, they may provide clues to the mechanisms of mass migrations of early Homo sapiens and later peoples when they moved through and out of Africa. These migratory routes are still poorly understood. Generally the Sahara has been considered a barrier to such movement and has been heavily discounted. Instead of pathways directly through the desert, several alternative routes have been suggested, including along the Red Sea coast and through the Nile Valley (Lahr and Foley, 2003). However, during key humid phases there may have been sufficiently widespread water to have allowed freer movement (Drake et al., 2008). This may have been achieved by "lake hopping" from one lake to another, provided that the distances were not too great (Figure 5.25). This would have allowed a more central route directly through the centre of the continent.

Mapping the remains of palaeolakes provides a further constraint when predicting the locations of archaeological sites in desert regions, around which many cultural remains have been found (El-Baz, 1998; McHugh et al., 1988a, 1988b; Wendorf, Close, and Schild, 1987).

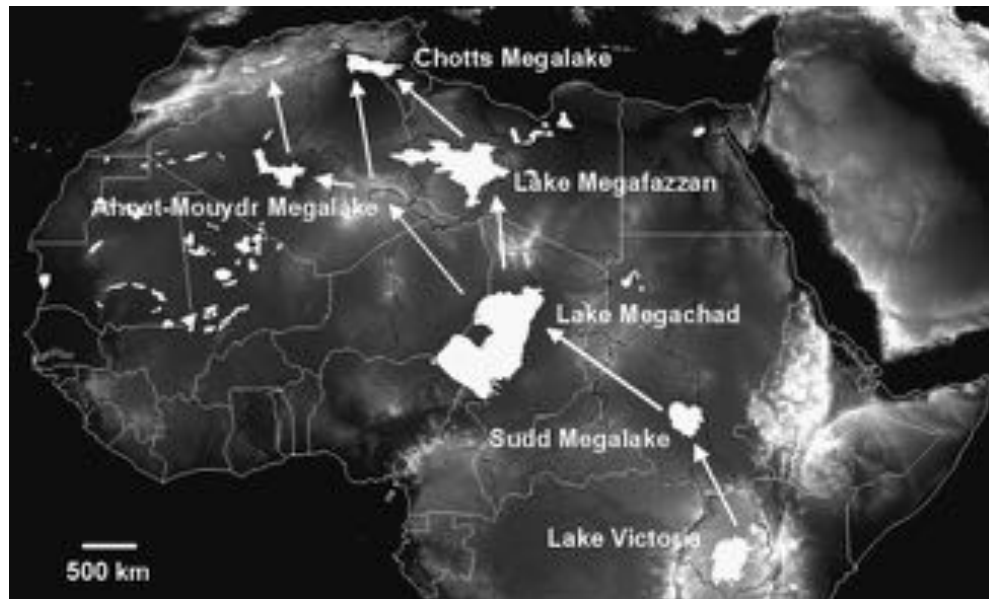


Fig. 5.25: Possible migration routes out of Africa via the Sahara Megalake basins.
Base imagery is SRTM30 (1 km) data (after Drake et al., 2008).

The final part of this case study discusses methodologies for locating where large volumes of water could have collected. Three strategies are presented: the use of band combinations, thermal infrared band ratios, and digital elevation models. Data and imagery derives from several remote sensing sources, including Landsat ETM+, ASTER TIR, and SRTM elevation data.

1. Band combinations

Landsat and ASTER are the sensors of choice for mapping a wide variety of rock and mineral types. Lacustrine (lake) deposits are chiefly composed of calcareous sediments (calcium carbonate sedimentary rock) and can be mapped by targeting regions of the EM spectrum where carbonate absorption features occur. For example, Drake (2012b) has used the Landsat ETM+ band combination 7, 4, 2 to map exposed lake deposits at Lake Megafazzan (Figures 5.25 and 5.26). A Landsat ETM+ colour composite (7, 4, 2) is shown in Figure 5.27. Lake deposits are displayed in a turquoise colour in the image. This band combination provides spectral information from each of three different regions of the EM spectrum (SWIR, NIR, and VIS-green). The resulting image displays greater spectral content due to less correlation of the data between the different channels.



**Fig. 5.26: Outcrops of calcium carbonate sediments at Lake Megafazzan, Libya;
Source: S. Armitage, Oxford**

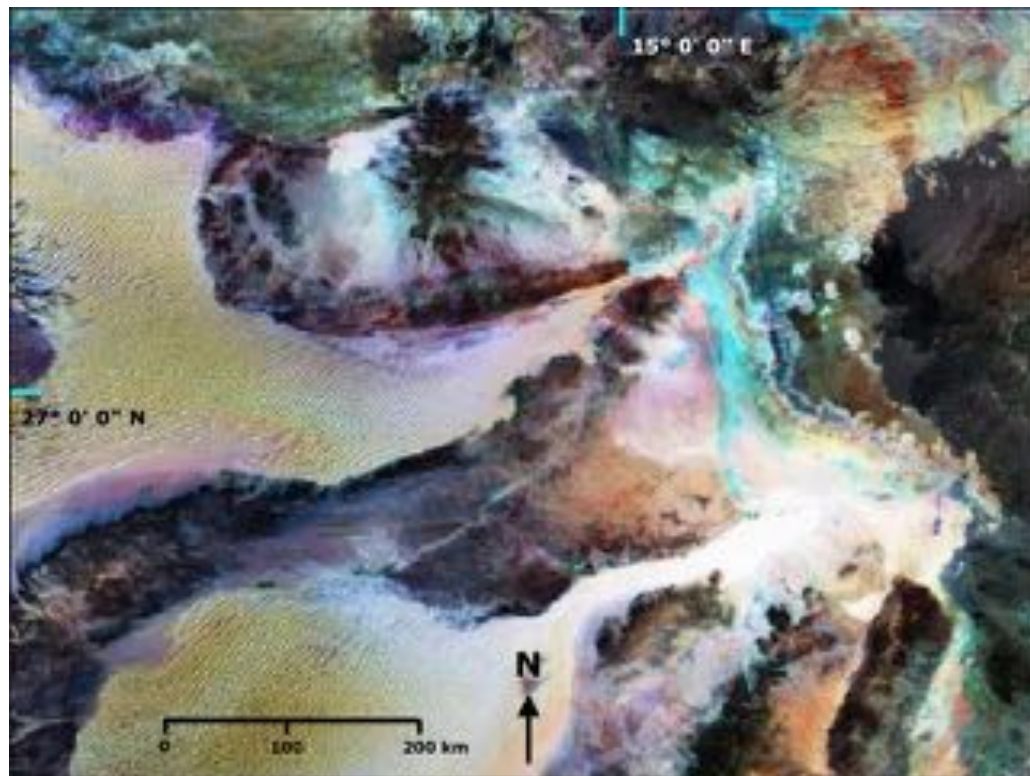


**Fig. 5.27: Central and western Lake Megafazzan as displayed by Landsat ETM+ (7, 4, 2).
Lacustrine deposits in the upper right portion of image appear as a blue-turquoise colour.
Extensive sand seas are shown in yellow, while the dark material to the north
and east consists of volcanic deposits.**

Optical remote sensing uses reflected light and as a result there is no penetration into the surface, so that the outcrops need to be sufficiently exposed in order to provide a significant spectral signature. Figure 5.28 shows a larger mosaic of ETM+ images, covering a greater extent of the eastern Sahara, using the same band combination. Again, a light blue/turquoise colour indicates possible lake sedimentary deposits (highlighted by yellow circles).

2. A study using thermal infrared band ratios

A second approach when mapping lake deposits in the spectral domain is to use band ratios in the SWIR and TIR. ASTER is particularly well suited to this task due to its increased sensitivity at these wavelengths, offering substantial improvements over previous earth observation satellites such as the Landsat series. At thermal infrared wavelengths, ASTER uses 5 channels at a spatial resolution of 90 m, compared to the Landsat Thematic Mapper (TM) and ETM+ sensors, which provide only 1 channel at 120 m and 60 m respectively. In the shortwave infrared, ASTER uses six channels compared to Landsat's two. At these wavelengths both sensors have a spatial resolution of 30 m (see Figure 2.5 and Tables 2.7 and 2.9 in Chapter 2). For the technique to be successful, spectral mapping relies on a significant quantity of the material being exposed at the surface (good surface outcrop and little vegetation cover). These conditions are commonly found throughout many arid regions of the world. The technique discussed in this subsection focuses on spectral mapping using ASTER thermal infrared band ratios.

Any material, either rock or mineral, can be identified from remotely sensed data acquired from spaceborne, airborne, or ground-based hand-held instruments – from its unique spectral signature. A spectral signature is defined as “a single feature or a pattern of features whose shapes, locations, and relative intensities are completely characteristic of a particular material” (Hunt, 1980). These patterns relate to variations in the material's reflected (or absorbed) electromagnetic energy as a function of its wavelength. Using this technique, former lake sediments can be identified in satellite imagery by searching for signatures of calcium carbonate (CaCO_3), which forms when water from a lake evaporates on a large scale. The presence of this mineral can therefore be valuable in locating past water-rich regions, which can be investigated for potential archaeological sites. However, detecting former lake systems is not as simple as it may seem as lake deposits can vary in composition. This is discussed further in the concluding statements of this chapter.

The characteristics of carbonate mineral spectra have been discussed at length in the literature (Rockwell and Hofstra, 2008; Salisbury and D’Aria, 1992; Adler and Kerr, 1963). The TIR portion of the spectrum extends from about 3–1,000 μm (1 mm). However, within this region sensors can exploit only two useable atmospheric windows from 3–5 μm and 8–14 μm . Fortunately diagnostic emissivity minima (absorption) features for the identification of silicates and carbonates can be found in these regions. Figure 5.29 shows the emissivity spectrum for a calcium carbonate sample between $\sim 5\text{--}50$ μm . The two largest absorption features at these wavelengths occur outside of Earth’s atmospheric window at ~ 7 μm and ~ 30 μm and cannot be detected by spaceborne instruments. A third, located at ~ 11 μm , is well within the second atmospheric window, and ASTER band₁₄ is sensitive to this absorption feature (circled in red).

Figure 5.30 shows the spectra for a series of limestone samples (carbonate rock) with characteristic absorption minima at ~ 7 , 11, 14, and 30 μm . The spectrum shown at the top of the figure represents pure calcite. As the spectra proceed down the graph, greater quantities of clays and quartz are introduced, producing the additional features in the 9, 13, and 20 μm regions. The red rectangle represents the spectral coverage of the ASTER instrument (8–12 μm), where the one identifying absorption feature at ~ 11.2 μm is located. This is the same absorption feature identified in Figure 5.29.

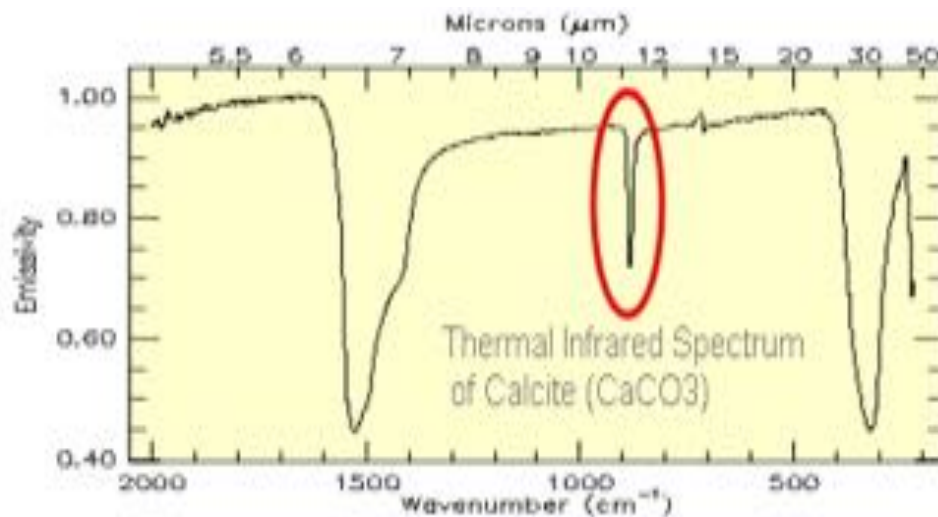


Fig. 5.29: TIR spectrum of a calcium carbonate sample.
Source: Arizona State University Thermal Emission Spectral Library.

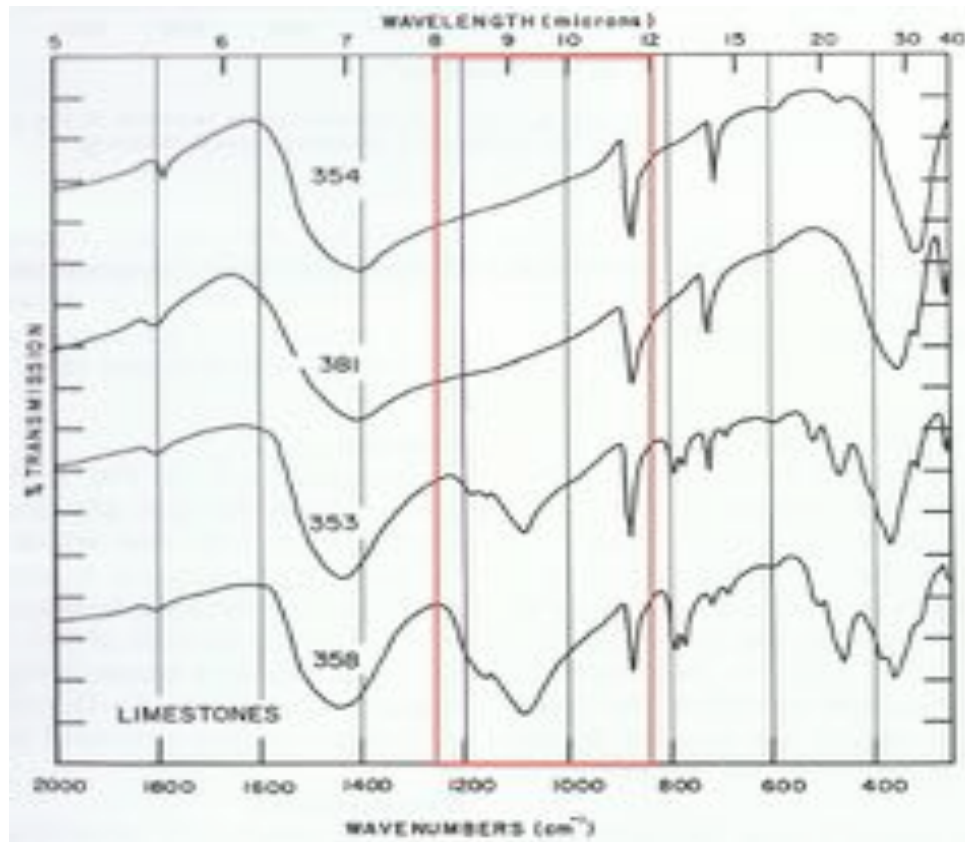


Fig. 5.30: TIR spectra for an assortment of limestone rocks; ASTER spectral coverage indicated by red box (after Hunt, 1980)

Based on an analysis of the TIR spectral characteristics of rocks, Yoshiki Ninomiya of the Geological Survey of Japan, Advanced Institute of Science and Technology (AIST), has pioneered several spectral indices for mapping quartzose, carbonate, and silicate rocks using ASTER data (Ninomiya, Fu, and Cudahy, 2005). Of particular relevance is the Carbonate Index (CI), which can be used for mapping lacustrine deposits of former lakes. Spectral indices (or band ratios) divide the digital number (DN) values of one band by the corresponding DN values of another band (or some other physical quantity, such as spectral radiance), displaying the result as a greyscale image. If ratios of bands are selected targeting specific spectral absorption features, the resultant image can help to identify the spectral variability and composition within a scene.

ASTER Level-1B (L-1B) imagery is supplied in terms of scaled radiance-at-sensor data, with radiometric and geometric corrections applied. At-sensor spectral radiance (units $\text{W m}^{-2} \text{sr}^{-1} \mu\text{m}^{-1}$) may be calculated for each DN value of an ASTER scene using the following conversion (Abrams, Hook, and Ramachandran, 2000):

$$L_i = (DN_i - 1) \times UCC_i \quad (\text{Equation 5.5})$$

where L_i = spectral radiance in band_{*i*} ($\text{W m}^{-2} \text{sr}^{-1} \mu\text{m}^{-1}$)
 DN_i = Digital number in band_{*i*}
 UCC_i = Unit Conversion Coefficient in band_{*i*}

At thermal infrared wavelengths the amount of radiation from a surface reaching the satellite sensor (spectral radiance) is a function of its temperature, emissivity (spectral composition), and the effects of the atmosphere. In isolating the spectral component, both the temperature and the atmosphere must be corrected for (this process is called normalization). Nevertheless, no atmospheric correction was applied to the imagery in this work as the indices seem stable against variations in atmospheric conditions, and previous work shows a good correlation between ASTER L-1B TIR imagery and surface geology (Ninomiya, Fu, and Cudahy, 2005).

Nevertheless, land surface temperature produces a strong masking effect that obscures emissivity; this was corrected for. Temperature effects are independent of wavelength, resulting in radiance images being highly correlated from one band to the next. To unmask the imagery, a temperature emissivity separation algorithm (TES) should be applied. Many techniques have been proposed over the years but the problem is complex because neither the temperature nor the emissivity is known a priori. As a result there is at least one more unknown value than the number of measurements in the problem. ASTER TIR uses five channels; there are therefore five unknown emissivity values for each channel, in addition to an unknown temperature value (which is the same for all bands) and atmospheric components. One solution is to estimate the temperature by assuming a value for emissivity in one of the bands (Kahle, Madura, and Soha, 1980). Planck's law (Section 2.5) can be used to solve for the ground temperature for each pixel in that band. Once temperature has been solved in one band, it can be considered the same value for all other bands, and the Planck equation can be inverted to solve for emissivity in the remaining channels. Many other solutions have been proposed, including performing a decorrelation stretch – a modification

of principal components analysis (Gillespie, Kahle, and Palluconi, 1984; Gillespie, Kahle, and Walker, 1986), and the use of more quantitative radiometric correction algorithms (Gillespie et al., 1998). A more in depth treatment of spectral radiance and emissivity can be found in Sections 2.6 and 2.7.

The carbonate minerals, calcite and dolomite, have a unique spectral absorption feature in ASTER band₁₄ (Figures 5.29–5.30, and 5.31a). As a result, based on differences in spectral emissivity between band₁₃ and band₁₄, the Carbonate Index (CI) is defined as:

$$CI = \frac{Band_{13}}{Band_{14}} \quad (\text{Equation 5.6})$$

CI is expected to be high for the carbonate minerals, calcite and dolomite, but is not expected to identify other carbonate rock types.

Similarly, silicate minerals and rocks have unique spectral properties in the thermal infrared. It is observed that the emissivity minimum moves to longer wavelengths as the chemical SiO₂ content of the rock type decreases (represented by the arrow in Figures 5.31 (b–f)). Rocks bearing pure silica (SiO₂, quartzose), such as quartzite, display a characteristic spectral feature between ASTER band₁₀, band₁₁, and band₁₂ in the TIR. Emissivity is higher at band₁₁ than at band₁₀ and band₁₂ (Figure 5.31b). On the basis of these spectral differences, the Quartz Index (QI) is defined as:

$$QI = \frac{Band_{11} \times Band_{11}}{Band_{10} \times Band_{12}} \quad (\text{Equation 5.7})$$

QI is expected to be high for quartzite and other siliceous rocks, but low for potassium feldspar and gypsum.

Furthermore, felsic rock types (e.g. granite) show a higher emissivity at longer wavelengths, that is, band₁₃, whereas more ultramafic types (such as peridotite) show a higher emissivity at shorter wavelengths, that is, band₁₂ (Figure 5.31 c–f). These spectral properties can be exploited to define the Mafic Index (MI):

$$MI = \frac{Band_{12}}{Band_{13}} \quad (\text{Equation 5.8})$$

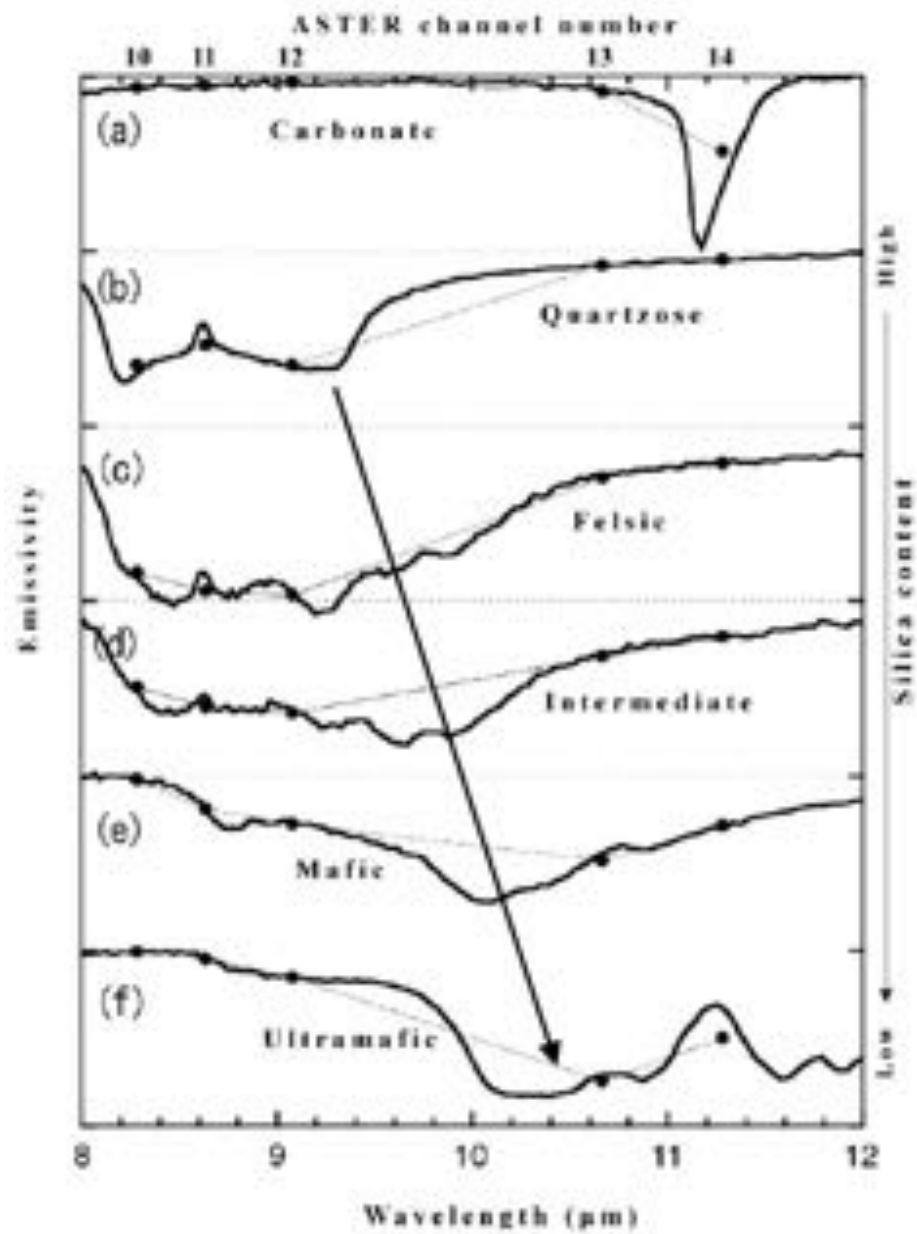


Fig. 5.31: Emissivity spectra for some common rock types
(after Corrie, Ninomiya, and Aitchison, 2010)

It is expected that MI will increase as the ratio of the two bands moves from a felsic to an ultramafic rock type. This is because MI has an inverse correlation to the SiO₂ content in silicate rocks – as MI increases, the silica content decreases, and vice versa.

In addition to being sensitive to the SiO₂ content of silicate rocks, MI is sensitive to carbonates. To reduce this side effect, a carbonate separation of $n = 3$ was introduced (Ninomiya, 2002; Ninomiya, Fu, and Cudahy, 2005).

$$MI(n) = \frac{Band_{12}}{Band_{13} \times CI^n}$$

$$= \frac{Band_{12} \times (Band_{14})^n}{(Band_{13})^{n+1}} \quad (\text{Equation 5.9})$$

$$MI(3) = \frac{Band_{12} \times Band_{14} \times Band_{14} \times Band_{14}}{Band_{13} \times Band_{13} \times Band_{13} \times Band_{13}} \quad (\text{Equation 5.10})$$

where n = degree of CaCO₃ separation; CI = Carbonate Index

Equation 5.9 represents an MI separation of zero, i.e., MI(0). For a more detailed discussion of the indices, the reader is directed to Ninomiya, Fu, and Cudahy (2005).

In the case of ASTER TIR, both the Quartz Index (QI) and the Mafic Index (MI) appear unaffected by surface temperature variations within a scene if atmospheric conditions are good. However, the Carbonate Index (CI) is directly affected by surface temperature changes (Ninomiya, 2002), because L1-B data is supplied without radiometric correction. To eliminate the temperature component, all ASTER L-1B at-sensor radiance values were normalized by converting the brightness temperature of ASTER TIR band₁₃ to a fixed value of 300 K using Planck's law. This creates a simple form of temperature emissivity separation by reducing the dependency of the CI on surface temperature (Ninomiya, 2002; Ninomiya, Fu, and Cudahy, 2005). Once normalized, the results suggest a marked improvement in the ability of CI to detect carbonate rocks. Normalized ASTER L-1B data can be calculated from Planck's law using Equation 5.11:

$$\hat{L}_i = L_i \times \frac{\exp\left\{\frac{\lambda_{13}}{\lambda_i} \times \ln\left(\frac{c1}{\pi(\lambda_{13})^5 \times L_{13}} + 1\right)\right\} - 1}{\exp\left(\frac{c2}{\lambda_i \times nT / \epsilon_{13}}\right)^{-1}} \quad (\text{Equation 5.11})$$

where L_i = spectral radiance in band_i ($\text{W m}^{-2} \text{sr}^{-1} \mu\text{m}^{-1}$)
 λ_i = centre wavelength of band_i (μm)
 c_1 = constant 1 = $3.74 \times 10^8 \text{ W m}^{-2} \mu\text{m}^4$
 c_2 = constant 2 = $1.44 \times 10^4 \mu\text{m K}$
 nT = temperature = 300 K
 ϵ_{13} = emissivity in band₁₃ = 1.0

The emissivity in band₁₃ is assumed to be 1 (blackbody); the radiation constants c_1 and c_2 are equal to $2hc^2$ and hc/k respectively, where h is Planck's constant ($6.626 \times 10^{-34} \text{ J s}$), c is the speed of light in a vacuum ($2.298 \times 10^8 \text{ m s}^{-1}$), and k is the Boltzmann constant ($1.38 \times 10^{-23} \text{ W s K}^{-1}$). The centre wavelengths for the ASTER TIR bands can be found or calculated from most remote sensing manuals (Table 5.4).

Sub system	Band number	Spectral range (μm)	Centre λ (μm)	Spatial resolution (m)
TIR	10	8.125–8.475	8.3	90
	11	8.475–8.825	8.65	
	12	8.925–9.275	9.1	
	13	10.25–10.95	10.6	
	14	10.95–11.65	11.3	
Table 5.4: ASTER TIR instrument characteristics				

The above methodology was applied to a region in northern Darfur, northwestern Sudan centred at 18° 15' N, 24° 45' E, which was identified as a testing area for the detection of spectral signatures of lake deposits. The region presents an ideal test case due to the well-exposed and widely distributed carbonate sediments (calcitic-aragonitic in composition), exposed as outcrops on the surface (Figure 5.32). In this SIR-C / XSAR image, lake deposits display as white speckled regions at (a) and (c). The former lake, which was first identified in 1997 (Pachur and Rottinger, 1997) and named the West Nubian Lake, has prominent shoreline features (d). Lake sediments appear bright in radar imagery, due to high backscatter values compared to the lower reflectivity of the surrounding sand-covered regions. Radiocarbon dating and chemical analysis of sediment samples indicate the presence of freshwater conditions from between 8,800 and 4,500 years ago, that is, early to middle Holocene (Pachur and Rottinger, 1997). More recent investigations using SRTM data have found the lake to be positioned at the centre of a large endorheic (closed) drainage basin, comparable in size to Canada's Great Bear Lake (30,000 km²), and thus important for future investigations of potential groundwater resources (Ghoneim and El-Baz, 2007a).



Fig. 5.32: SIR-C / X-SAR image of the West Nubian lake basin (RGB: L-HH, C-HH, X-VV). Exposed lake deposits indicated at (a) and (c). Palaeoshoreline observed at (d) (after Pachur and Rottinger, 1997).

Sixteen ASTER Level 1B (L-1B) scenes were acquired from Japan's Earth Remote Sensing Data Analysis Centre (ERSDAC, <http://www.ersdac.or.jp>). Imagery was recorded between the months of April and July from 2006 to 2012. The data was delivered in a Hierarchical Data Format (HDF), which provides two files for each scene – a binary .hdf file containing the imagery and an ASCII text .met file containing the metadata. The imagery was checked for acceptable levels of cloud cover ($< 1\%$) and for sensor errors, such as banding and other geometric distortions. The TIR channels (bands 10–14) were extracted, and the raw Digital Number (DN) values converted to physical units of spectral radiance using the Unit Conversion Coefficients (UCCs). The UCCs, supplied in the .met file, correct for sensor gain and offset and are different for each ASTER band and for each gain setting used to acquire the image.

After pre-processing, the three indices, QI, CI, and MI, were computed and applied to normalized at-sensor radiance values, producing greyscale images for each satellite scene. A false colour composite image (FCC) was created for each scene by sending the indices to the separate colour guns of the display (RGB: QI, CI, MI). Finally, the FCC images were mosaicked and a linear contrast stretch applied before output. Note that the normalization and the application of the indices were applied to the sixteen scenes on a scene-by-scene basis before they were mosaicked into a single coverage. No colour correction (i.e., histogram matching) was applied during the mosaicking process, as this was considered a more favourable approach compared to mosaicking the imagery first and applying indices second. The reasoning for this choice is that each satellite scene contains unique scene-dependent spectral radiance values that vary according to date and time of day of acquisition. To create a consistent workflow all indices were applied to normalized L-1B imagery. The mosaicking and radiometric correction of thermal infrared ASTER data has been discussed at length in the literature (Scheidt, Ramsey, and Lancaster, 2008).

Processed greyscale images of QI, CI, and MI, for the West Nubian palaeolake deposits, are shown in Figures 5.33A, B, and C, respectively. They are enhanced with linear contrast stretches of 1.070 to 1.216 for QI, 1.021 to 1.034 for CI, and 0.105 to 0.111 for MI. Contrast stretching increases intensity in order to improve the visual enhancement of those regions. Figure 5.33D shows the FCC image after assigning QI to red, CI to green, and MI to the blue colour guns of the display. The greyscale and FCC images should be referred to side by side

when interpreting imagery. While the greyscale images are useful for identifying individual rock types, the FCC image is superior for understanding the spatial extent of the geological outcrops. Use of both types of images is therefore essential when making a detailed geological analysis of a study area.

Bright regions displayed in each of the greyscale images refer to high signal content of the respective index. Referring to Figure 5.33D, generally, an orange-red colour represents quartz-rich, feldspar-poor sedimentary rocks, a light green colour represents carbonates (i.e., calcite and dolomite-rich limestone), and a blue-purple colour identifies mafic rock types (silica poor).

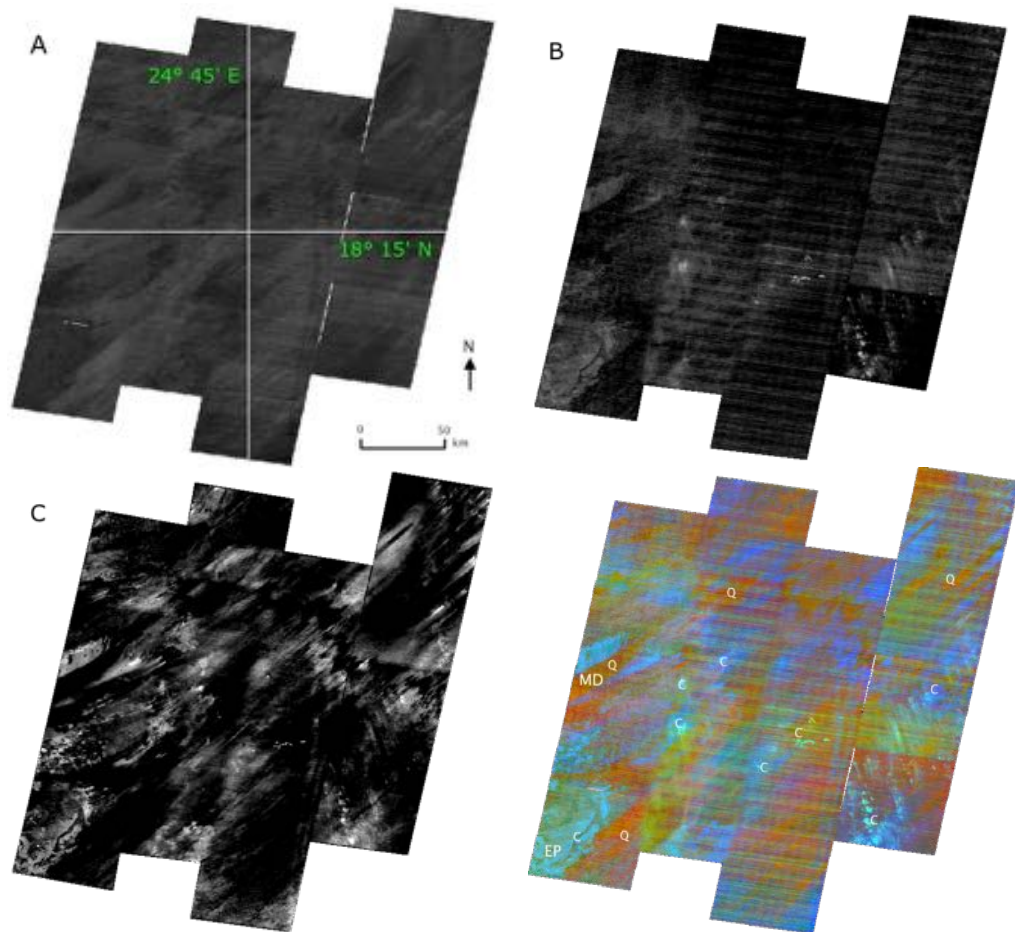


Fig. 5.33: West Nubian palaeolake deposits in northwestern Sudan (centred at 18° 15' N, 24° 45' E) detected using ASTER TIR band ratios. Greyscale images of QI (A), CI (B), MI (C), and FCC where RGB: QI, CI, MI (D).

Generally, the FCC image (Figure 5.33D) agrees well with the known geology of the region: Q and C labels are used to indicate quartz-rich and limestone-rich areas respectively. The Ennedi Plateau (identified in the lower left corner as EP), presents as low QI, high CI, and high MI). This is consistent with the geology of the plateau, which is composed predominantly of limestone. Large swaths of sand deposits, such as those in the Mourdi Depression (low lying region, MD) to the north of the Ennedi Plateau, have a high QI signal, indicative of a high quartz content due to wind-blown sand.

Although the FCC image appears successful in separating different rock and sediment types, there remain problems with the underlying radiometric correction, as is shown by the non-uniformity of the colour ranges across the different scenes, where a red-green colour represents quartz rich areas and cyan-blue represents carbonates and silicate-poor rocks. This is most likely a consequence of not applying an atmospheric correction. Ninomiya's ASTER TIR indices have been used in previous studies in areas of high elevation, such as the palaeolake regions of the Tibetan Plateau, and have achieved good results without the need for such correction (Ninomiya, 2002; Ninomiya, Fu, and Cudahy, 2005; Corrie, Ninomiya, and Aitchison, 2010). The Tibet study found that there was a good correlation between emissivity (spectral component of the signal) and surface geology. Tibet, however, has an average surface elevation exceeding 4,500 m and therefore less thickness of atmosphere for the signal to travel through. In contrast, the eastern Sahara has much lower elevations (much of the Sahara lies at an elevation of about 300 metres). The highest elevation is Emi Koussi (3,445 metres), a shield volcano southeast of the Tibesti Mountains in northern Chad. These Mountains can be seen as a bright (high) area in the northwestern corner of Chad (Fig. 5.19). Contributions from atmospheric path radiance will therefore be greater, resulting in greater masking of the spectral content derived from the area of interest on the ground.

Without an atmospheric correction it is difficult to interpret the extent of lacustrine deposits, but previous fieldwork has shown them to be extensive (see, for example Pachur and Rottinger, 1997). A simplified atmospheric correction can be achieved by applying a decorrelation stretch, which uses a modification of principal components to emphasize variations in the spectral signal (Bierwith, Huston, and Blewett, 2002). Figure 5.34 shows the same scene after application of a decorrelation stretch to bands 13, 12, 10 (RGB). Quartzites

are displayed in red, carbonates in green, and silicates in blue. This may provide a somewhat clearer picture of the exposed geology and has the advantage of requiring minimal manipulations of the underlying pixel values.

3. Digital elevation modelling of lake basins

The previous discussion presented a spectral-based approach using band combinations and spectral ratios as a strategy for mapping lacustrine deposits of former lake systems. However, the process relies on sufficient quantities of the material to be exposed at the surface in order for a unique spectral signature to be detected by the satellite sensor. In the absence of exposed deposits a second strategy is to use digital elevation data to identify topographic depressions and relict shoreline features. Usually topographic depressions are first identified by means of

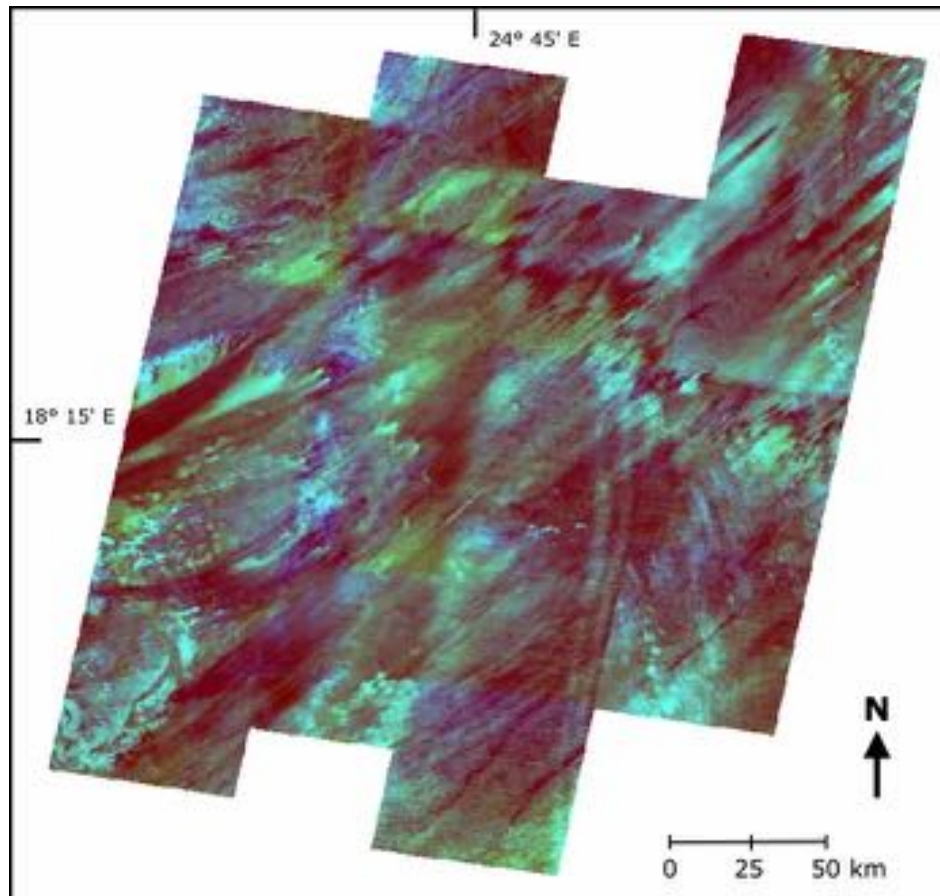


Fig. 5.34: ASTER TIR mosaic of the West Nubian Lake (13, 12, 10) after applying a decorrelation stretch

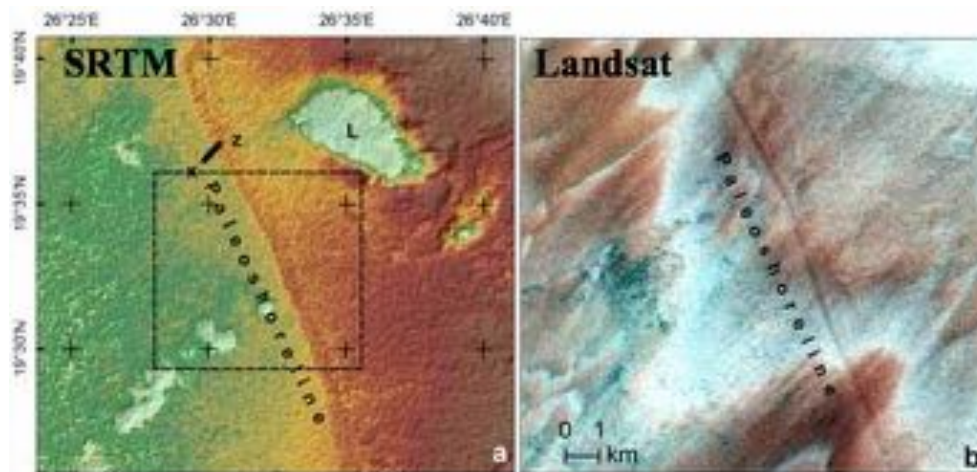


Fig. 5.35: Segment of a palaeoshoreline feature derived from SRTM3 at the eastern edge of the Northern Darfur Megalake (a); Landsat image of same area shown in (b). The shoreline feature correlates well with a 573 m contour line associated with a pre-Holocene lake level (after Ghoneim and El Baz, 2007a).

using contouring techniques. Satellite imagery is then examined for evidence of palaeoshoreline features, that which, if present, can provide compelling evidence for where large bodies of water may have formed.

Around many relict lakes are found prominent shoreline features. These features indicate phases of a lake's evolution where water levels have risen and fallen, leaving evidence in the form of strandlines. If the shoreline features are well preserved they can be identified by means of remote sensing imagery (Figures 5.32 and 5.35). By using the elevation data that each strandline provides, a range of areas and volumes for the lake can be estimated. Several investigations have successfully employed digital elevation data to map palaeolakes across the eastern Sahara with these same techniques (Drake and Bristow, 2006; LeBlanc et al., 2006; Ghoneim and El-Baz, 2007a; and Maxwell, Issawi, and Haynes, 2010).

Lake Megachad (Figure 5.25) provides the best example for evidence of preserved shoreline features, with twelve currently identified (Drake and Bristow, 2006). Ground truthing has shown that the deposits consist of fine-grained sediments and gravels that could only have been deposited by water. When at its largest, between 5,500–4950 BC, the lake measured approximately 361,000 km² in extent, roughly equivalent to the surface area of the Caspian Sea (Schneider, 2010). Cultural artifacts, including stone tool assemblages, are commonly

found along the shorelines of palaeolakes, and these should be investigated when searching for archaeological remains (Wendorf and Schild, 1980; El-Baz, 1998).

Modelling the locations of possible archaeological lake sites involves generating contour lines derived from digital elevation data. The contour lines are displayed over the DEM or some other type of imagery. To better visualize lake perimeters, “digital water” is poured over the surface and filled to predetermined contour levels. The idea is that the water will collect in natural depressions in the landscape. Finally, the image is analyzed to examine potential locations where lakes could have formed. Figure 5.36 shows the extent of a lake system located in the Northern Darfur Basin in northwestern Sudan derived from SRTM3

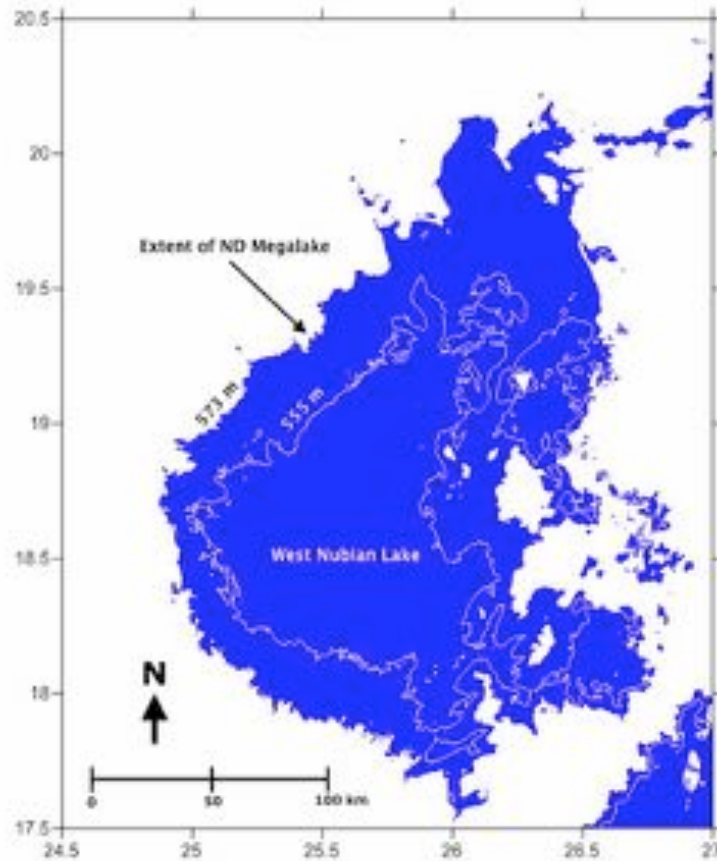


Fig. 5.36: The Northern Darfur (ND) Megalake (573 m) and the West Nubian (WN) lake (555 m) derived from SRTM3 digital elevation model data. “Digital water” has been poured to the 555 m and 573 m contour levels to simulate different lake levels.

elevation data. The inner contour (white line) represents a previously identified strandline at 555 metres and depicts the extent of the former West Nubian Lake that existed during the early to middle Holocene Epoch (11,500–5,000 BP). Dating is based on earlier investigations of the freshwater lake sediments (Abell and Hoelzmann, 2000; Hoelzmann et al., 2001; Hoelzmann, 2002). The maximum water level shown is derived from several identified strandlines corresponding to a 573 m contour level, depicting the full extent of the Northern Darfur (ND) Megalake system (Ghoneim and El-Baz, 2007a). These strandlines are visible in both SRTM data and Landsat ETM+ images and correspond well with the 573 m contour level. Dating of the larger lake is more problematic but is believed to be from a pre-Holocene time (Ghoneim and El-Baz, 2007a). Figure 5.37–5.38 shows these same lake systems overlaid onto Google Earth Landsat base imagery. This test shows how simulating the flow of water over a land surface using a DEM can be very useful in identifying regions where lakes may have existed. Palaeoshoreline features and corresponding lake deposits can provide further evidence for the existence of past lake systems.

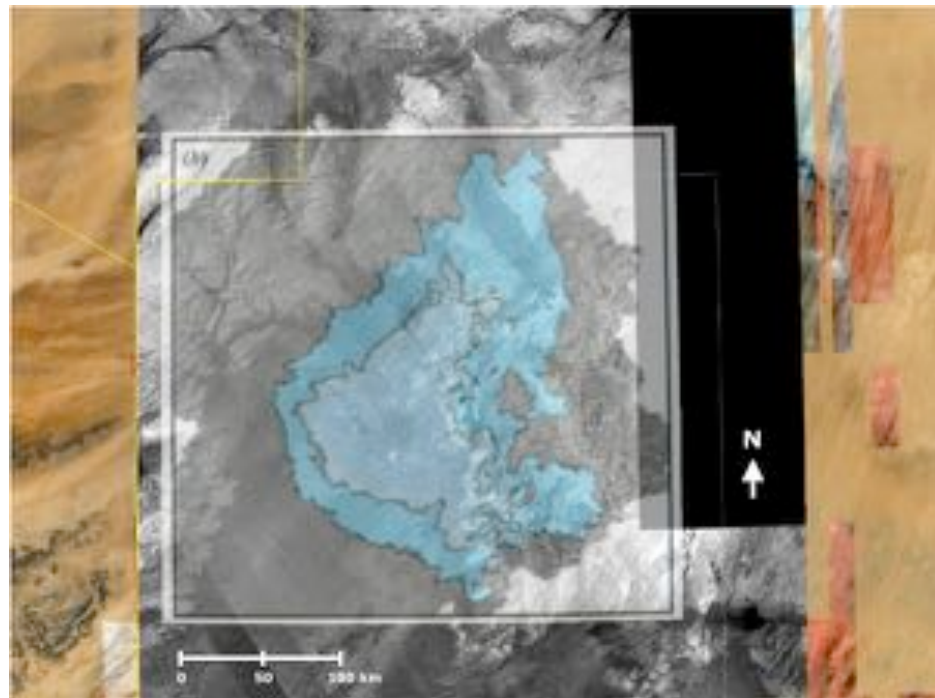


Fig. 5.37: Simulated lake levels depicting the Northern Darfur (ND) Megalake (outer lake) and the West Nubian Lake (inner lake) at contour levels of 573 and 555 m respectively. Lake levels superimposed over SRTM imagery and Landsat Google earth imagery (after Ghoneim and El-Baz, 2007a).



5.5 Conclusions

The palaeohydrological and geoarchaeological record strongly suggests that the Great Sahara of North Africa has undergone extreme climate shifts in its past, experiencing both wet and dry periods. These were cyclical in occurrence and are most likely the result of orbital forcing events due to slow changes in the tilt of the Earth's axis and the shape of its orbit (Berger, 1978). During the pluvial periods the landscape was savannah-like, dotted with large lakes and inland deltas, and veined by large rivers and tributary systems. Animal and plant life was abundant owing to an accessible and stable supply of fresh water. The last wet phase ended approximately 5,500 years ago, turning the Sahara once again into a hyper-arid desert (Foley et al., 2003). Desert-dwelling people sought to locate alternative sources of water, resulting in large migrations of people out of the Sahara towards the more water-rich inland areas and coastal regions. This is thought to have been a major stimulus that enabled the rise of the ancient Egyptian civilization around the Nile Valley and Delta (Kuper and Kröpelin, 2006; Butzer, 1976). More recent work by Wengrow et al. (2014) have challenged climate change and environmental stress as the sole drivers of cultural adaptation, linking Egypt's early development with that of its neighbours Nubia and central Sudan proposing a 'north-south axis of Neolithic development'.

During the Shuttle Imaging Radar (SIR) experiments of the 1980s and 1990s, the spatial coverage provided by the satellites were limited. This often produced discontinuous strips of imagery and an incomplete picture of the Sahara. In contrast, SRTM and PALSAR coverage is complete and provides regional-scale mapping of the drainage network that should prove valuable for both archaeological and hydrological studies, in addition to water resource management. The use of radar data in this work provided a synoptic subsurface view of the eastern Saharan landscape at a scale of 30 m by uncovering the remains of relict palaeodrainage channels that cannot be observed either from the ground or by means of optical sensors. These features once formed a network of surface-flowing rivers, which when mapped can provide clues to mechanisms of climate change. This is the first time that the palaeohydrology of the eastern Sahara has been mapped using radar and presented at a regional scale for geoarchaeological analysis. Earlier studies have focused on smaller and more local areas of interest using a non-synoptic approach (Robinson et al., 2000; Paillou et

al., 2003; Robinson et al., 2006; Ghoneim, Robinson, and El-Baz, 2007; Ghoneim and El-Baz, 2007a, 2007b).

Currently ASTER is the only spaceborne sensor with sufficient spatial and spectral resolution in the thermal infrared for this type of spectral mapping. Drawbacks to ASTER data are its small swath footprint (60 x 60 km), complex radiometric correction, and it is not freely available to those who do not have an academic affiliation. It is therefore not well suited for surveying large areas due to the large numbers of tiles that are required to cover a study area. In contrast, all SRTM products are packaged into 1° x 1° tiles with a footprint of approximately 120 x 120 km. This is four times the area of an ASTER tile and therefore that many fewer SRTM scenes are needed to cover a similar extent. This is not too much of a problem when just a few scenes are required but when hundreds are needed it can impact on processing time and financial resources.

The central theme discussed in this chapter and presented in this second case study has been the search for water. Locating water sources has to remain the prime focus in the search for archaeological remains in desert regions. Water has always been vital to the development of agriculture, the grazing of animals, the siting of settlement sites, and the support of travellers as they went about their daily lives. Permanent water sources were a precious resource, and knowledge of their locations would have been passed down through the generations. Three strategies were discussed which used a multispectral approach for locating sites. These included mapping highly vegetated areas (oases) by means of the vegetation indices, locating subsurface river channels (palaeorivers) with SAR imagery, and mapping palaeolake systems utilizing thermal infrared band ratios and digital elevation data.

Two methods were discussed for mapping palaeolake systems in both the spectral and spatial domains. Thermal infrared (and the shortwave infrared) wavelengths are sensitive to surface composition such as silicates and carbonates. Carbonate minerals are found in limestone rocks and can indicate the presence of palaeolake sediments. In the spectral domain the Carbonate Index (ASTER Band₁₃ / Band₁₄) was used to map outcrops of limestone associated with the West Nubian Lake basin. This index has been shown to perform well for detecting palaeolake deposits on the Tibetan Plateau (Corrie, Ninomiya, and Aitchison, 2010; Ninomiya, Fu, and Cudahy, 2005). The results from the present work show that the Carbonate Index signal

correlates well with known lake deposits, as shown and field-tested in Pachur's radar image of the West Nubian Lake (Pachur and Rottinger, 1997). However, the resulting mosaic shows that there is an underlying problem with the radiometric correction. Although Ninomiya's indices perform demonstrably well for regions of high elevation and where outcrops are rich in calcite and dolomite limestone, such as the Tibetan Plateau, they are not yet proven for areas at lower elevations and where the carbonate mineralogy may be different.

The Carbonate Index may only be applied in the search for certain type of limestone – such as calcite and dolomite. Because palaeolake sediments can vary widely in their composition, this is a potential problem that can complicate the detection strategy. For example, Saharan lake deposits can be rich in travertine (a type of limestone) deposited by mineral springs and found in playa clay (Marinova, Meckler, and McKay, 2014). As a result, the Carbonate Index may not be sensitive to these compositions and therefore may not produce a correct signal.

An additional problem is that some lake sediments may be principally composed of silica-rich diatomaceous deposits with very little carbonate. Diatoms are a major group of algae which occur in oceans and lakes, including the fresh water lakes of Lake MegaChad. Their decomposition leads to the deposition of organic and inorganic (silica-rich) sediments. As indicated in Figures 5.31a and 5.31b-f the spectral signature for carbonates is very different when compared to silicates. Palaeolake samples taken from Bodélé Depression (palaeolake basin of Lake Megachad), for example, indicate large amounts of diatomaceous (silica-rich) dust deposits with only small quantities of calcium carbonate (Bristow, Drake, and Armitage, 2009). In the Landsat ETM+ FCC image (7, 4, 2), shown in Fig. 5.28, Lake Bodélé appears as a dark blue colour (indicated by a red circle). This is in contrast to the carbonate deposits of the surrounding lakes which are light blue / turquoise. The differences in colour may result from different compositions and therefore spectral characteristics of the lake sediments. If a ground-based campaign is possible, a better strategy may be to ascertain the mineralogical character of the region before undertaking a remote sensing survey. The indices can be updated using the locations of specific absorption features of deposits found during the ground investigations (see Subsection 5.4.3 and Fig. 5.30).

Although the thermal infrared mapping of carbonate deposits has its merits, this study suggests that better results may be achieved by using a digital elevation model to locate

depressions where water may have formed, followed by a search of associated palaeoshoreline features.

A second approach for locating palaeolakes used digital elevation data in the spatial domain, which is considered an essential remote sensing asset when lake deposits are not sufficiently exposed at the surface and therefore spectral detection is not an option. DEMs are invaluable in the search for depressions or basins where water may have collected. Elevation data can also be employed to search for palaeoshoreline features which are often found surrounding many of the relict lake systems. Often only partial strandlines from former lakes are found but these markers can provide further clues when employing a DEM model. Contour lines derived from a DEM are filled with “digital water” up to the maximum strandline level. This can help in identifying and visualizing some of the megalakes that are known to have existed across the Sahara. These regions can later be searched for the remains of cultural artifacts. This second approach using spatial profiling proved a much more efficient and reliable technique. A topographic study involves less image processing when compared to performing a spectral analysis and as a result tends to be less time consuming and less computationally expensive. Secondly, there is no need to change the underlying pixel values in a topographic study whereas this is usually a concern when working in the spectral domain. Combining both spectral and spatial approaches provides a robust methodology for the mapping of past palaeolake systems.

The final case study in chapter 6 examines the remote sensing of trading routes and uses their locations as further constraints when searching for archaeological sites. Various data sets are input into a geographical information system (GIS), which is used for predicting possible locations of archaeological sites in Egypt’s Western Desert.

Chapter 6

Case study 3: Remote sensing of trading routes; archaeological site location using a GIS

6.1 Introduction

Surveying large parts of the Sahara by remote sensing involves the processing of substantial amounts of data. Locating sites in such broad swaths of imagery becomes a problem of scale and resolution. Archaeological sites and features tend to be small, and high spatial resolution is needed to locate them. Furthermore, high-resolution multispectral data is costly, which tends to be prohibitive when searching for sites in the vast expanses of the desert. For locating these types of sites, search areas must be reduced so that higher resolution imagery can be used more effectively to find them. On the other hand, the presence of specific environmental features, such as water, which often point towards the potential presence of archaeological sites, tend to be much larger in scale, so that the resolution required to detect them is lower. The location of archaeological sites can often be inferred from the presence of environmental features. It is therefore often practicable to sacrifice the spatial resolution of the sensor in order to process larger amounts of imagery needed for regional coverage. Using environmental features to narrow down areas for searching has been the approach taken throughout this dissertation.

One of the priorities in this work has been to reduce the size of the dataset so that the problem can become more manageable. This can be achieved by focusing on locations that possess higher probabilities of containing features of archaeological interest. It is reasonable to assume that archaeological remains in arid regions, especially settlement sites, were located close to water sources and travel ways. This may have become less relevant following the introduction of the camel to the Sahara but proximity to water would still have been seen as essential. The principal beast of burden in Egypt and throughout the eastern Sahara until the first millennium BC was the donkey, after which the domesticated camel was introduced (Förster, 2007). The camel allowed extended incursions into the desert due to its increased carrying capacity and its ability to go days without water. The average daily reach for a camel is dependent on many factors including its load, the type of landscape relief it travels through,

and of course the daily temperatures. A range of values is cited in the literature – between 40 km per day (Harding-King, 1930) to 60–70 km per day (Beadnell, 1909).

Mapping sources of water is one indirect method for constraining the search locations of sites; this was the subject of the previous chapter. The present chapter considers a further indirect technique for locating sites, by using satellite imagery to identify networks of transportation links (observed as surface lineaments in the desert) that used to connect them. This is a compelling strategy, because travel ways are very often found to pass close by features of cultural interest or terminate at large settlement centres.

In this context, a ‘surface lineament’ refers to a linear feature that has formed on the surface of the desert as a result of the movement of animal and human traffic over prolonged periods of time. Desert lineaments cover a whole range of feature types, all of which can be considered types of travel way. They include caravan routes, tracks, and paths (from larger to smaller scale) that formed during antiquity. They also include roads and pathways that have been constructed recently to accommodate modern day travellers and motor vehicles. Travel ways are usually found to converge at, and connect to, populated areas such as major settlements, trading and commercial centres, and resting stops (caravanserais). A smaller type of lineament, the “hollow way”, although not well represented in the Sahara, may be observed in certain areas where the ground conditions allow for them. Hollow ways are a very common type of feature found throughout much of the Middle East and are further discussed in Section 6.3. Naturally occurring lineaments may be of similar appearance to travel ways when viewed using remotely sensed imagery. These include tectonically produced joints (rock fractures) and faults and are not considered further in this study.

Mapping the distributions of trading routes can offer an enhanced understanding of the spatial distribution of sites. Trading routes, also known as caravan routes, have been used since antiquity to transport goods, people, and supplies. They also provided the means for the spread of knowledge, technology, culture, and religious ideas between different locations often separated by great distances. Some of the best-known trading routes include the Silk Road (not a single route but a series of caravan tracks) extending across the Asian continent connecting China to the Mediterranean Sea and eastern Europe; the Indian Ocean trading routes linking Java in the east to Zanzibar and Mombasa in the west; and the Trans-Saharan

trading routes connecting the African continent to Europe and the eastern Mediterranean seaboard (also known as the Levant).

During times of extreme aridity the Great Sahara of North Africa acted as a natural barrier to the movement of people. Long-distance travel through the Sahara was a dangerous endeavour due to lack of water, little relief from the relentless sun, and the great distances often involved. Desert travel in this part of the world therefore presented a logistical challenge (Drake, 2012a). As a result, trading routes often followed the most efficient path through the desert to reach their destinations. That often did not mean the most direct path as a travelling caravan can only carry a finite amount of water for a limited number of days. Sufficient quantities of water were needed for both travellers and animals. Therefore the major caravan routes followed the well established oases by “hopping” from one to the next, giving travellers time to rest and acquire supplies before engaging on the next leg of their journeys (Rossi and Ikram, 2013; Förster et al., 2010).

The major trans-Saharan caravan routes connected Sub-Saharan Africa to the North African coast and beyond to Europe and the Levant. Of these, two major caravan routes served the eastern Sahara in a north – south corridor. The first route includes the well-documented Darb el-Arbain extending from Kobbe in western Darfur (Sudan) to Asyut west of the Nile in northern Egypt, passing through Selima and Kharga oases. The second route connected Wara (or Ouara) in southeastern Chad to the Mediterranean Sea passing through the Kufra oasis and Jalu in northern Libya. These routes in addition to several others are shown in Figure 6.1.

This chapter consists of two parts. In the first, the major trading routes of Egypt’s Western Desert are discussed alongside the challenges of using satellite remote sensing to locate them. Nighttime TIR imagery is also discussed as a technique for detecting lineaments based on their thermal infrared properties. Parallels are made between detection strategies for desert lineaments found in the eastern Sahara and for those found in other arid regions of the world, including the “hollow ways” of the Middle East. The second part forms the practical component of this final case study and addresses the post-processing of datasets created

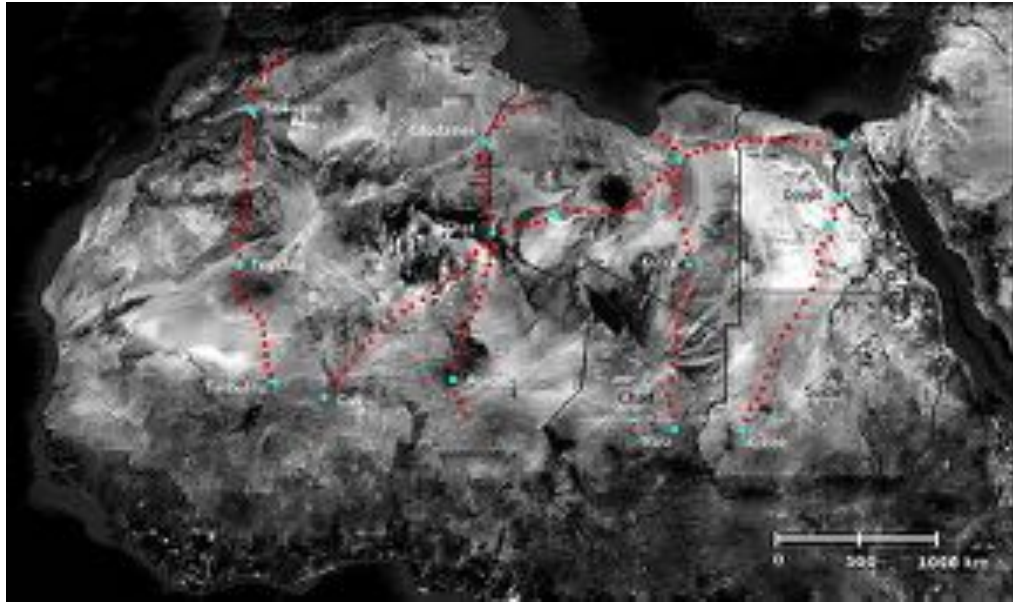


Fig. 6.1. The Great Sahara desert showing several historical caravan routes across the region (Source: MODIS image, NASA)

throughout this work, where the data is collated into a geographical information system (GIS). Proximity analysis (buffering) is applied to predict the locations of potential new sites and Google Earth is used to zoom into areas of special interest. Inputs into the GIS include SRTM3 derived maps of slope and aspect, palaeohydrology (palaeochannels), and locations of caravan routes.

6.2 Caravan routes of Egypt's Western Desert

This section contains a brief outline of the travel routes of the Egyptian Western Desert and the various oases and the Nile Valley that they connected to. For a more in depth treatment, see Bubenzer and Bolten, 2013; Rossi and Ikram, 2013.

The caravan routes of Egypt's Western Desert are among the most widely known in the eastern Sahara. Most have been identified and mapped directly from historical and oral sources, especially those originating from regions along the Egyptian Nile valley, which connected to various oases throughout the Western Desert and beyond. These include the Darb el-Bahnasa (connecting to Bahariya Oasis), the Darb el-Farafra (Farafra Oasis), and the Darb el-Tawil (Dakhla Oasis). Many of these routes are shown in Figure 6.2. Perhaps the best known, connecting the Nile valley to northwestern Sudan, was the Darb el-Arbain

(Figures 6.1–6.3), described by Herodotus in the fifth Century BC, as “a road traversed in forty days”. The route, which is still in use today, is believed to date back at the very least to the Roman period, if not earlier (Roe, 2005) and is thought to have originated at the village of Kobbe in Darfur, northwestern Sudan. The route continued for over 1,700 kilometres in a northeasterly direction through the Merga, Selima, and Kharga oases before terminating in Assyut at the Egyptian western Nile Valley. The representation of a route on a map is often not precise and some routes often have several different variations (such as the Darb el-Tawil, which was a desert track connecting the Nile Valley to Dakhla Oasis). Table 6.1 lists some of the most prominent routes and their characteristics. The distribution of the routes are shown in greater detail in Figures 6.2, 6.3, and 6.17.

Alongside many of the routes are found pot sherds – the remains of vessels used to transport a variety of provisions, including water, oil, fat, and other precious supplies (Eichhorn et al., 2005). The Abu Ballas Trail, a Pharaonic period donkey caravan route, is especially noted for its pottery dumps, which are found at various locations along its course (Kröpelin and Kuper, 2007; Förster, 2007). Recently relocated by the German traveller, Carlo Bergmann, in 1999 and 2000 (Bergmann, 2001), the Abu Ballas connects Dakhla Oasis with the Gilf Kebir Plateau and is thought to have continued onwards to the Jebel Uweinat (“Mountain of the springs”) on the borders of Egypt, Libya, and Sudan. During the Roman period many of the desert routes were considered of such economic importance that fortresses were built to protect the passage along which their goods passed. More specifically, Late-Roman forts have been found in close proximity to Kharga Oasis along the Darb el-Ain Amur and Darb el-Arbain caravan routes (Rossi, 2013).

6.3 The remote sensing of desert surface lineaments: a multispectral approach

Desert caravan routes and other types of travel way can under certain circumstances be observed using satellite imagery. To understand how this is possible we need to examine the mechanisms for how tracks are formed in desert regions. For this to be possible there needs to be a measurable contrast difference between the surface lineament and the matrix that surrounds it.

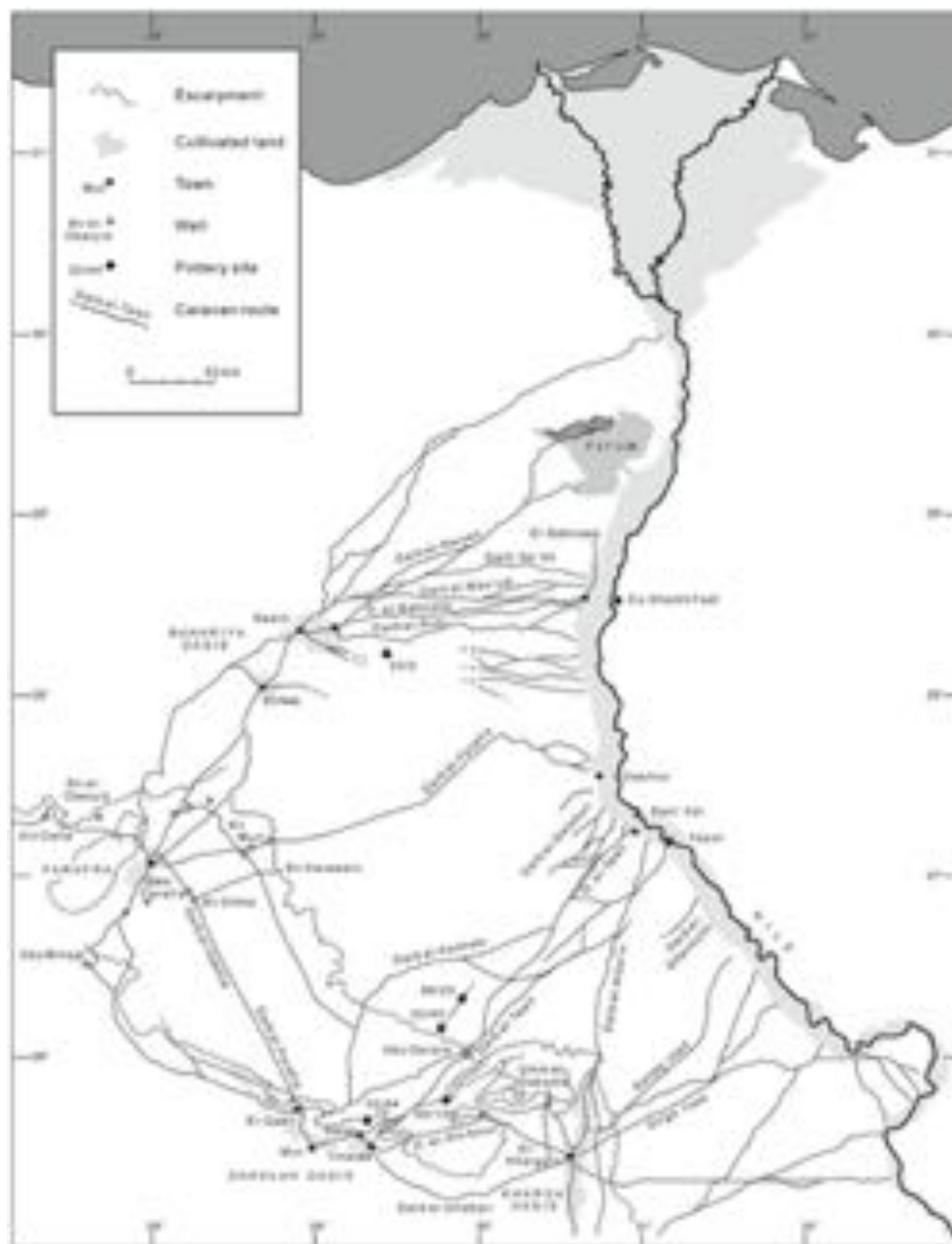


Fig. 6.2: Caravan routes connecting the major oases of Egypt's Western Desert (after Eichhorn et al., 2005)

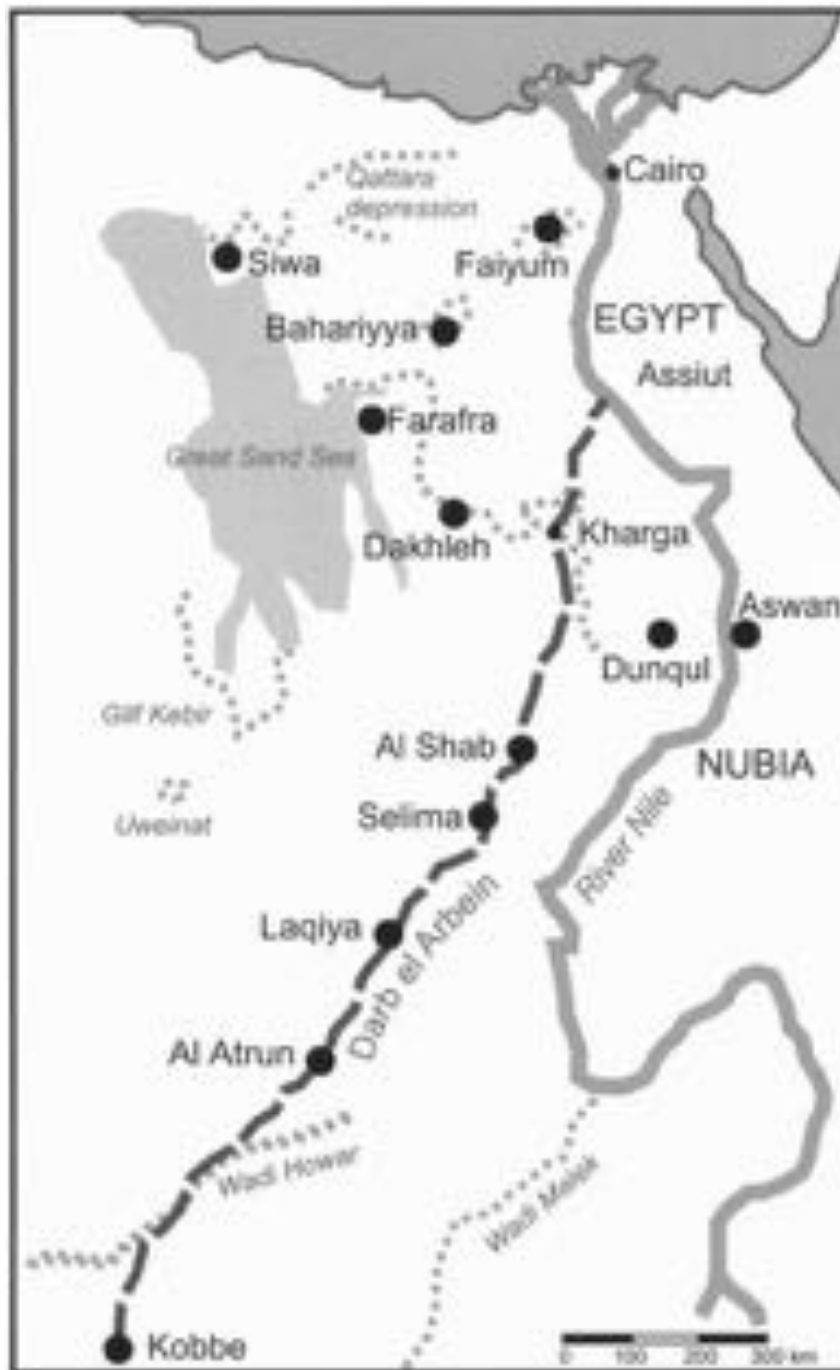


Fig. 6.3: The Darb el-Arbain caravan route originating in northwestern Sudan, with a destination in Egypt's Nile Valley (after Roe, 2005)

Route	From - to	Distance (Km)	Days to travel	Reference / Notes
Darb el-Bahnasa	NV - Bahariya	190-200	4	Surveyed by Ball and Beadnell in 1897; in general use until 1934; Giddy (1987).
Darb el-Farafra	NV - Farafra	280-300	7-8	Paved part of the way; Fakhry (1974); Giddy (1987)
Darb el-Tawil	NV - Dakhla	250	6.5	“The Long Road”; Giddy (1987).
Darb el-Arbain	NV - Kharga	200-210	4	“Forty Days’ Road”; the best known desert route in Egypt; it’s full reach covers a total of 1,700 km; part of the route is sand paved; Giddy (1987).
Darb el-Dakhla	Farafra - Dakhla	200	4	Has remained a dirt track due to passing through difficult terrain; Vivian (2008).
Darb el-Gabari	Dakhla - Kharga	190	4	“The dust road”; originally mapped in 1898 by the Geological Survey; modern roadway follows route of ancient track; Vivian (2008).
Darb el-Ain Amur	Dakhla - Kharga	180	5	“The Road of the Lovely One”; alternative route to Darb el-Gabari and has the advantage of a water source half way between the two oases; Vivian (2008).
Darb el-Khashabi	NV - Dakhla	220	6	Also known as “The Wooden Road”
Abu Ballas Trail	Dakhla - Gilf Kebir	440	10	Dates to as early as the 4 th Dynasty and represents the earliest known Egyptian presence in this part of the Western Desert; a series of 30 pottery stations have been discovered along this route; Vivian (2008).
Table 6.1: Major caravan routes between the Nile Valley and the desert oases; NV = Nile Valley. Days of travel are either quoted or interpolated from the literature. Refer to Figures 6.2, 6.3, and 6.17 for detailed maps.				

The measurement of contrast changes (either directly or by proxy) forms the basis for the detection of all feature types or phenomena in remote sensing (Beck, 2007). With respect to detecting travel ways, the contrast difference is caused by changes to the ground surface by the repeated movement of animals and people over narrow strips of terrain over considerable periods of time. Observed changes in reflectance values result from the compaction of sand particles and their redistribution over the ground surface. It is these contrast differences (when examined using optical regions of the electromagnetic spectrum) between the compressed sand and its surrounding matrix that enable the changes to be recorded by the remote sensing instrument. However, not all travel ways leave an appropriate ground signature and this will depend on the nature of the ground cover. Several regions of the EM spectrum can be used for mapping desert routes, including the visible, near infrared, and thermal, with the most typical satellite sensors employed being Landsat ETM+, ASTER, and Corona. Radar imagery may also be employed on the basis of detecting changes in texture (in contrast to optical sensors that record reflectance values according to spectral content).

Caravan routes can range in dimension – not only in length but also in width. When detecting these features higher spatial resolutions should be used when possible. Some of the larger routes may be detected however using spatial resolutions of up to 100 m (see later discussion of ASTER TIR sensor). Desert caravan routes usually consist of unpaved tracks and are therefore found in a generally poor condition. There is evidence that some roads were paved, but this was not the standard practice. One of the earliest known examples of paved roads is found in Egypt close to a quarry site southwest of Cairo. Approximately eleven kilometres in length, dating from the Old Kingdom, its surface was covered with an assortment of slabs consisting of sandstone, limestone, and logs of petrified wood (Harrell and Bown, 1995).

A research group at the NASA Jet Propulsion Laboratory first used spaceborne imagery to locate archaeological sites from desert tracks. The “lost city” of Ubar, in modern Oman, an ancient centre for the frankincense trade in Arabia, was located from the identification of caravan tracks leading to the site. Imagery used included a combination of Landsat Thematic Mapper (TM), SPOT, and SIR. Figure 6.4 shows a subset of Landsat TM data of the Ubar site (Path 160 Row 47 acquired on 13 January, 1986). Both modern and older tracks are identified in the image, in addition to the modern site of Shisr, which is thought to be the location of Ubar legend (Blom et al. 2007, 1997).

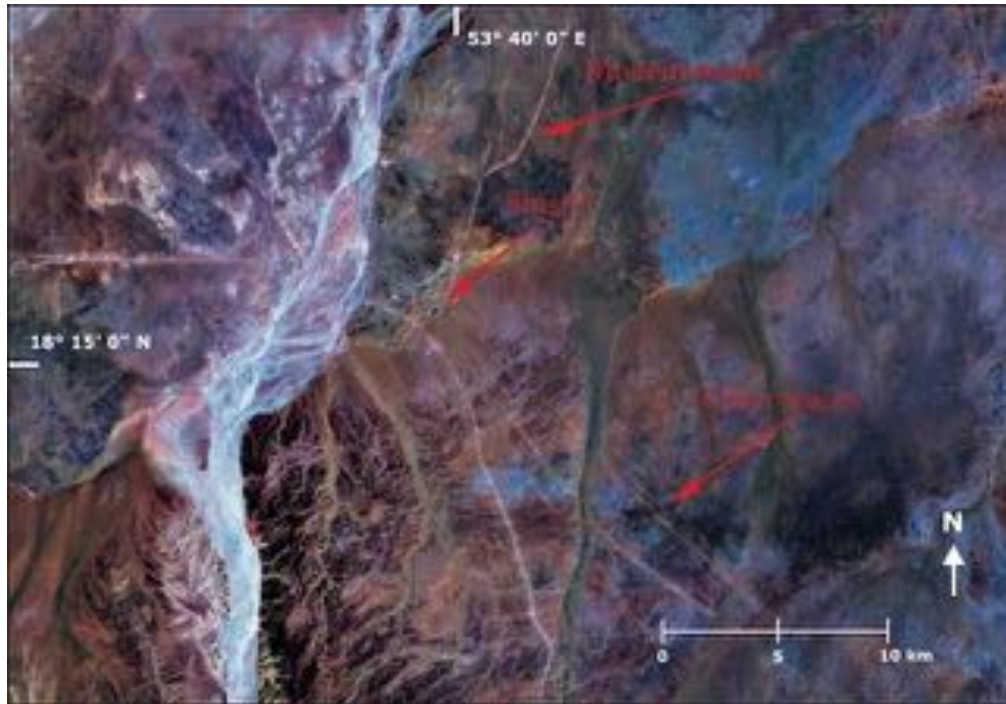


Fig. 6.4: Subset of Landsat TM image of the Ubar site situated in the Empty Quarter, Oman. Ubar is identified by the modern site of Shisr (after Wiseman and El-Baz, 2007).

Extensive work has been carried out in northern Mesopotamia and other regions of the Middle East (Iraq, Syria, Iran) to locate traces of ancient route systems using optical satellite imagery, such as ASTER and declassified Corona spy photography (Wilkinson et al., 2010; Altaweel, 2005; Ur, 2003). These ancient roads, or so-called “hollow ways” (see Chapter 3), were first identified by Van Liere and Lauffrey (1954) and subsequently studied by Wilkinson and Tucker (1995). They are variously described in the literature as shallow linear depressions, linear hollows, or sunken lanes, and can be identified from the characteristics of their soil, moisture and vegetation content (Altaweel, 2005). Hollow ways often form a series of radial patterns that converge at major settlements or connect to adjacent fields. Figure 6.5 shows a Corona photograph taken in November 1968 of Tell Brak and surrounding area in northeastern Syria. Numerous hollow ways are seen converging at the site. When mapped at a more regional scale, hollow ways often form elaborate spoke-like patterns (Figure 6.6). A study of their spatial distributions can provide a better understanding of ancient settlement patterns.

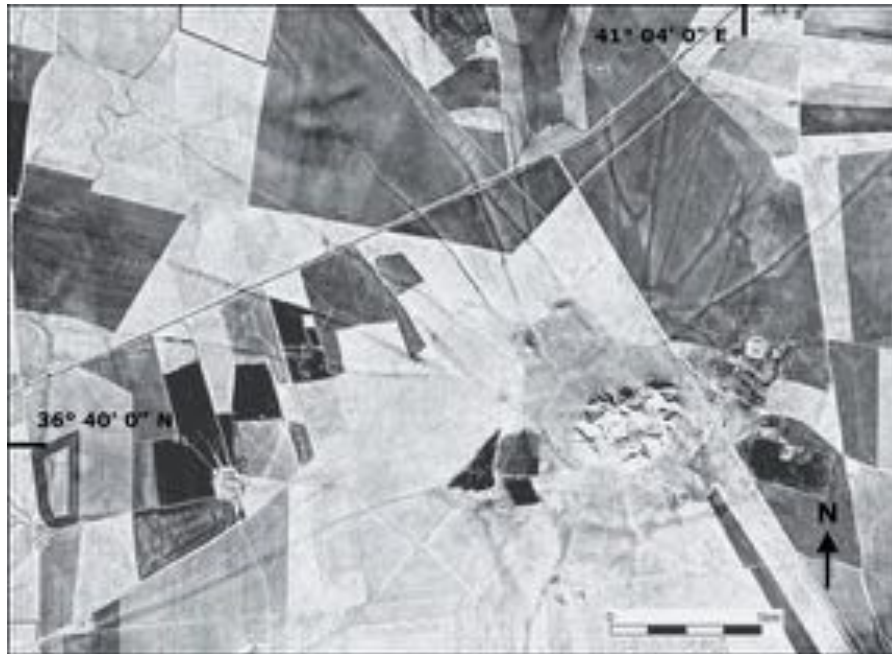


Fig. 6.5: November 1968 Corona photograph showing hollow ways converging at the Syrian site of Tell Brak, which can be seen in the lower right quarter of the figure (after Ur, 2003)



Fig. 6.6: Elaborate spoke-like networks formed from converging hollow ways in the Upper Khabur basin and surrounding areas of northern Mesopotamia (after Ur, 2003)

Usually invisible from the ground for most of the year hollow ways can often be observed when the moisture content of the earth is high. The lighting quality recorded by a particular scene of a satellite sensor is also important. Ideally shadowing should be present to assist in their detection. If imagery of these features is acquired during a dry season or when the sun is high in the sky (preventing sufficient shadowing), the hollow ways may be invisible or easily misinterpreted.

Although hollow ways are commonly found in the Near East, little definitive evidence for them has been identified across the desert regions of the Sahara. The lack of moisture in the hyper-arid desert environment may not be conducive to their preservation, because they are best detected from the differential growth patterns of local vegetation. Whereas their detection in the Near East depends on soil moisture and vegetation patterns, the eastern Sahara relies more on rock cover type. In the Egyptian Western Desert, for example, trading routes tend to be visible if the lineaments are situated along the stony ground, which is characteristic of the Egyptian Limestone Plateau. This is in contrast to sandy surfaces, which are not conducive to the preservation of such features (Bubenzer and Bolten, 2013). Desert lineaments may be visible from the ground given a sufficiently good vantage point and appear as linear pathways across the arid landscape. These types of desert tracks are visible due to either the stones having been deliberately cleared or due to the erosive action of many feet through the passage of time. In the Western Desert, several routes, including sections of the Darb el-Arbain and Darb el-Tawil, are particularly well preserved and detectable by satellite. Figure 6.7 shows an ASTER image where a section of the Darb el-Tawil is clearly visible when recorded using the visible bands of the EM spectrum.

As previously noted, caravan routes through desert regions of the Sahara tend to follow the most efficient path through the desert. Although some routes follow relict water courses, suggesting that ancient peoples were aware of their locations, it has also been found that other routes simply bridge the waterless desert by following either the easiest, or the fastest, pathways. The Darb el-Arbain, for example, passes directly through or close by to several oases, including Kharga and Selima, as it connects Sudan to the Nile Valley. It is also observed that the caravan route follows closely the course of a palaeochannel for approximately 150 km, as it runs in a northeasterly direction from Selima Oasis (Figure 6.8).

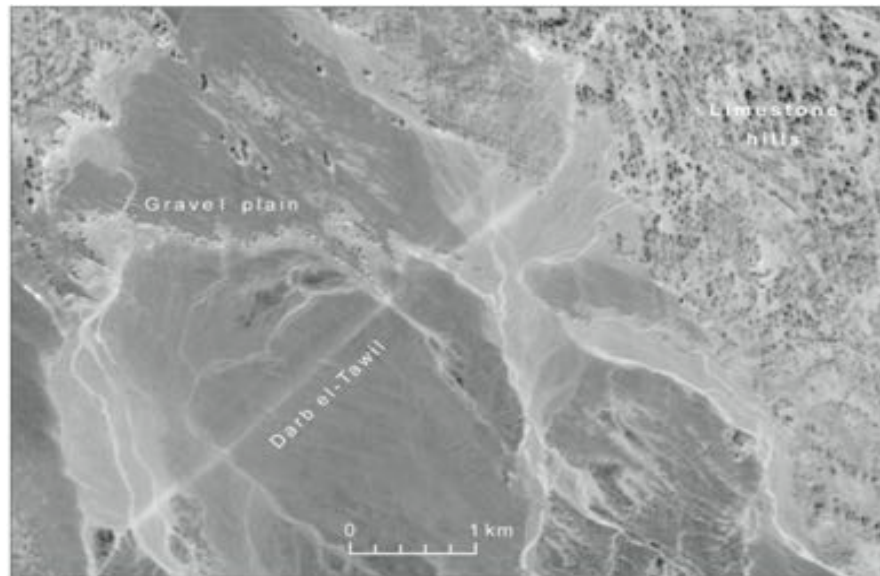


Fig. 6.7: ASTER satellite image showing part of the Darb el-Tawil caravan route (after Altaweel, 2005)

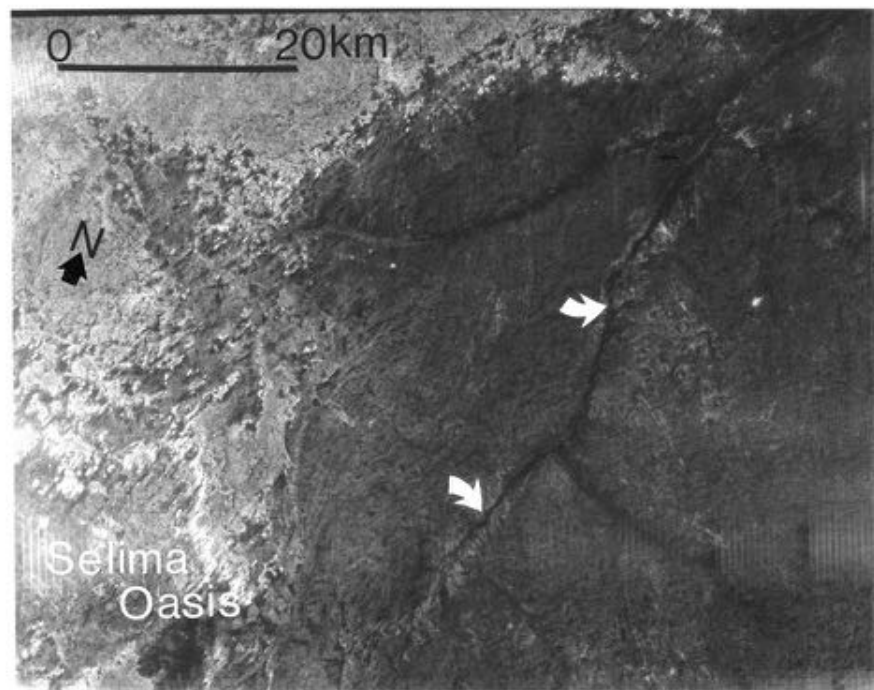


Fig. 6.8. Relict fluvial channels leading away from Selima Oasis (lower left). For about 150 kilometres the Darb el-Arbain caravan route closely follows one of the palaeochannels as indicated by the white arrows (after McCauley et al., 1997).

Little work had been carried out prior to the mid 1990's to establish a database of trading routes and related archaeological sites in Egypt's Western Desert. One such project –“Routes and trade in arid zones”, part of Arid Climate, Adaptation, and Cultural Innovation in Africa (ACACIA), has sought to correct this. Led by a team from the University of Cologne, its efforts have sought to trace old caravan routes in Egypt's Western Desert and in northern Sudan by using a combination of remote sensing, GIS analysis, and ground-based surveys (Förster et al. 2010; Bubenzer and Riemer, 2007; Förster, 2007; Kröpelin and Kuper, 2007; Kuper and Kröpelin, 2006; Eichhorn et al., 2005).

A second study conducted by John and Deborah Darnell, of Yale University, developed a similar approach called ‘desert road archaeology’ to initiate a detailed survey of parts of the Western Desert. They used a combination of remote sensing techniques, ground-based investigations, and searches on foot, to search for further trails and archaeological remains, initially between Thebes and Kharga Oasis. This endeavour became known as The Theban Desert Road Survey and was successful in locating several sites including substantial caches of pottery and other artifacts (Darnell and Darnell, 1997). These projects have raised awareness for the significance of caravan routes and desert oasis settlements and have been instrumental in providing much of what we know today about the distribution of trading routes in this region. The work has also provided further insight into rock art dating to the period of Egyptian state formation. Additional information about desert archaeology, including detailed source maps, can often be found from valuable interwar work carried out by the adventurers and travellers of the day (Bagnold et al., 1939; Bagnold, 1935, 1933, 1931; and Beadnell, 1909).

The dating of desert tracks can be problematic as a lineament may theoretically be of any age. This is because recently created roads and tracks crisscross the desert and can be difficult to distinguish from historical routes. Many tracks can be attributed to the increasing numbers of people venturing into the desert using four-wheel drive vehicles. In some cases, it may be possible to determine a relative age through the principle of superposition. Indeed, if the region cannot be visited from the ground this may provide the only clue. The principle of superposition, also known as the theory of cross-cutting relationships, can be applied to give a relative age when the lineament is overlain by river channels or by wind-blown sand deposits (such as dunes). More precise dating may be achieved through examination of any roadside

surface ceramic remains and associated epigraphic materials if present (Darnell and Darnell, 1997). As previously discussed, the remains of pottery assemblages used to store water and luxury items have been found in significant quantities along many routes, including the Abu Ballas Trail, which connected Dakhla Oasis to the Gilf Kebir Plateau and beyond. In this instance, the ceramic remains were instrumental in dating the route between the Old Kingdom and First Intermediate Period, 2,700-2,055 BC (Kröpelin and Kuper, 2007).

Orbital photography from the declassified spy reconnaissance satellites Corona, Argon, and Lanyard (American) and the KVR-1000 (former USSR), may provide an additional asset for detecting routes and determining their relative ages. Although not global in coverage, many images are available for regions of the eastern Sahara and the Near East. Imagery is publicly available for dates between 1959-1963 and 1981-2005, for the American and Russian imagery respectively. This material has become an invaluable resource for site detection, feature mapping, and change detection studies.

Some lineaments appear invisible when viewed at the shorter wavelengths, such as the VNIR. This is where the use of daytime thermal infrared (TIR) and nighttime thermal infrared (NTIR) may prove valuable. Tom Farr, of the NASA Jet Propulsion Laboratory, has identified several caravan routes in the Sahara using 90 m ASTER TIR data. Figure 6.9 (top) shows a subset of an ASTER NTIR mosaic of an area west of the Tarso Tousside volcano, Tibesti Mountains, in northwestern Chad. A lineament can be seen trending in a north-northwesterly direction (indicated with green arrows), where the same feature is invisible using VNIR. This image was produced by averaging the DN's from the five ASTER TIR channels. The lower image shows part of the same subset overlaid onto Google Earth base imagery. In this image the lineament is highlighted using a red line. Inset image (lower right) is an unannotated version showing the lineament more clearly. The feature is also visible in single channel TIR Landsat ETM+ data. This may be due to differences in the thermal properties of the sand where sand compaction over time has changed its moisture content and density. These changes have affected the cooling rate and therefore the thermal inertia (a measure of the heat capacity of surface materials) in those regions. As a result, in the TIR, caravan routes appear warmer (and therefore brighter), when compared to surrounding materials (Farr, personal communication).

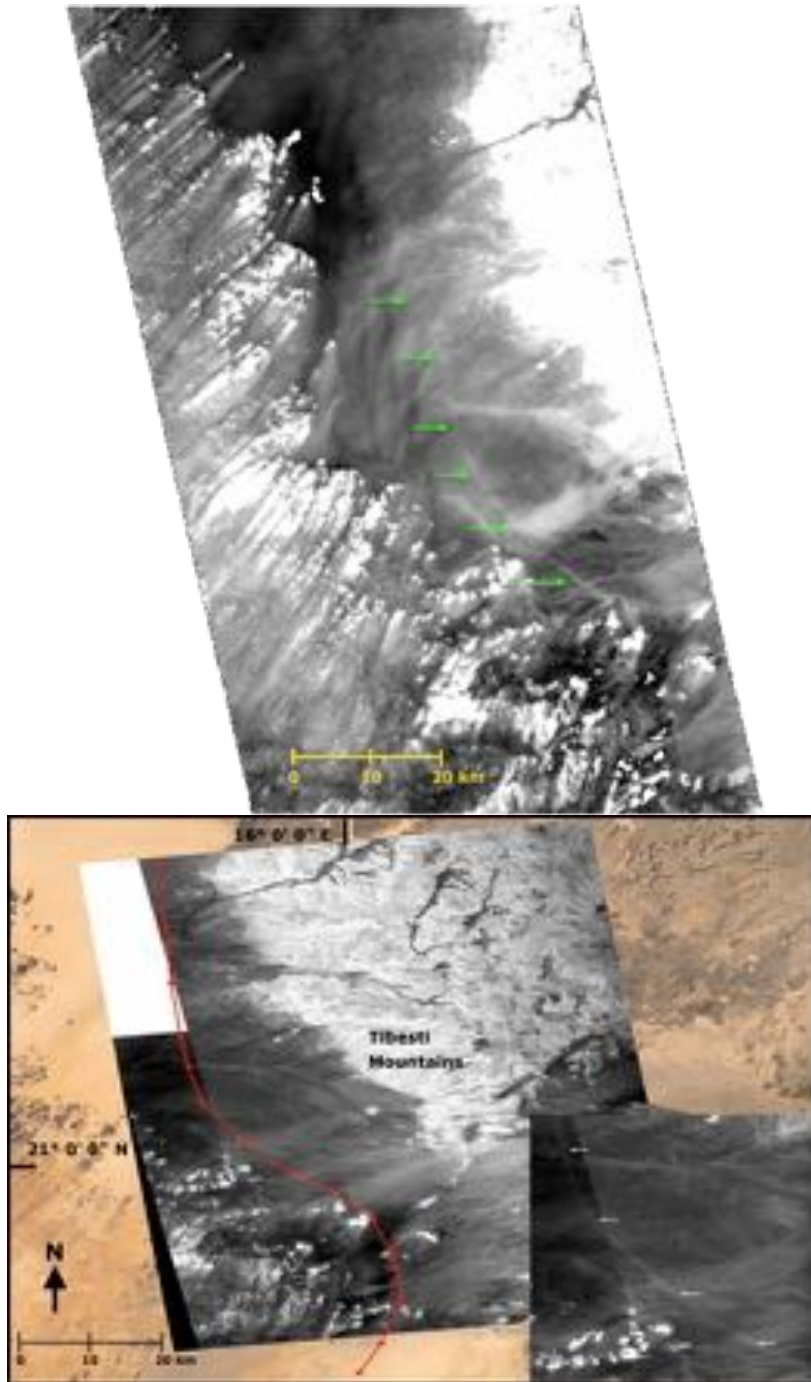


Fig. 6.9: Unreported lineament observed west of the Tibesti Mountains in Chad. The feature is clearly visible for approximately 100 kilometres using ASTER NTIR, but is invisible when examined using high-resolution optical data from Google Earth.

6.4 Site prediction using a Geographical Information System (GIS)

6.4.1 GIS – a short introduction

The real world is an extremely complex environment made up of an infinite number of known and unknown variables. To be able to model the world on any practical level becomes impossible. A geographical information system (GIS) can be used to help reduce the complexity by asking spatial questions of the data using a reduced set of variables. In the GIS the model is treated as an approximation by producing a simplified view of the environment.

A GIS is a computerized set of tools for the input, analysis, and display of spatially referenced data. Unlike some other graphics tools, such as computer-aided design (CAD), data in a GIS is geo-referenced to a particular coordinate system, representing the real world in the form of a “digital map”. Principally, a GIS consists of three components: spatial data referenced to a geographic location, the computer hardware and software used for the storage and analysis of the data, and a relational database management system (RDBMS) for storing attributes, or tabular information, relating to the spatial data. A GIS makes it possible to combine different layers of information that can be used to identify patterns that may not be immediately obvious. If appropriate queries are given, the analysis can unlock previously unseen patterns that may exist in the data (Figure 6.10).

Data can be represented using either a raster or a vector model. In a raster model, features on the earth’s surface are represented by a linear array of cells, called pixels. Each pixel grid is divided into rows and columns and is given a unique reference coordinate either at its corner or at the centre of the cell. The cells are usually square, contain a single value, and may have attribute information attached to them. Attribute data is non-graphic information linked to the spatial features that describe them. The resolution of raster data is a function of the pixel grid size and can vary from sub-metre to many kilometres. Examples of raster data include satellite imagery, scanned aerial photography, results from a geophysical survey, and digital elevation model data. In contrast, the vector model stores data as discrete points, lines, and areas (polygons). Similar to raster data, vector data can also contain attribute information. A vector layer has data structures and algorithms that manage connections between objects (topology). Examples of vector data include well sites (represented as points), roads and rivers (lines, also called arcs), and lakes, houses, and hand drawn maps (polygons).

Each of the two data models offers several advantages and disadvantages. Raster data uses a more simplified data structure and is good for analyzing continuous phenomena, such as elevation, land use, and land cover. However, it is less compact, and its topological relationships are more difficult to represent. Vector data, on the other hand, is more compact, encodes attribute data more efficiently, and is therefore better for analyzing topological relationships, such as adjacency and connectedness. Vector data also has the advantage of not changing appearance when regions are magnified, whereas raster data can often become blocky and pixelated. The disadvantages of using vector data are that it tends to form complex data structures and is inefficient at representing high spatial variability. There are many good resources discussing GIS and their application to the field of archaeology (see Di Iorio, Straccia, and Carlucci, 2010; Di Iorio et al., 2009; Gaber et al., 2009; Bubenzer and Bolten, 2003; Lock, 2000, 2003).

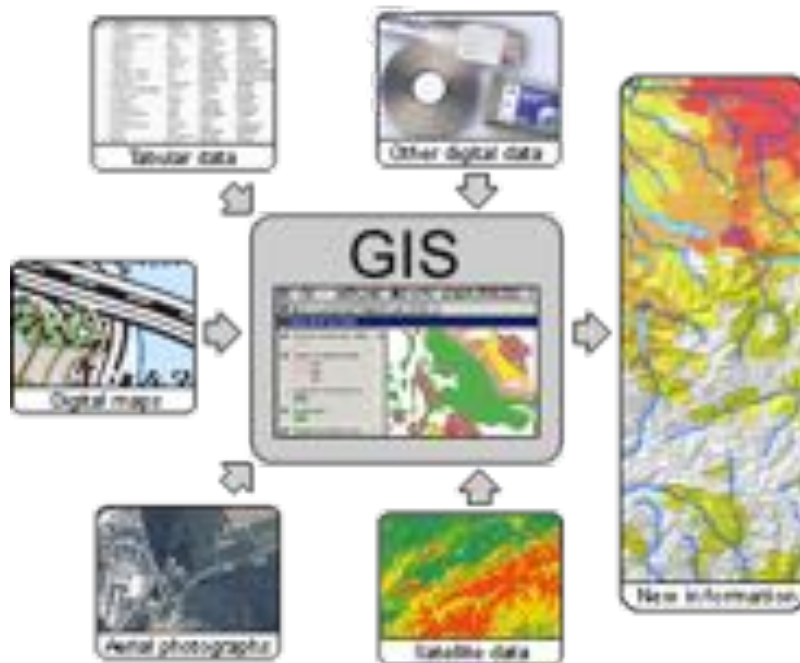


Fig. 6.10: A Geographical Information System (after Geographic Information Technology Training Alliance, GITTA)

6.4.2 Archaeological predictive models

Archaeological predictive modelling (APM) provides a set of tools that can be used in a GIS to model and predict the locations of archaeological sites on the basis of observed patterns or assumptions of human behaviour (Kamermans, 2000). The location for a settlement site is not chosen at random. Locations were carefully selected based on a number of natural (environmental) and cultural factors. This is of course also true today, but in the past it would have been even more so, due to the greater dependency of people on their natural environment. The foundations of archaeological predictive modelling were built in the 1950's with Gordon Willey's work in the Virú Valley of Peru (Willey, 1953), which concentrated on the relationship between settlement patterns and the environment. However, the discipline saw its greatest expansion between the 1960's and 1980's with advances in quantitative techniques and the availability of larger volumes of data.

APM can be divided into two schools of thought according to the decision rules used. These follow either an inductive or deductive approach. Both models attempt to predict the locations of new archaeological sites by means of a set of criteria. The inductive or empirical approach uses observed environmental data to determine site locations. This is the most common method for archaeological site prediction, attempting to find a correlation between specific environmental variables and site locations. Environmental variables may include elevation, soil type, proximity to water or transportation links, and slope and aspect. In contrast, the deductive approach is based on theory and previous knowledge of cultural patterns. Kohler (1988:37) describes the deductive approach as starting 'with a theory as to how people use a landscape and to deduce from that theory where archaeological materials should be located'.

The results obtained from predictive modelling should always be regarded with caution. They can only be as good as the data and the models used to locate them. Often the techniques are subject to the criticism that they are environmentally deterministic, that is, that when an empirical approach is taken, only environmental data is used in the analysis, and cultural data are neglected. A hybrid approach is therefore often taken, combining inductive and deductive models. For further discussion on predictive modelling techniques used in archaeology, see Verhagen, 2007 and Kvamme, 1990.

6.4.3 Towards predictive modelling: background information and objectives

The practical component of this final case study focuses on the use of a GIS to identify areas of archaeological interest surrounding the Abu Tartur region of Egypt's Western Desert. Radiocarbon dating indicates that the region was occupied during the Holocene wet phase of ~6,000 BC (Bubenzer, Hilgers, and Riemer, 2007), so that it provides an appropriate area for further study. However, detailed archaeological maps were lacking which precluded a full predictive study. This absence of site data from fieldwork is very common for areas in the Sahara, where a database of sites is not available and a great deal of survey work is yet to be done. As discussed earlier, various desert road surveys, such as ACACIA, are gradually making good on this shortfall (see Section 6.3). This study uses various datasets for GIS analysis. Inputs include raster slope and aspect maps, derived from the underlying digital elevation model (DEM), in addition to vector layers of digitized caravan routes and a DEM derived palaeohydrological layer. From these datasets a number of new layers were constructed using buffering tools, including distance to streams, distance to oases, and distance to roads. After converting all data to vector format, a final map was output, identifying those regions that met a set of specified criteria. These included areas that are relatively flat (low slope), with an E-W orientation, and with close proximity to both water and major caravan routes. All spatial analysis was carried out using ESRI's ArcGIS software suite. Computing the Time From and Distance From rasters was performed using the ArcGIS Predictive Analysis Add-In tool.

6.4.4 Site description

The study area was centered on the Abu Tartur Plateau (~ 25° 5' N latitude, 30° 0' E longitude), between Dakhla and Kharga oases, in the hyperarid Western Desert of Egypt (black rectangle in Figure 6.11). This represents approximately a 160 x 80 km region. The plateau, known for its large phosphate deposits (Bubenzer, Hilgers, and Riemer, 2007), dominates the region, having an average elevation of 560 metres that contrasts with the surrounding lowlands, which stand at approximately 220 metres. The plateau forms the southernmost portion of the Egyptian Limestone Plateau, and its southern edge forms a 300 – 400 metre high escarpment.

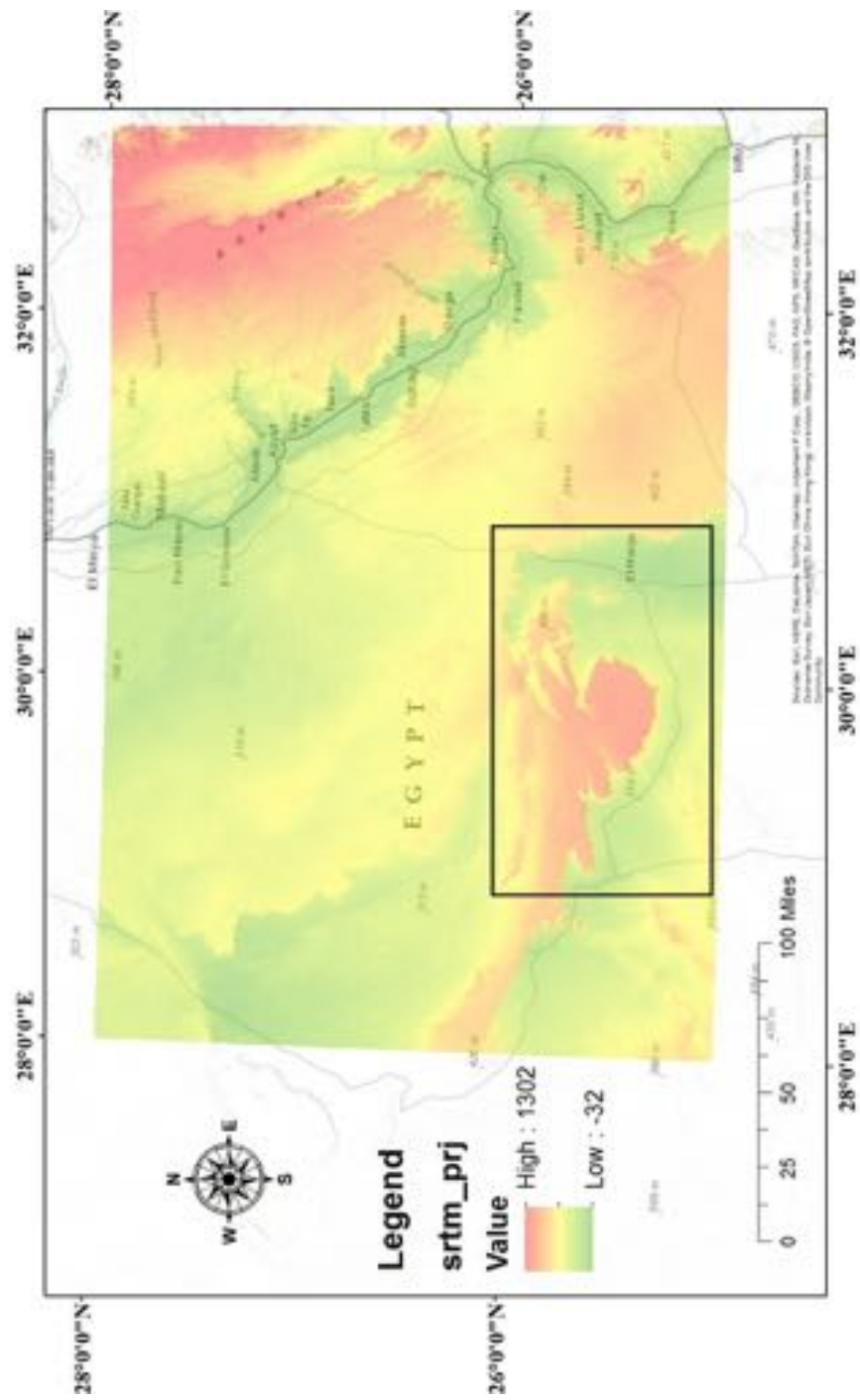


Fig. 6.11: DEM of the study area draped over its derived hillshade with custom colour ramp and 50% transparency applied; footprint: 25 - 28° N latitude, 28 - 33 E longitude; main focus in this study indicated by black rectangle

6.4.5 Modelling environmental variables

The environmental variables considered important for archaeological site location in this study include slope and aspect derived from the SRTM3 (3 arc seconds, 90 m) DEM, together with the locations of caravan routes and palaeohydrology sources. These datasets comprise the foundation of the GIS and are described in further detail below.

Slope - The slope of a surface describes the steepness or gradient of a terrain. Site selection is affected by slope but tends to vary greatly depending on the location. In desert regions, such as the Sahara, large swaths of ground can be very flat, and slope criteria may be less important for areas away from plateaus. The average slope of the Abu Tartur scarp is 7 degrees, and its steepest slope is over 28 degrees. A slope of 6 degrees or less was used in this study for the modelling of possible regions of interest. In the output raster, slopes of less than or equal to 6 degrees were assigned a value of 1; all other grid cells were assigned a value of 0.

Direction of slope (aspect) - The aspect of a terrain describes the direction that a surface faces and is measured in degrees from 0 to 359.9 clockwise from north. Cells that are flat (i.e., zero slope) are assigned a value of -1. In Egypt the location of burial sites play a major role in their orientation. As a very general rule, which often varies according to period, sites on the west bank of the Nile were west facing, whereas those on the east bank of the Nile were east facing (Cao, 2011). The output raster was assigned a value of 1 for aspects with approximate east and west orientations; all other grid cells were assigned a value of 0.

Water sources (Distance to water) – Proximity to water sources (including oases, palaeolakes, and palaeorivers) in desert locations is a primary factor affecting site location decisions. A distance of 2 kilometres was set as a buffer around all water features.

Caravan routes (Distance to travel way) – The locations of caravan routes influenced where sites were established. Travel through the desert used a network of transportation links connecting major and minor population centres. A search criterion within the GIS of 3 kilometres was set as a buffer zone around all mapped travel ways. Previous examples for determining the ideal distance to a buffer could not be found in the literature. However, the parameters used for ‘distance to water and ‘distance to travel way’ seemed reasonable.

6.4.6 Methodology

Determining potential archaeological site locations involved nine main steps:

1) Pre-processing of the digital elevation model; 2) Deriving palaeostream channels from the underlying DEM; 3) Digitizing caravan routes from satellite image and map data; 4) Deriving slope and aspect from the DEM; 5) Selecting suitable slope and aspect (raster output); 6) Buffering hydrology and caravan routes (vector output); 7) Intersecting vector buffer layers (vector output); 8) Converting from raster to vector layers; 9) Selecting optimal locations (final vector layer). These steps are further described in the remainder of this subsection.

1. Pre-processing of the DEM: Mosaicking, subsetting, re-projection

The initial base imagery consisted of SRTM3 data (90 m horizontal, 16 m vertical) downloaded from CGIAR-CSI – the Consortium for Spatial Information (<http://www.cgiar-csi.org/data/srtm-90m-digital-elevation-database-v4-1>). CGIAR's latest version (4.1) uses improved hole-filling algorithms by making use of ancillary data sources where available. The majority of spatial operations discussed in this chapter were performed on data derived from this source.

The first stage of work involved pre-processing the SRTM dataset. This was performed in three steps: mosaicking, subsetting, and re-projection. Mosaicking involved stitching together four 5x5 degree tiles into a super mosaic. The output was saved as a 16 bit signed data type, representing values between -32768 to +32767 with Nearest Neighbour re-sampling so as to preserve the original pixel values in the scene. In earlier versions, voids had not been removed and were assigned a value of -32768, whereas in version 4.1 these had been filled and the lowest value was no longer used. The super-mosaic was subset to the study area. Finally, the image was re-projected from its original Geographic Coordinate System (aka Plate Carree) to a Universal Transverse Mercator (UTM) Projected Coordinate System (UTM Zone 36N, WGS1984) using cubic re-sampling. It is usually easiest to re-project an image to a UTM coordinate system, as many spatial operations are much simpler to perform when the horizontal units are in metres instead of degrees.



2. Deriving palaeoriver networks

The steps involved in deriving palaeochannel drainage networks are described below and summarized in Figure 6.12 (as shown on the previous page). ArcGIS's Model Builder in the ArcToolbox was used to construct the model. The input DEM is shown as a blue oval, while processing operations and their outputs are represented by yellow rectangles and green ovals respectively. Some of the steps have been previously discussed in Chapter 5 (Subsection 5.4.2) using the Golden Software Surfer application; however, ESRI's ArcGIS provides more comprehensive and robust techniques that deserve a fuller treatment. The hydrology toolkit within ArcGIS can be used to process the DEM in six steps: filling sinks, calculating flow directions, computing flow accumulations, conversion of pixel numbers to volumes, performing threshold classification, and conversion from a stream raster to a vector feature.

2.1. Filling sinks/pits (ArcGIS Fill utility) – Extracting stream networks typically requires that the DEM first be 'hydrologically conditioned'. This process corrects any sinks or 'pits' in the DEM that may obstruct digital water flow. Sinks are depressions in the landscape that have a lower elevation than surrounding cells. They can form naturally, such as from karst topography, where the dissolution of soluble rocks (such as limestone) in the landscape form sinkholes, caves, and underground caverns. Sinks may also arise due to small elevation errors in the data. Sinks should be filled in order to calculate consistent flow directions and accumulation patterns before water is digitally poured over the surface. After reconditioning, pixel values represent corrected elevation data after sinks have been filled. A z-limit (in metres) can be set in the software to control the maximum depth of the depression that the tool will fill. However, after repeated iterations of the utility using a range of parameters, the Fill utility in ArcGIS proved unsatisfactory, as it was unable to model realistic hydrological networks. This problem was most likely due to the low relief of the desert topography, which is known to create problems for the hydrological algorithms built into ArcGIS (Metz, Mitasova, and Harmon, 2011). Stream channels that pass under roads or beneath bridges may also produce similar artefacts by becoming dammed and will need to be corrected before reconditioning of the data. An improved algorithm for the pit filling procedure was used - the Optimized Pit Removal Tool (<http://tools.crwr.utexas.edu>), produced by the Centre for Research in Water Resources (CRWR) at the University of Texas at Austin. This alternative to the standard ArcGIS utility provides more realistic flow paths by means of an ArcGIS geoprocessing script and therefore can be used from within the ArcGIS application.

Figure 6.13 shows flow accumulation of a region west of the Abu Tartur plateau in Egypt's Western Desert, after applying the built-in ArcGIS fill utility (6.13 top) and CRWR's improved algorithm (6.13 bottom). The standard utility outputs straight lines where the flow-routing algorithm encounters difficulties. As shown in the lower caption, this is corrected for when running the new and improved algorithm.

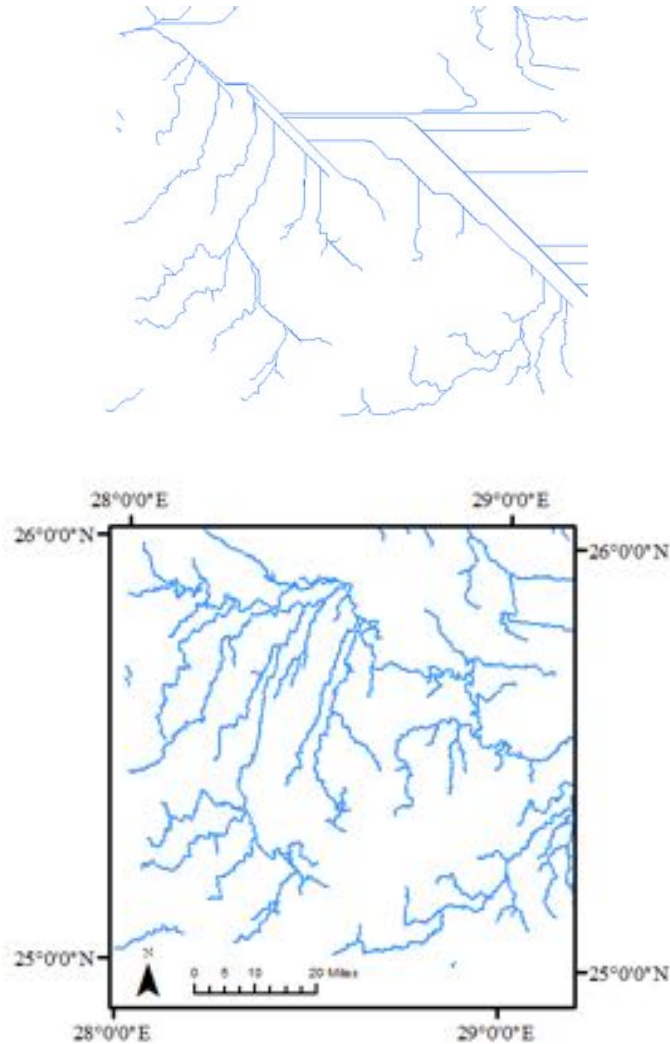


Fig. 6.13 (top): Drainage networks of a region in Egypt's Western Desert (50 km² flow accumulation) using ArcGIS SRTM Fill utility. Note the straight and parallel drainage lines, which indicate problems with the underlying algorithm used to implement the fill process;
6.13 (bottom): Flow accumulation (50 km²) of the same region using CRWR's improved Optimized Pit Removal utility. The drainage channels are now more reasonably delineated.

2.2. Calculating flow directions (ArcGIS Flow Direction utility) – Once the sinks are filled, the next step determines the outgoing flow directions of water for each pixel using the steepest descent slope from its neighbouring pixels. Flow directions are determined from the eight-direction pour point (D8) method (Tarboton, 1997; Costa-Cabral and Burges, 1994), where it is assumed that water in each cell flows towards only one of its eight neighbouring cells. By convention, each cell is assigned one of eight possible values, representing a specific direction, and which varies by a power of two (Figure 6.14). For example, a value of 128 indicates a flow direction to the northeast, whereas a value of 4 indicates a direction due south.

2.3. Computing flow accumulations (ArcGIS Flow Accumulation utility) – Flow accumulation is determined from the input flow direction raster. The value of each pixel in the output raster is equal to the sum of the total number of cells that are located upslope or upstream of that cell (Figure 6.15). Cells located directly inside stream networks therefore have substantially higher grid values compared to those on steep slopes.

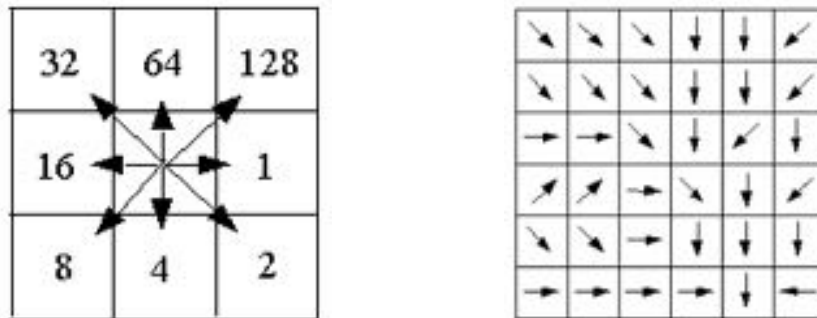


Fig. 6.14: Flow direction codes (left); representation of flow directions (right)

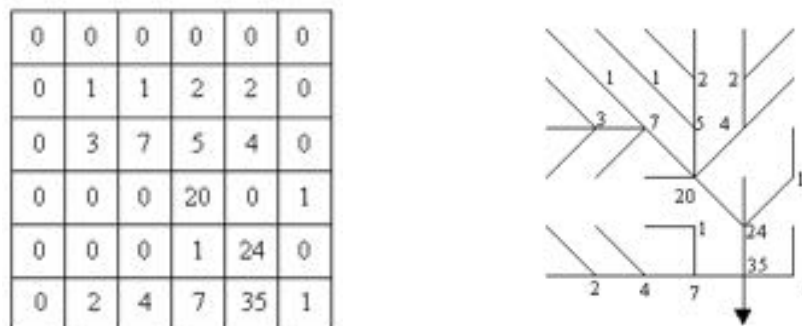


Fig. 6.15: Flow accumulation grid (left); derived drainage networks (right)

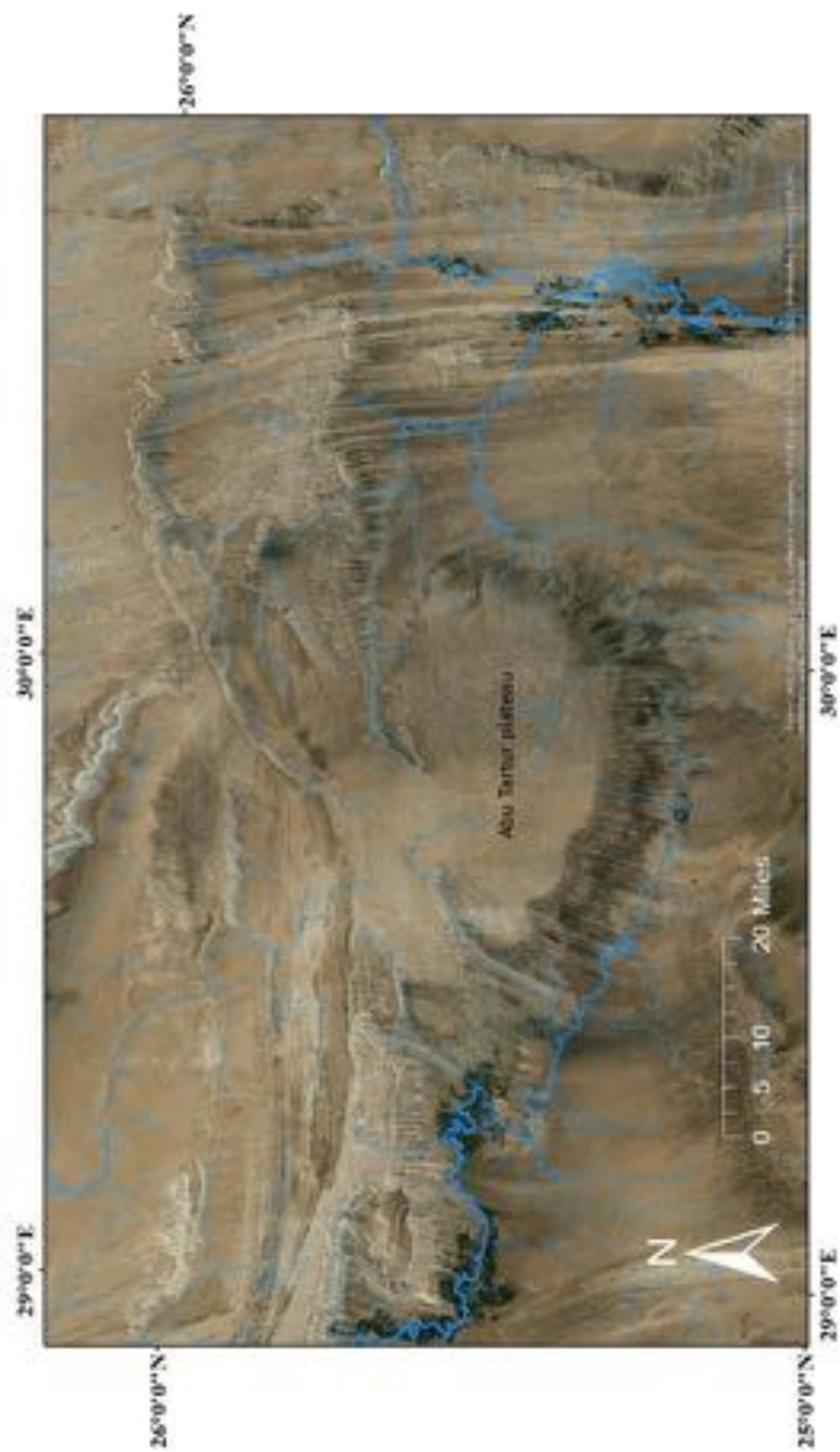
2.4. Conversion to flow volume (ArcGIS Raster Calculator) – The output from the flow accumulation calculation from step 3 represents the total number of cells of water that are flowing into any given cell. This is not a very meaningful value. A more useful quantity for understanding the amount of water flowing through a stream should be measured in volume, that is, the total volume of water that is upstream of the cell. This conversion can be performed by multiplying each pixel in the flow accumulation grid by a factor of 0.0081, which can be found in any hydrology workbook. The result from this calculation is the total water volume flowing from upstream in square kilometres.

2.5. Threshold classification (ArcGIS Raster Calculator) – This step defines a minimum threshold volume of water to be used in the construction of drainage networks. The smaller the value used, the greater the number of channels produced. After a process of trial and error, a threshold of 50 km² was found suitable for channel delineation. The flow accumulation grid was classified by setting non-stream data below 50 km² to a value of 'NoData', while stream data above this threshold remained unchanged.

2.6. Conversion of stream raster to vector feature (ArcGIS Stream to Feature) – Inputs from the flow direction and volume accumulation rasters, from steps 2 and 5 respectively, were used to convert the stream raster into a vector shapefile. Figure 6.16 shows the complete vector shapefile of the stream networks for the study area. Higher order streams are displayed using thicker lines.

3. Mapping caravan routes

The major caravan routes were digitized manually with the on-screen digitization utility in ArcGIS. Location data for route-ways were compiled primarily from satellite data, when possible using both ASTER and high-resolution QuickBird imagery from Google Earth. In many instances, modern roadways were found either to closely follow the course of the caravan routes or to have replaced large portions of them through re-surfacing; they were therefore much easier to view by means of satellite imagery (e.g., the Darb el-Gabari and



portions of the Darb el-Arbain: Figure 6.17). When caravan routes were not directly visible from satellite data, their locations were estimated from published sources (e.g., Bubenzer and Bolten, 2013; Skriwanek, 2007; Eichhorn et al., 2005). The routes were initially digitized as polyline features, which were saved as a shape file (.shp), before being imported into the GIS as a discrete layer. The spatial reference for the new shape file was imported from base imagery added in from the ArcGIS cloud (Geographic Coordinate System). The complete vector layer of caravan routes is shown in Figure 6.17.

4. Creating maps of slope and aspect

Maps of slope and aspect were derived from the SRTM DEM mosaic (Figures 6.18 and 6.19 respectively). As discussed earlier, the slope of a terrain identifies the gradient or rate of maximum change in z-values for each cell of the raster surface and was computed in degrees (0 to 90). The output map was colour coded to better visualize angles of slope with a dark green colour representing a low slope and a red colour indicating a high slope. In contrast, aspect identifies the downslope direction of the maximum rate of change of each cell to its surrounding neighbours (0 to 359.9). A variety of colours were used to represent a range of aspects in relation to the compass directions (i.e., north, northeast etc.).

5. Selecting suitable slope and aspect

The Raster Calculator utility in ArcGIS was used to select those regions where the slope was less than or equal to 6 degrees and where the aspect was either east or west facing. This was performed using the following formula (& = logical AND; | = logical OR):

$$("srtm_slope" \leq 6) \& (("srtm_aspect" \geq 67.5) \& ("srtm_aspect" \leq 112.5)) \\ | (("srtm_aspect" \geq 247.5) \& ("srtm_aspect" \leq 292.5)),$$

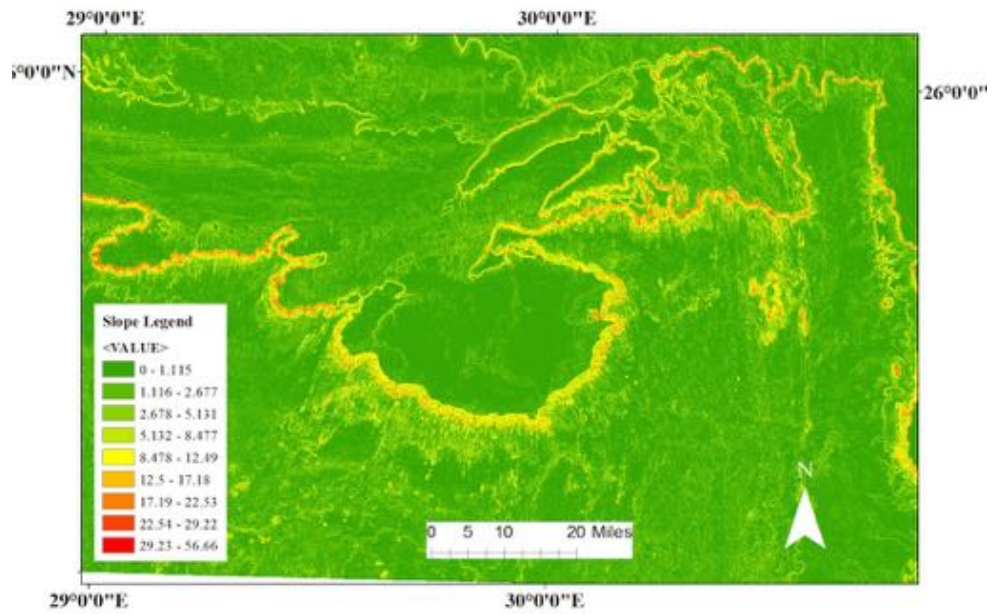


Fig. 6.18: Slope map derived from the SRTM3 data (in degrees)

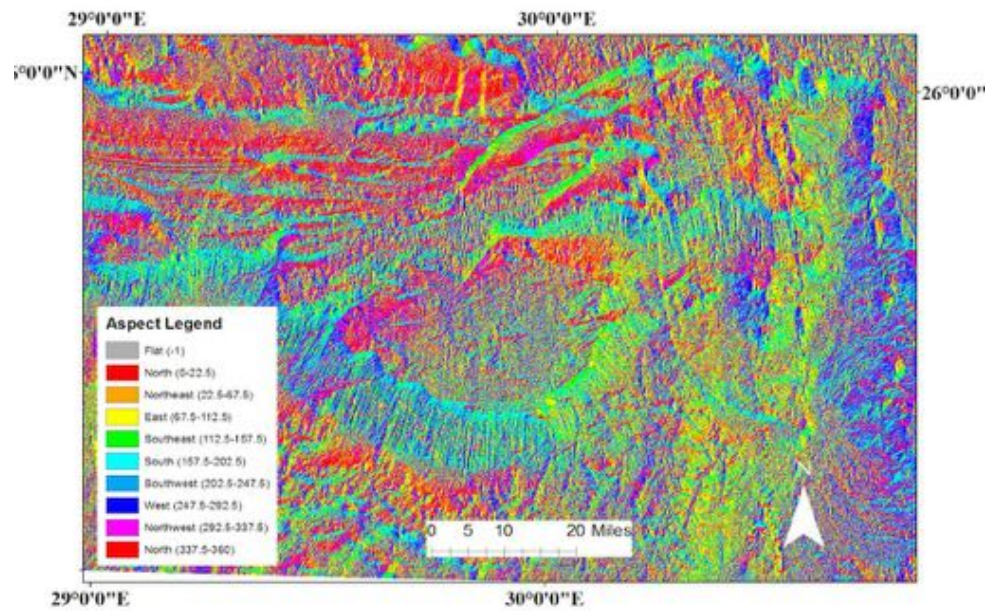


Fig. 6.19: Aspect map derived from SRTM3 data (in degrees)

6. Buffering streams and roads

Buffers were drawn around all water features. Buffering creates polygons around input features to a specified distance. A distance of 2 km was used around hydrological features, extending each side of the buffer from the central line. Figure 6.20 shows a 2 km buffer drawn around all stream lines. Blue lines indicate streamlines and cyan polygons indicate the extent of the hydro buffer around each streamline. Caravan routes are also displayed (red lines). Dissolve type was set to ALL in the software so that all buffers were dissolved into a single feature, thereby removing any overlap. The same procedure was repeated for caravan routes using a 3 km buffer (Figure 6.21).

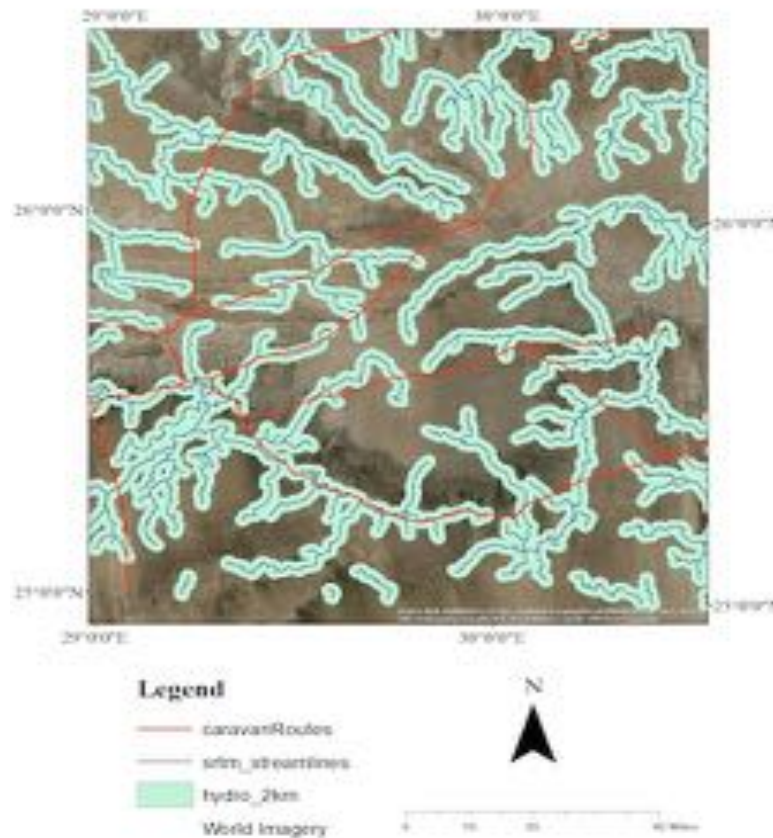


Fig. 6.20: Buffering around palaeorivers. Hydrology is shown in blue, caravan routes in red, and hydrological buffers extending around the hydrology in cyan.

7. Intersecting buffered regions

The overlaps from the hydrology and caravan route buffers were combined into a single buffer shape file using ArcGIS's Intersect Tool. This tool computes a geometric intersection of its input features, outputting those regions that overlap in all layers to an output feature class. Figure 6.21 shows the region surrounding the Abu Tartur Plateau. Caravan routes are displayed as red lines with their 3 km buffers as cream polygons. Palaeochannels are shown as blue lines with their 2 km buffers as light blue polygons. Orange coloured polygons show regions where the two buffers intersect, therefore representing areas where there is both water within 2 km and a trading route within 3 km.

8. Converting raster layers to vector

The final step before identification of the optimal locations for potential sites was to decide how the data should be represented spatially before performing the spatial analysis. Some layers were stored as vector (e.g., routes and palaeochannels buffer intersections), while other data was stored as raster (e.g., slope and aspect). When performing the spatial analysis, all the layers need to be stored in the same data type. In this workflow the vector format was selected; the slope and aspect maps were therefore converted into vector format ready to be input into the GIS. The raster to vector processing was achieved using ArcGIS's Raster To Polygon Tool.

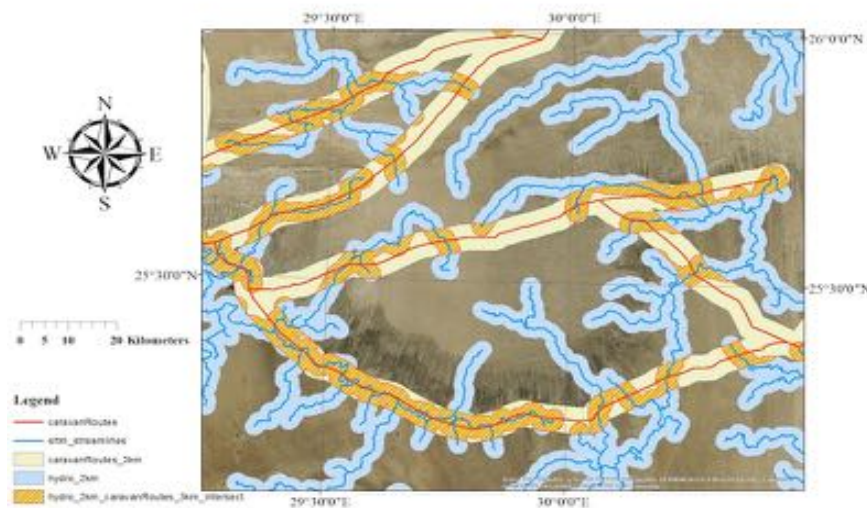


Fig. 6.21: Intersected hydrology and caravan route buffers (orange)

9. GIS analysis: Identifying optimal site locations

In summary, the following criteria were used in order to produce a final map of potential locations for archaeological sites in Egypt's Western Desert:

- Areas located ≤ 2 km from a source of water (palaeorivers)
- Areas located ≤ 3 km from a caravan route for easy access
- Areas located on a slope of ≤ 6 degrees to maximize ground stability
- Areas located in an east- or west-facing direction (aspect) for religious purposes

To qualify, potential locations should meet all of these conditions. The palaeorivers and caravan routes had been previously buffered and combined into a single shape file by means of the Intersect Tool. Likewise, maps of slope and aspect had also been combined into a single shape file with the Raster Calculator. The slope and aspect maps had been converted to a vector data format, so as to be compatible with the rest of the dataset. All shape files had been projected into the same UTM projected coordinate system (UTM Zone 36N, WGS1984). The final step to produce a map of optimal archaeological site locations was to use the Intersect Tool to intersect (bisect) the combined slope and aspect shape files with those of buffered hydrology and caravan routes.

Figure 6.22 shows the final map of potential archaeological sites, where the locations are highlighted in red. As expected, site locations follow closely the distribution of caravan routes, as this is the dominant variable in the dataset. This is especially the case for the southern region of the Abu Tartur Plateau, shown in Figure 6.23 (top), which has been expanded from box A in 6.22, and where a palaeochannel runs in close proximity to the Darb el Gabari trading route. North of the Abu Tartur, potential site locations are more scattered, due to the fluvial features being less prevalent and more discontinuous. Figure 6.23 (lower left) shows a magnified region from box B in Figure 6.22. Streamlines and caravan routes are shown in blue and yellow respectively, and illustrate how areas of interest are determined.

The predicted regions included a substantial number of smaller isolated polygons. These are mainly present due to the aspect constraint, where all surface directions other than east-west have been eliminated. This has resulted in groups of small polygons which tends to add noise

Fig. 6.22: Final output from spatial analysis identifying regions where archaeological sites are more likely to be found

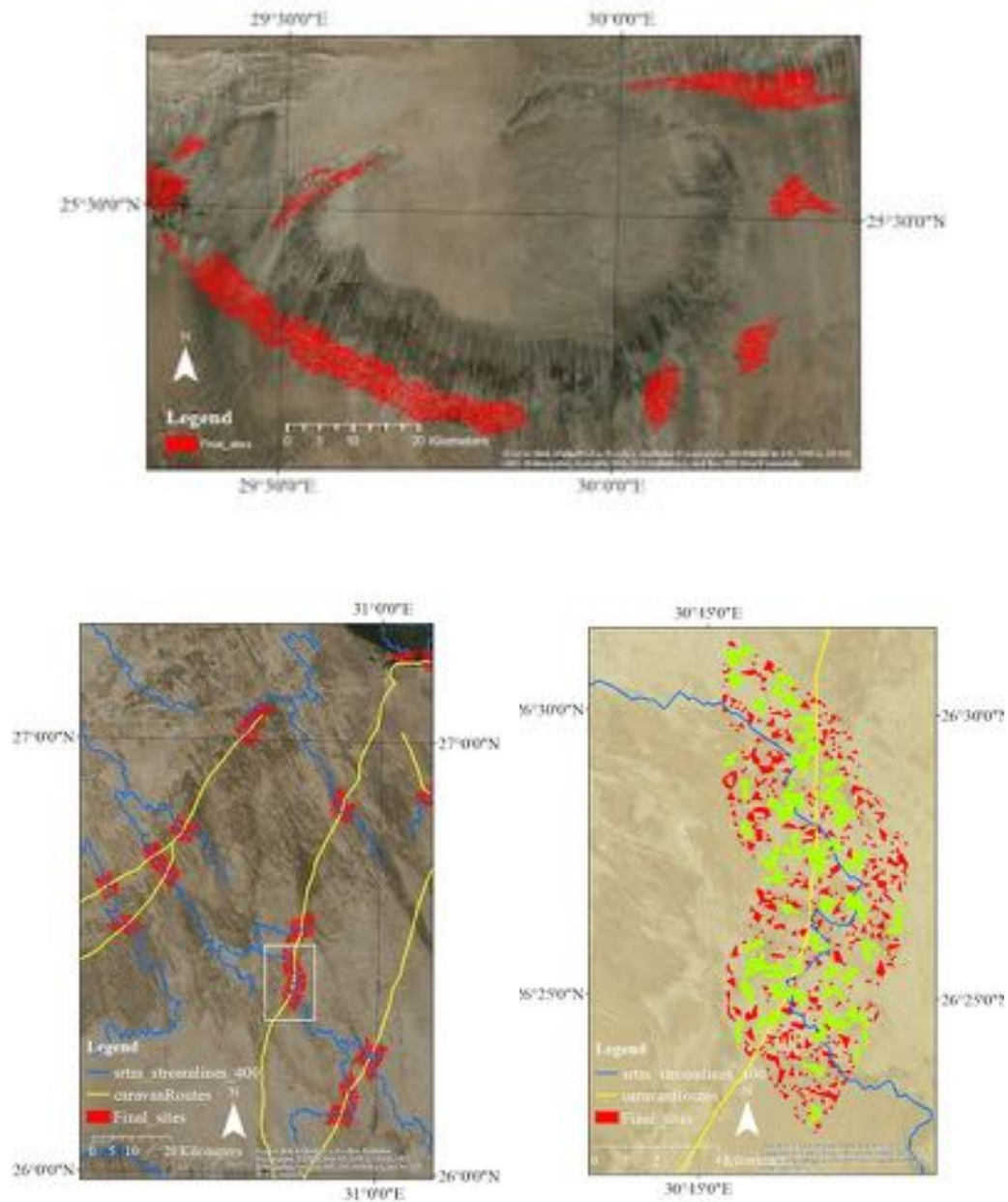


Fig. 6.23: Final map of potential sites: Abu-Tartur plateau of Egypt's Western Desert (top) enlarged from box A in Fig. 6.22; region of interest from box B (lower left); selected polygons larger than 100,000 m² are highlighted in green (lower right).

and an undesired ‘salt and pepper’ effect, especially when zooming into regions at higher magnifications. It may be desirable to discard smaller polygons when determining survey regions. They may be eliminated directly from the dataset by using a majority filter, although this will have to be run on a raster image file, so that some transformations of the dataset may be necessary (see Section 3.8). Alternatively, larger polygons may be selected directly from the attribute table of the shape file according to their size (area). The selected pixels can be highlighted in the display using a preselected colour, which makes visualization easier. An ‘Area’ column was added to the table and populated with area statistics (using the ‘Calculate geometry tool’, specifying the units in square metres). The column was sorted in descending order. Polygons over a predetermined size were selected from the table and then highlighted in the display. Figure 6.23 (lower right) shows in green the selected polygons that satisfy polygon areas greater than 100,000 square metres.

6.5 Conclusions

Egypt is experiencing an unprecedented increase in population, requiring the expansion of new settlement sites and the development of sufficient agricultural resources. As a result, further encroachment into desert regions seems inevitable. To cope with larger numbers of people and to modernize services, improvements must be made to the infrastructure, including provision of efficient transportation links in order to connect greater numbers of desert communities. Many cultural features, such as caravan routes and the archaeological remains found close to them, are under constant threat. The increased proliferation of four-wheel drive vehicles for recreation and other purposes is also of concern as they continue to be responsible for the destruction of archaeological sites throughout the Western Desert and beyond. A degree of protection is afforded by circumstances to sites that have been abandoned and forgotten, and are therefore well preserved. However, many desert routes continue to be used, and traffic is taking a toll on the preservation of these delicate remains. One example is the Darb el-Arbain, which has now been partly paved between Asyut and Kharga in order to increase traffic capacity. It is expected that many more of these ancient tracks will be surfaced over time. It is therefore important to map as many routes and other archaeological remains as possible before they are lost forever.

A Geographical Information System (GIS) can be a useful tool for displaying and integrating different types of data, for archaeological site visualization, and for predicting possible site locations. Inputs from a variety of imagery sources may be added as separate layers into a GIS. Sources used in this work included a digital elevation model, which was used as a base map, and various raster and vector sources, including slope, aspect, hydrology, and caravan routes. Buffering analysis was used as the main tool to identify regions where human populations could have gathered. Buffering around features such as water sources allows specific questions to be asked of the data, such as what are the common land areas that are 'less than 2 kilometres from a mapped source of water AND less than 3 kilometres from a trading route'. In this study the type of result from the GIS will depend to a large degree on the threshold used for the delineation of the stream networks. The threshold value (volume of water in km²) is the minimum needed to form a channel. Therefore a smaller number will produce many more channels. A value of 50 km² was used in this study as this gave a reasonable and not excessive number of channels. The accuracy of the map will also depend on the accuracy of the placement and number of caravan routes noted. Once archaeological site data becomes available through survey work, this additional resource can be added to the GIS. It will then become possible to determine how many known sites were correctly predicted as falling within the identified areas.

One criterion used in the construction of the GIS was to identify only east- or west-facing regions because these would have had specific religious associations. This approach applies only when searching for cemeteries, not for settlement or other types of sites, and it may therefore be treated as an optional step. Furthermore, a second factor to consider when constructing a GIS is that one would not expect to find contemporary sites to be less than a certain distance apart (Baines, personal communication). This constraint could be implemented in a GIS for which a site database was available. An age attribute could be attached to each site in the attribute table and buffering applied using a specified distance around each site.

Chapter 7

Conclusions

7.1 Overview and summary

Satellite remote sensing is revolutionizing the way new archaeological sites are being detected. Advances in the engineering of sensor systems allow satellite data to be recorded at increasingly higher spatial and spectral resolutions. This requires the processing of much larger images as well as the use of more sophisticated computer hardware systems to handle them. Fortunately, the processing power of computers has continued to double approximately every two years – a phenomenon widely known as “Moore’s Law”. In addition to improvements made to sensor design and processing performance, the development and implementation of increasingly elegant and complex software algorithms have translated into faster computation speeds for image processing operations, all of which can now be executed on a single desktop computer. These technological advances are benefiting all disciplines within the earth and social sciences, including archaeological remote sensing.

Remote sensing offers many advantages when compared to more traditional surveying techniques, by providing a safe, cost-effective, and synoptic view of the landscape. Data obtained via satellite can be viewed and analyzed in an image-processing laboratory from anywhere in the world, making possible international and multidisciplinary collaborations. Most importantly, remotely sensed data can be safely collected from a distance, whereas collection may not be possible on the ground. For example, it may not be feasible to travel on foot through difficult terrain, the area may be within a war zone, or the site may be on privately owned land. Visiting many hundreds of sites is beyond most budgets, especially when they are scattered across very large regions. Surveying such areas with traditional ground-based techniques is impossible due to constraints of time, personnel, and budget. Most importantly, remote sensing offers a non-intrusive method for archaeological reconnaissance, contributing greatly to conservation strategies and to the preservation of sites for future generations.

Given the many advantages that remote sensing can offer, it is appropriate to discuss its major disadvantage: the information gathered can only provide an approximation of what is present

on the ground and therefore should never replace a comprehensive ground-based survey. The technology is not yet sufficiently developed, and because of this the results should always be viewed with caution. In ideal conditions, radar imaging can provide information about the top few metres of the near surface; only ground surveys and excavation can record what truly lies beneath the surface and at deeper levels. However, excavation should be used to sample sites selectively because resources are limited and for reasons of conservation; only the most exceptional sites should be excavated in any detail. Excavation is paramount in providing both spatial and temporal information about a site. By contrast, remote sensing can inform us about the spatial aspect but is blind to the temporal.

The primary aim of this research is to develop robust methodologies (referred to as protocols) for locating and characterizing archaeological sites located in large areas of semi- to hyper-arid environments of the Sahara by using imagery principally collected from satellite. The methods presented here may also be relevant to archaeologists working farther afield in landscapes where there is little moisture content and little vegetation cover (best for radar) or where there is some moisture content (best for optical). The work is perhaps most relevant to Egyptologists, although the methodology may also prove useful to Near Eastern specialists, where the chapter on tell site detection, for example, could be of interest.

Three case studies were presented, with each setting out a detailed plan for locating sites in contrasting regions of the eastern Sahara. The first, which unlike the others addressed a humid environment, used Principal Components Analysis (PCA) and a thresholding approach to detect tell sites in the northwestern Nile Delta by means of optical data. The second case study highlighted the importance of mapping sources of water on the surface and in the near surface when locating desert sites, applying a combination of optical and radar imagery respectively. The final case study discussed the remote sensing of trading routes, their correlation to the placement of settlement sites, and the use of digital elevation models and a geographical information system (GIS) to constrain and predict site locations.

The search for archaeological remains in desert regions may seem like a formidable task given the vastness of search areas and the unwelcoming physical environments. However, target regions for search can be greatly reduced in area by devising protocols that can assist in the search process. One such strategy, which provides the foundation for the second case

study and indeed underpins much of the dissertation, is to search in locations that were known to have had past sources of water. Access to a permanent water supply would have been essential for surviving extended periods of time in the desert and when traversing large distances. Locating water is therefore key to finding where people would have gathered and where settlement sites could have developed.

A variety of techniques are proposed to locate both past and present sources of water. Vegetation indices, such as the NDVI – the Normalized Difference Vegetation Index – computes the spectral ratio of red to near-infrared light and is sensitive to vegetation and moisture content. Vegetation indices were key to mapping the major oases of Egypt's Western Desert. These water-rich locations provided havens of refuge during antiquity, as is evidenced by the many caravan routes that are found connecting to them. A second strategy mapped the remains of subsurface palaeochannels, also known as “radar rivers”, by means of long-wavelength radar. The remains of these drainage features cover what are now large expanses of desert terrain and, together with former lake systems, may have opened up migratory routes through Sub-Saharan Africa northwards to the Mediterranean coast. Previous workers have demonstrated a positive correlation between the presence of subsurface fluvial channels and the occurrence of past material remains (e.g., McHugh et al., 1988b). Therefore, creating maps of the distributions of past fluvial channels can assist in determining where to conduct more detailed archaeological surveys. Finally, the locations of former lake systems were mapped by means of a range of techniques including ASTER thermal infrared (TIR) band ratios in the spectral domain for detecting lake deposits and SRTM digital elevation models in the spatial domain for identifying former lake depressions. The locations of lakes and the immediate vicinity of their shorelines would have attracted human activity, including the development of settlement sites.

When considering different types of satellite imagery products, first thoughts should be given to whether to use multispectral optical or radar. The two imagery types can provide complimentary information about a landscape and any archaeology that may be located on it. For example, passive multispectral systems should be employed for sensing chemical changes in the environment—through analysis of their spectral properties—that have directly resulted from activities related to human occupation, whereas radar should be used for sensing physical changes in the environment. Many techniques have been discussed throughout this

dissertation (principally in Chapters 3–6) for the detection of archaeological features in desert terrain using both spaceborne optical and SAR sensors. To assist the reader in finding this information easily, a quick look guide is shown in Table 7.1. It is hoped that the archaeological community will find this reference useful as a tool for what types of imagery datasets can be used, in what regions they may be applied, and what end results may be achieved. References are included for further information about a specific technique, both within the content of the dissertation and, when those methods are not explicitly referenced in the text, where they may be found in external literature.

7.2 Tell sites revisited

Principal Components Analysis (PCA) was first used in Egypt as a site detection tool by Sarah Parcak (now at the University of Alabama, Birmingham), who applied it to a 40 x 50 km region surrounding the Late Period settlement of Tell Tebilla in the eastern Nile Delta, and a second region of 15 x 30 km, on the western Nile floodplain of Middle Egypt, south of Ashmunein and west of Amarna (Parcak, 2007, 2008). The results from these investigations showed that PCA was successful in locating sites in the eastern Delta but failed to detect any in the more southerly floodplain. My own research focuses on a region in the northwestern Nile Delta and adopts a fully multispectral approach. Parcak's work was not multispectral, using only the 4 Landsat bands in the VNIR; I added to those bands the 2 SWIR channels, as well as the higher spectral resolution ASTER data with 9 bands in the VNIR and SWIR. I also employed a thresholding approach to better identify potential tell site locations.

Two databases were reviewed when checking the locations of known tell sites in the northwestern Delta: the Egypt Exploration Society's Delta Survey (EES) catalogue, which remained the primary source, and Uppsala University's Ancient Near Eastern (UU) catalogue (see Sections 4.3, 4.5). These catalogues were chosen for their wide coverage of sites and detailed reporting of site descriptions. Both databases are available online and are downloadable as .kml files to be used in the Google Earth application. The Keyhole Markup Language (KML), first developed for Google Earth, is a file format that enables geographic annotation and visualization (including archaeological site data) to be displayed in a three-dimensional Earth browser, allowing the sites to be viewed in relation to other known

Objectives – I want to find out about how to map..	Predominant datasets to be used	Specific methodologies / image processing techniques that can be applied	Relevant dissertation section or reference
Archaeological sites where soil crop marks are the dominant feature	High spatial resolution imagery; aerial photography; hybrid use of optical (vegetation vigour) and SAR (topographic roughness, structures, and dielectric properties)	Band combinations; classification; NDVI	Wilson, 2000; Lasaponara and Masini, 2007; Agapiou et al., 2013
Archaeological sites with soils rich in phosphates	ASTER SWIR / TIR; hyperspectral datasets	Spectral band ratios	Siegal and Gillespie, 1980; Herz and Garrison, 1998
Tell sites and other mounded archaeological features	1) Spectral: any multispectral dataset, such as Landsat ETM+ and ASTER (at least 30 m spatial); 2) Spatial: DEM	PCA, Classification	Sections 3.7 and 4.9 (PCA); Sections 3.8 and 4.8 (Classification); Wilson, 2006; Wilson and Rowland, 2006; Parcak, 2007, 2008; Wilson and Grigoropoulos, 2009; Trampier et al., 2013
Agricultural land (fields and crop types)	Landsat ETM+ multispectral	Band combinations, classification and image segmentation; NDVI	Sections 3.8 and 4.8; Lenney et al., 1996; Lillesand, Kiefer, and Chipman, 2007
Geological lithology and mineralogy	Hyperspectral and multispectral (ASTER) imagery	SWIR and TIR spectral band ratios	Subsection 5.4.3 (theory); Siegal and Gillespie, 1980; Crippen and Blom, 2001; Ninomiya, 2004; Ninomiya, Fu, and Cudahy, 2005; Corrie et al., 2010
Time change studies of the archaeological landscape	Landsat, Corona (USA), KVR-1000 (former Soviet)	Corona and KVR-1000 originally supplied on photographic film	Subsection 3.9.1 and 3.9.2; Table 3.2; Section 6.3; Galiatsatos, 2004; Ur, 2003
Table 7.1: Quick look guide for archaeological applications using satellite remote sensing in arid / semi-arid environments (continues on next page)			

Desert subsurface water (palaeo-channels)	Radar (e.g., SRTM image, PALSAR) combined with optical (e.g., Landsat)	Use radar image data to map extents of palaeofeatures; DEMs may then be used to further delineate channels and compute flow directions	Section 5.2 (radar theory); Subsection 5.4.2 (mapping techniques); McCauley et al., 1982, 1986; Wiseman and El-Baz, 2007; McHugh et al., 1988a, 1988b, 1989; Wendorf, Close, and Schild, 1987
Desert surface water (vegetation, oases, springs, wells etc.)	Any multispectral dataset with red and near-infrared bands (e.g., Landsat ETM+ and ASTER)	Vegetation indices NDVI, NDWI, IVI etc.	Section 3.5, Subsection 5.4.1; Hurcom and Harrison, 1998; Hirata et al., 2001; Schmidt and Karnieli, 2002; Luedeling and Buerkert, 2010
Lacustrine deposits	Spectral-based approach: SWIR and TIR (e.g., Landsat ETM+ and ASTER) or Spatial approach: DEM (SRTM or ASTER GDEM)	Spectral indices / DEM contouring	Subsection 5.4.3; Pachur, 1997; Drake, 2012a, 2012b
Desert surface lineaments (Tracks – paved / eroded), “hollow ways”	High spatial resolution VNIR imagery / airborne TIR	Edge enhancement digital filters; characterization through TIR	Section 6.3; Förster, 2007; Kröpelin and Kuper, 2007; Förster et al., 2010; Rossi and Ikram, 2013; Wilkinson et al., 2010; Altaweel, 2005; Ur, 2003; Wilkinson and Tucker, 1995
Basin depressions, palaeolake shoreline features	Digital elevation model, such as SRTM or ASTER GDEM	Gridding and contouring software (Golden Surfer etc.)	Subsection 5.4.3; Ghoneim and El-Baz, 2007a, 2008; Ghoneim, Benedetti, and El-Baz, 2012
Table 7.1: Quick look guide for archaeological applications using satellite remote sensing in arid / semi-arid environments (end)			

features. For example, if the location of a tell site was in doubt, Google Earth made it easier to identify by zooming to the corresponding high-resolution satellite image. Potential tell site locations may also be deduced from their modern day place names, where the words ‘kom’ and ‘tell’ are often used. Many of the sites surveyed by the EES were originally identified from these words by using early 20th Century maps of the region.

Results from the investigations are discussed at length in Chapter 4. However, a number of points can be raised here. First, the EES and UU databases that were consulted in this study were published in early 2011. Though 8 new sites were detected using this technique, it was later found that they had been previously mapped by the EES Delta Survey but had not been included in their Google Earth database (Wilson and Grigoropoulos, 2009). Site information was also lacking from the GE database itself and from any online map resources that were consulted. Thus, although the sites were not new, their identification can still be considered a good result: all high brightness signals in Landsat PC4 and ASTER PC5 were found to correlate well with published tell site locations. This finding validates the methodology and the soundness of the detection approach.

Both Landsat PC4 and ASTER PC5 were successful in detecting tell sites in the northwestern Delta. However, many questions remain. For instance, can PCA be successfully applied across other regions of the Nile Delta, Middle Egypt, Upper Egypt, and perhaps elsewhere? Is there a range of spectral signatures that is representative of most tell sites? Or do the signatures vary as a function of location? What are the characteristics of tell sites that allow them to be differentiated from other materials in the surrounding landscape? Mud bricks are the main constituents of sites of this kind, but it may not be the mud brick material that is producing the signal. Many of the sites are buried by a surface layer of organic silty soil, and it is this soil layer that retains a higher moisture content compared to non-tell sites. It may be this material that is important in the detection process. Other factors at play may include increased phosphate levels in the tell earth. Since the early twentieth century links have been established between increased levels of phosphates and areas of previous human occupation (e.g., Arrhenius, 1929; Barker et al., 1975; Herz and Garrison, 1998; Goldberg and Sherwood, 2006). Biological activity has modified the chemical composition of these soils through an increase in plant nutrients derived from animal and human and animal waste.

Further studies will be able to shed light on the components of tell sites that enable them to be detected by the satellite sensor. This will only be possible if a comprehensive ground survey is run in parallel with a satellite remote sensing study. Samples of mud brick will need to be studied in the laboratory by means of a variety of techniques including Fourier Transform Infrared (FTIR) Spectroscopy, where a database of absorption and emission minima and

maxima can be recorded. Samples collected from many different tell sites in different locations will be able to shed light on whether the tell earth has a characteristic profile that can be used to help in its identification. It is illegal to remove samples of mud brick when they are found in situ. Therefore, it is often difficult to obtain samples for spectral analysis.

Even though the techniques employed here proved successful in locating tell sites, there were problems with the underlying PCA classification. False positive signals were found in the southeast corner of the images (see Figures 4.25 and 4.26 of Chapter 4). Examination of the anomalies in Google Earth imagery seems to suggest they are not tell sites because they do not exhibit typical characteristics, that is, they are not mound-like in appearance and they don't appear texturally different from the surrounding landscape. Until these sites are visited on the ground, they should be classified as unknowns.

PCA, coupled with high spectral resolution sensor data, can be used for the rapid surveying of large geographical areas, for example in the Egyptian Nile Delta. My work suggests that the technique works well in regions of the northwestern Nile Delta, but it has not yet been tested on other locations. Parcak's results show that PCA works well for the eastern Delta but not for Middle Egypt. Thus, what may produce valid results in the Egyptian Delta may not necessarily do so in the Nile floodplain or in the arid environments of the Western or Eastern Deserts. Therefore this technique should be used with caution until it has been applied to a wider variety of locations, including other regions of the Middle East, where tell sites are very commonly found.

Little is known about the true extent of the settlement sites of ancient Egypt. This is especially true in comparison with knowledge of sites across the Middle East, where we have a much greater understanding. Mapping of sites using satellite with PCA analysis can help and is a step in the right direction. But many sites have been lost, especially over the last 50 years. Tell sites across the Nile Delta are disappearing at an ever-accelerating rate. As population density increases, more land is needed for the cultivation of crops and for housing. This often leads to the levelling of entire sites, for example the Ptolemaic and Roman site of Tell el-Barnugi (El-Bahari) in the Damanhur administrative unit of Beheira Province (Wilson and Grigoropoulos, 2009), which is just one example of many. These developments can only have a negative impact on their long-term survival. Furthermore, the mud bricks of which the sites

are largely composed have been and continue to be exploited as a rich source of fertilizer for farming. They also continue to be recycled in the construction of new settlements, where the bricks are often fired to make burnt brick to be used as infill in concrete-frame structures, although this practice is less common today with the introduction of materials such as modern concrete. If the spectral signal arises from the mud brick, their recycling will make it impossible for the satellite sensor to distinguish between ancient and modern. The Egyptian government has started to be aware of the importance of these monuments and of Nile silt and mud brick as a resource, and has made it illegal to remove and recycle it, but little is being done to enforce this regulation. Only time will tell how many of these ancient settlement sites can be saved.

7.3 Concluding remarks: towards the future

We are living in an exciting era of technological innovation. The first satellites, launched in the late 1950s, collected relatively simple data about the Earth by today's standards. Since that time, in the comparatively short period of a little over fifty years, we have witnessed the development of increasingly more sophisticated systems. Thousands of satellites are now in orbit, each sending back data about specific geophysical parameters of the Earth. Commercial optical sensor systems are now capable of recording imagery at spatial resolutions of less than half a metre, at near-global coverage, and in many different regions of the electromagnetic spectrum. Recently launched high-resolution SAR systems are both multi-frequency and quad-polarization capable (such as the new Japanese PALSAR-2 sensor). It has been found that multi-band and multi-polarization radar interacts in specific ways with locations strongly associated with human remains and occupation and can therefore provide a range of means for identifying archaeological patterns. A recent study, for example, has assessed the potential for using the COSMO-SkyMed X-band SAR sensor for detecting archaeological features, including crop, soil, and shadow, and results show that X-band SAR can be an effective approach in archaeological prospection (Chen et al., 2015). All of these advances favour the detection of new archaeological sites, especially when greater amounts of data become free of charge for research purposes.

Archaeological remote sensing continues to mature and has experienced a revolution over the past two decades. The availability of earth observation data has become commonplace, with

many providers now releasing their data free of charge to the public, including the Landsat archive, which represents over 40 years of legacy data. The application of SAR in archaeological remote sensing is less developed and the interaction of microwaves with archaeological materials is less understood when compared to the use of optical satellite data. However, the use of multi-band / multi-polarization SAR holds great potential in the detection and identification of sites (Comer and Blom, 2007). The development of Google Earth and similar virtual globe software applications has provided a means to access these resources, opening up the world of geographical information science and ushering in a new age of desktop exploration. However, the use of such data has remained almost exclusively in the domain of the physical sciences, leaving behind other, less quantitative fields, including archaeology. Legacy radar data is gradually becoming available to researchers, including both PALSAR-1 and SRTM products.

The archaeological community is not embracing the technology as quickly as it could. As a result, a multispectral approach has been lacking when scholars have been searching for sites. In recent years this has begun to change as archaeology moves from a social science / humanities discipline to one increasingly more scientific in its nature and use of techniques. Even so, it has been slow to adopt and adapt to the new role that satellites play as data providers. This could be due in part to several reasons. Firstly, the data can be prohibitively expensive and often beyond the budget allocated to archaeological projects, especially when compared to the so-called “hard sciences”, where funding for imagery is not usually a problem. Secondly, many archaeologists do not have adequate training, experience, or are even aware of the potential to enable them to undertake a remote sensing survey themselves, where sophisticated instrumentation (such as ground imaging radars) and complex image processing techniques (for example multivariate statistics) are often employed. Data costs should become less of a problem in the future as greater amounts of legacy data become available at little or no cost to the user. At the time of this writing (September, 2015) ALOS-1’s PALSAR Level 1.0 (unprocessed / raw) and Level 1.5 (geo-referenced amplitude image) radar data has been released free of charge to scientists and researchers around the world, although it is unclear whether this applies to worldwide data or is limited to imagery collected over the Americas. The release of PALSAR data by the Japanese was most likely in response

to NASA's lifting of restrictions on the SRTM1 data (1 arc-sec or 30 m) for imagery outside of the United States at the end of 2014.

In relation to the second problem, archaeologists can embrace the technology more fully if the course content delivered in university archaeological science curricula is updated to include a greater physical sciences component, including courses in remote sensing, GIS, and statistics, at both undergraduate and graduate levels. Hopefully, these tools will become more commonplace in the future as archaeology and remote sensing / GIS theory is made more tightly integrated. Perhaps a third obstacle to the widespread use of remote sensing in archaeology is that many remote-sensing technologies are still used predominantly in the geosciences and have not yet been fully adapted to address specific archaeological questions. Such adaptation requires specialists who have knowledge of both disciplines in order to be able to reverse-engineer and re-task software packages specifically written for the geoscientist and modify them for archaeological problems. The development of new remote-sensing software packages with the archaeologist in mind will be a major step in the right direction.

Several new high-resolution sensors offering enhanced capabilities have been launched recently or are scheduled to be. These include the WorldView-3 and Earth Explorer-7 Biomass sensors. WorldView-3, launched in August 2014, offers unprecedented sensor resolution (31 cm panchromatic, 1.24 m multispectral) with the benefit of eight SWIR and twelve Clouds, Aerosols, Vapours, Ice, and Snow (CAVIS) bands for imaging desert clouds and aerosols. The increased spatial and spectral resolution will be beneficial for site identification, verification, and spectral analysis. Furthermore, the first P-band SAR spaceborne mission, Biomass, is due to be launched by ESA in 2020. Biomass is the seventh satellite in the Explorer mission concept developed to further understanding of the Earth. Although primarily designed to provide biomass estimates of global tropical forests, it is also expected to contribute new science in several other research areas, including subsurface geology in arid regions. The Biomass sensor will therefore be ideal for examining the so-called "radar rivers" of the Sahara in greater detail. For example, with P-band's increased depth of penetration, it may be possible to find evidence for a connection for the Kufrah River linking the southern Kufrah Basin to the Mediterranean Sea through the Gulf of Sirt (see Subsection 5.4.2). Past experiments using the shorter wavelength L-band sensors have failed in this endeavour due to extreme mantling by the Calanscio Sand Sea. If such a route can be

found, it will have important implications for understanding the corridors of human and animal dispersal in the eastern Sahara and may indicate regions where further archaeological exploration should be concentrated (Paillou, Tooth, and Lopez, 2012).

The value of multispectral and hyperspectral sensors cannot be overstated. Most archaeological investigations do not yet exploit the full range of the electromagnetic spectrum and so may be limiting themselves by not exploring the full potential of their datasets. Where possible, the practical work in this dissertation adopts a fully multispectral approach, by using wavelengths from each of the subsystems, including the VNIR, SWIR, TIR, and microwave (radar). Moreover, in interpreting imagery it is not enough to simply display the original bands in a specific band combination of the original dataset. The channels should be decorrelated and redisplayed using the set of bands containing the greatest variance in order to reduce data redundancy. In this work that was achieved by means of a decorrelation stretch or by applying principal components analysis to the relevant channels.

Although sufficient resources should be dedicated to locating and uncovering new sites, the protection and conservation of existing sites should be of equal if not of greater importance. During the writing of this dissertation archaeological sites have been destroyed and mass plundering of antiquities in museums has taken place across large regions of the Middle East, including Iraq, Syria, and Libya by the Islamic State of Iraq and the Levant (ISIL) and its affiliates. These events underscore the fact that archaeological remains are fragile and heritage needs to be protected.

In this dissertation I have endeavoured to present a robust set of methodologies for detecting new archaeological sites by using a selection of the latest remote sensing techniques. The examples cited and the case studies presented demonstrate that archaeological sites do emit distinct spectral signatures that can be detected, analysed, and differentiated. Further work needs to be carried out to better understand the nature of spectral signatures produced by archaeological sites and whether they can be isolated from similar sites around the world. Unfortunately, during the course of this work it was not possible to visit potential sites on the ground, so that no ground truthing could be carried out in order to ascertain their authenticity. As it stands, this dissertation is therefore a theoretical work and provides no verification of the accuracy of the potential sites mentioned in the text. Nonetheless, the identification from

remote sensing of Delta tells that proved to have been independently discovered through field survey provides a valid confirmation of one of the methodologies presented. For the other case studies and methods developed, testing the locations or reviewing records are beyond the dissertation's scope.

Appendices and bibliography

Download resources

Many World Wide Web (WWW) resources are available for the download of free and commercial remote sensing imagery. Some of the better websites have sophisticated graphical user interfaces with intuitive search capabilities. For instance, being able to draw a box around a search region makes it much easier than having to remember and type in geographic latitude and longitude coordinates. The following websites were accessed for the download of data in this dissertation and may be valuable as a basis for other research:

The Global Land Cover Facility (GLCF) of the University of Maryland:

<http://www.landcover.org/>

The Land Processes Distributed Active Archive Centre (LP DAAC) of the United States Geological Survey (USGS):

<https://lpdaac.usgs.gov/>

The Warehouse Inventory Search Tool (WIST) of the USGS:

https://lpdaac.usgs.gov/lpdaac/get_data/wist/

Jet Propulsion Laboratory (JPL) Imaging Radar:

<http://southport.jpl.nasa.gov/>

The NASA Earth Observing System Data and Information System (EOSDIS):

<http://reverb.echo.nasa.gov/>

EarthExplorer:

<http://earthexplorer.usgs.gov/>

The Earth Resources Observation and Science (EROS) Centre:

<http://eros.usgs.gov/>

The USGS Global Visualization Viewer (GloVis):

<http://glovis.usgs.gov/>

National Geospatial Intelligence Agency:

http://geoengine.nima.mil/geospatial/SW_TOOLS/NIMAMUSE/webinter/rast_roam.html

European Space Agency (ESA) Earth Online:

<https://earth.esa.int/>

Declassified high-resolution photography can be ordered from:

Corona: http://eros.usgs.gov/#/Find_Data

KVR-1000: <http://www.sovinformsputnik.com/>

Digital Elevation Model (DEM) data is available from two primary sources: SRTM, and ASTER GDEM:

- (1) The Shuttle Radar Topography Mission (SRTM) acquired radar interferometric data to create a near-global digital elevation model of the Earth (between 60 degrees north and 56 degrees south) using modified Shuttle Imaging Radar (SIR-C) hardware. Collected on board the Space Shuttle Endeavor, it is available in 3 datasets, referred to as SRTM1, SRTM3, and SRTM30, with sample spacing of data points at 1 arc-second (30 m), 3 arc-seconds (90 m), or 30 arc-seconds (~ 1 km). SRTM1 data is considered restricted use and is available only within the continental United States. All SRTM data is available free of charge from the United States Geological Survey's EROS Data Centre (<https://eros.usgs.gov/>). The restricted SRTM-1 dataset of the eastern Sahara was used in the practical portions of this dissertation.
- (2) ASTER Global Digital Elevation Model (GDEM) acquires data between 83 degrees north and 83 degrees south with coverage of 99 percent of the Earth's landmass. It is also offered in 1 degree tiles with 30 m postings between data points. ASTER data is free and can be downloaded from NASA Reverb (<http://reverb.echo.nasa.gov/>), the LP DAAC Global Data Explorer (<http://gdex.cr.usgs.gov/gdex/>), and J-spacesystems (<http://GDEM.ersdac.jspacesystems.or.jp/>)

Radar image data is available from a number of sources:

PALSAR: (J-spacesystems):

<http://gds.ersdac.jspacesystems.or.jp/?lang=en/>

SRTM Image data: (USGS EROS Centre:

<https://eros.usgs.gov/>

Shuttle Imaging Radar (Jet Propulsion Laboratory)

<http://southport.jpl.nasa.gov/sir-c/>

An advantage of using SRTM amplitude data as a radar asset is that it is registered to the underlying SRTM DEM 1 degree tiles. This facilitates input into an image processing system or a geographical information system when combining datasets.

Acquiring radar imagery can be expensive, but pricing is becoming more competitive, especially with the launch of next generation instruments, including PALSAR-2. Radar imagery may be acquired free of charge or at minimal cost through the NASA Jet Propulsion laboratory (JPL) Imaging Radar Program Outreach Opportunity. This is a storehouse for SIR, AIRSAR, and other SAR data that can be made available if the applicant meets certain qualifications. Further information can be found at the JPL Imaging Radar website:

<http://southport.jpl.nasa.gov/outreach/info.html/>

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