Using remote sensing and aerial archaeology to detect pit house features in Worldview-2 satellite imagery.

A case study for the Bridge River archaeological pit house village in south-central British Columbia, Canada.

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Abstract

It is well known that archaeological sites are important sources for understanding past human activity. However, those sites yet to be identified and further investigated are under a great risk of being lost or damaged before their archaeological significance is fully recognized. The aim of this research was to analyze the potential use of remote sensing and aerial archaeology techniques integrated within a geographic information system (GIS) for the purpose of remotely studying pit house archaeology. As pit house archaeological sites in North America have rarely been studied with a focus in remote sensing, this study intended to identify these features by processing very high resolution satellite imagery and assessing how accurately the identified features could be automatically mapped with the use of a GIS. A Worldview-2 satellite image of the Bridge River pit house village in Lillooet, south-central British Columbia, was processed within ArcGIS 10.1 (ESRI), ERDAS Imagine 2011 (Intergraph) and eCognition Developer 8 (Trimble) to identify spatial and spectral queues representing the pit house features. The study outlined three different feature extraction methods (GIS-based, pixel-based and object-based) and evaluated which method presented the best results. Though all three methods produced similar results, the potential for performing object-based feature extraction for research in aerial archaeology proved to be more advantageous than the other two extraction methods tested.

Keywords: Remote Sensing, Aerial Archaeology, Pit House Archaeology, Geographic Information Systems (GIS), Satellite Imagery
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1 Introduction

1.1 Research Context
It is well known that archaeological sites are important sources for understanding past human activity. However, those sites yet to be identified and investigated are under a great risk of being lost or damaged before their archaeological significance can be fully recognized. Threats such as road construction, urban and rural developments, mining and agriculture are listed as some of the greatest threats that face the initial detection and the subsequent conservation and preservation of archaeological sites (Chen, Priebe, Sussman, Comer, Megarry, and Tilton, 2013). Aerial archaeology defined simply is the integration of geographic information systems (GIS) and aerial or satellite remote sensing data to detect, prospect and further investigate archaeological sites with minimal physical contact with the study area (Beck, 2009). Employing aerial archaeology techniques and incorporating remotely sensed data in a GIS can help researchers detect known and unknown sites, reduce costs, time and risks involved in archaeological investigations, as well as support conservation and preservation strategies created for each site (Lasaponara and Masini, 2011).

Exploration into remotely sensing archaeological sites with the integrated approach that aerial archaeology offers has arguably not been as extensively employed in archaeological investigations within North America as they have in the rest of the world. Though aerial archaeology is one of the most recent advancements in the field of remote sensing; the majority of past archaeological studies involving aerial and satellite remote sensing have generally been situated in Northern Africa, the Middle East, Europe, and South America (e.g. Ciminale, Gallo, Lasaponara and Masini, 2009; Contreras and Brodie, 2010; Garrison, Chapman, Houston, Roman and Garrido Lopez, 2011). Digitally identifying and mapping these sites using GIS and remote sensing is an important archaeological tool as it allows for an extensive study of them with minimal physical contact by the researchers, furthering research possibilities in identifying unknown sites (Beck, 2009; Giardino, 2010). With aerial archaeology, sites with high susceptibility to deterioration and erosion caused by human traffic can be initially explored digitally, rather than exposing them to the traditional means of site exploration where the site is subjected to potential destruction (Lasaponara and Masini, 2011).

1.2 Research Aims
The objectives of this study are to gather a background on aerial archaeology and to identify and examine some remote sensing and aerial archaeology techniques suggested from the literature that would be useful in identifying the remnants of the buried pit houses in North America. The area of interest in this study is the pit house village site at Bridge River in south-central British Columbia, Canada. Overall, the aim of this research is to evaluate how well these non-destructive
archaeological methods detect the buried features of the pit house village; the results of which will be compared to those produced from the geophysical and archaeological investigations previously undertaken at the site. The level of accuracy the methods offer and whether or not they are viable choices to base future pit house archaeology on will also be evaluated. The methodology this study attempts to create can be used as a means of initial exploration of the area and to help researchers identify archaeological features before site surveying and excavation begins. This would also help in reducing costs of archaeological endeavours where unnecessary expenses can be avoided by the extra level of preparation.

1.3 Thesis Outline
The structure for the rest of this work includes: an introduction to remote sensing and aerial archaeology based on the literature reviewed; a description of the methods used in this research including details on the specific methodologies from the literature that this study tested; followed by a section detailing what results were found; and finally a section discussing these results and how they benefit the study at hand and what significance and potential this research has for the discipline of remote sensing archaeology. Clarification of any limitations recognized during the study will also be discussed.

1.4 What is Remote Sensing?
Terrestrial remote sensing is generally known as the recording and analysis of land information gathered by cameras and technologies that can collect more than just the optically visible features on the Earth’s surface. Sanderson (2010, p. 4) defines it as “the collection and interpretation of information about an object, area, or event without being in physical contact with the object”. De Laet, Paulissen and Waelkens (2007) describe a similar definition of remote sensing additionally explaining that it involves the collection of remotely sensed data through various techniques; these being sub-surficial remote sensing, aerial photography, aerial spectroscopy and satellite remote sensing. Remotely sensed photography involves capturing the different levels of electromagnetic energy reflections and absorptions from the Earth's surface. The most common photographic collection comes from capturing reflections from the visible portion of the electromagnetic spectrum. More recently though, in the wake of improvements in remote sensing technology, information is also being collected from capturing the reflections and absorptions of the other electromagnetic wavelengths: ultraviolet, the infrareds (e.g. NIR, MIR and Thermal), and microwave, using both passive and active sensors such as multi-spectral scanners and radar (Cracknell & Hayes, 2007; Sanderson, 2010). The interpretation of remotely sensed data is based on the varying surface anomalies in the geometries, gray levels (or colour changes) and general contrasts detectable in the data (Natural Resources Canada-Canada Centre for Remote Sensing, 2003).
1.4.1 Remote Sensing Data Acquisition Process

For a brief explanation, as outlined by the Natural Resources Canada-Canada Center for Remote Sensing (or NRC-CCRS from here on) (2003); the data acquisition process of remote sensing starts with an energy source and follows a complex procedure that finally results in user-ready, interpretable data. The energy source (most often the sun) ‘illuminates’ the surface, emitting electromagnetic energy which the surface then reflects and that sensors are able to detect and record. As well as interacting with the surface, the energy also interacts with the atmosphere and its atmospheric properties as it travels through it. The energy then reaches the remote sensor that scans the Earth as it either orbits around the planet or flies over it with a sensor/scanner mounted on airborne vessels (e.g., airplanes, drones or balloons). This information is then electronically transmitted to receiving stations on the ground where it is processed into interpretable images, ready for the end users to extract the information they provide.

Table 1 shows the organization of the electromagnetic spectrum and which wavelengths belonging to it are used in terrestrial remote sensing. Extensive studies have been performed to evaluate which wavelengths or spectral windows are the most suitable for detection of various Earth features. Remote sensors are able to distinguish between the wavelengths and record them as separate bands, the most commonly used in photography are Red, Green and Blue (from the visible portion of the electromagnetic spectrum); producing “True Colour” images. Because electromagnetic energy is absorbed and reflected at different wavelengths and frequencies by the Earth and atmosphere, detection of certain features is not always best performed with the use of the visible wavelengths alone. Combining various spectral bands to help extract information has become a major part of remote sensing studies, especially in aerial archaeology and land cover analysis (Van Niel & McVicar, 2004; Agapiou, Hadjimitsis, Sarris, Georgopoulos and Alexakis, 2012).

Table 1. The distribution of the electromagnetic spectrum highlighting what is suitable for remote sensing. (As adapted by Brandt, 2004 from Lillesand and Kiefer, 2004).

<table>
<thead>
<tr>
<th>Region Name</th>
<th>Wavelength</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gamma Ray</td>
<td>&lt; 0.03 nanometers</td>
<td>Entirely absorbed by the Earth’s atmosphere and not available for remote sensing.</td>
</tr>
<tr>
<td>X-ray</td>
<td>0.03 to 30 nanometers</td>
<td>Entirely absorbed by the Earth’s atmosphere and not available for remote sensing.</td>
</tr>
<tr>
<td>Ultraviolet</td>
<td>0.03 to 0.4 micrometers</td>
<td>Wavelengths from 0.03 to 0.3 micrometers absorbed by ozone in the Earth’s atmosphere.</td>
</tr>
<tr>
<td>Photographic</td>
<td>0.3 to 0.4 micrometers</td>
<td>Available for remote sensing the Earth. Can be imaged with photographic film.</td>
</tr>
<tr>
<td>Visible</td>
<td>0.4 to 0.7 micrometers</td>
<td>Available for remote sensing the Earth. Can be imaged with photographic film.</td>
</tr>
<tr>
<td>Infrared</td>
<td>0.7 to 100 micrometers</td>
<td>Available for remote sensing the Earth. Can be imaged with photographic film.</td>
</tr>
<tr>
<td>Reflect Infra</td>
<td>0.7 to 3.0 micrometers</td>
<td>Available for remote sensing the Earth. Near Infrared 0.7 to 0.9 micrometers. Can be imaged with photographic film.</td>
</tr>
<tr>
<td>Thermal Infra</td>
<td>3.0 to 14 micrometers</td>
<td>Available for remote sensing the Earth. This wavelength cannot be captured with photographic film. Instead, mechanical sensors are used to image this wavelength band.</td>
</tr>
<tr>
<td>Microwave or</td>
<td>0.1 to 100 centimeters</td>
<td>Longer wavelengths of this band can pass through clouds, fog, and rain. Images using this band can be made with sensors that actively emit microwaves.</td>
</tr>
<tr>
<td>Radar</td>
<td>&gt; 100 centimeters</td>
<td>Not normally used for remote sensing the Earth.</td>
</tr>
</tbody>
</table>
1.4.2 Resolutions in Remote Sensing

The resolutions of remote sensing influence the amount of detail and therefore the amount of interpretation that can be performed on an image. Having a high resolution and a more detailed image is often preferred in remote sensing; especially for military purposes or site-specific aerial archaeology for example (NRC-CCRS, 2003; Lasaponara and Masini, 2011). The four most common remote sensing resolutions are geometric, spectral, temporal and radiometric, according to the NRC-CCRS (2003) and Weng (2012).

The geometric (or spatial) resolution refers to the size of the smallest feature that can be detected in the image and is “a function of the sensors altitude, detector size, focal size, and system configuration” (Weng, 2012, p. 35). The spectral resolution is dependent on the ability of the sensor to distinguish between the different wavelengths and is based on the number and location of the bandwidths of spectral bands. These range from multispectral to hyperspectral. For example, there are 4 bands in SPOT, 7 in Landsat, 14 in ASTER, 36 in MODIS, and in the hyperspectral class there are AVIRIS and EO-1 with 224 bands (Weng, 2012). The variety of materials found in the land cover on Earth’s surface all have a certain spectral values, therefore land cover analysis and mapping can be done by separating these values into similar classes (Weng, 2012). Temporal resolution refers to the variations in time between data capture, referring to the repeat cycle of the time interval between acquisitions of two successive images. This is important for monitoring change, atmospheric differences, and vegetation cycles for example (Weng, 2012). And finally, the radiometric resolution depends on the ability of the sensor to detect variations in grey levels only, and the subsequent storage size of the image.

1.4.3 Image Processing and Analysis

Image processing is the main method of extracting useful information from aerial and satellite imagery. This is usually done by performing various processes within applications like ArcGIS and ERDAS for example, and producing images that provide more information than the unprocessed image initially did. Depending on the areas of interest within an image, various measurements or analyses can be made to gather more information on the spatial or spectral relationships and characteristics between features present in the image (NRC-CCRS, 2003).

1.4.4 Ground-Based Remote Sensing

In addition to aerial means of data collection, there also exists another form of remote sensing. Ground-based sensors are often used in remote sensing studies and can accurately record the soil properties of an area based on magnetic susceptibility, electrical resistivity, electromagnetic conductivity and ground penetrating radar techniques (Alvey, 2006). As Alvey describes, these techniques record soil information with the use of handheld or wheeled equipment being
passed over the surface systematically, of which the results of the soil properties can be easily visualized in GIS applications.

1.5 Remote Sensing and Archaeology: Aerial Archaeology

Aerial photography has, for many years, been used by archaeologists for site detection and prospection in archaeological research. As Lasaponara and Masini (2011, p. 2001) describe; “over the last century, aerial reconnaissance has been one of the most important ways in which new archaeological sites have been discovered through[out] the world”. In modern times the shift from basic aerial photography to satellite remote sensing, has led to many advances in archaeological research. The advancement of remote sensing technologies has helped researchers realize the enormous potential for superior results in non-destructive archaeological studies. The improvement in resolution, the increasing availability of data, software, processing and analysis tools and the various techniques developed all aid in reducing the costs, time and risks involved in site prospection and excavation, as well as supports the development for conservation and preservation strategies for each unique archaeological situation (Giardino, 2010; Lasaponara and Masini, 2011). Aerial archaeology concerns the reconnaissance and interpretation of both satellite and aerial photographs to identify potential and existing areas of archaeological importance. As identifying the spatial characteristics of archaeological sites at ground level can be somewhat difficult to perform; De Laet et al. (2007) explain that intensive survey campaigns and fieldwork can be easily conducted with the use of remote sensing methods in combination with traditional archaeological surveying methods. Using a combination of aerial photographs (both oblique and vertical), satellite imagery, and geophysical surveys (Macleod, 2011; Sarris et al., 2013), the photo-interpreter has all the visual information he or she needs to employ methods of remotely detecting or investigating the site.

1.5.1 Aerial Archaeology and Geographical Information Systems

Aerial archaeological investigations can be performed or extended within a GIS, where all information and data can be organized and further analysed using many of the tools available. As Church, Brandon and Burgett (2000) state, there are three main uses of GIS in archaeology: visualization, spatial analysis and modelling. With additional datasets derived from existing maps, GIS data, field surveys, and digital elevation models (DEMs); the potential for deriving any sort of information sought for becomes enormous. As described by Kaimaris, Sylaiou, Georgoula and Patias (2010); creating a GIS for the documentation, management, study and analysis of an archaeological study not only keeps all information and data organized but also provides useful tools for spatial, spectral and descriptive information and even provides a platform that can be utilized by those with limited computer knowledge.
Integrating GIS and remote sensing for archaeological purposes has led to the detection of previous settlements (buried or low-relief); used for modelling past habitation (Alexakis, Sarris, Astaras and Albanakis, 2010); mapping and assessing looting and site damage (Parcak, 2009; Contreras and Brodie, 2010); as well as reconstructing past landscapes and past land use patterns, and creating predictive models for archaeological research (Montufo, 1997). Predictive models, similar to multi-criteria analyses yet more automatic are used in the remote detection of archaeologically important areas by identifying regions where it would be most likely to find archaeological sites. This is carried out by highlighting areas that are most suitable for specific human activities based on various region-specific parameters and factors identified by the developers of the model (Chen et al., 2013).

For example, analyses performed within the GIS for the study of detecting ancient magoules (a form of Neolithic settlements) in Thessaly, Greece, by Alexakis et al. (2010), produced enough information to construct three different predictive models to help with further detection. The information derived from the various spatial analyses in the study helped the researchers understand the local characteristics of the magoules; extract statistics based on aspect and slope and relief heights; and calculate distances from each settlement to natural resources and to one another. This all lead to insight on potential hierarchal differences, density, visibility connections, distributions, and the spatial territorial limits and communication routes of the area. All this derived information, in addition to other geographical, statistical and archaeological parameters, were integrated using a multi-parametric spatial analysis method to construct the predictive models (Alexakis et al., 2010). The overall aim for Alexakis et al. was to understand the human partitioning and the territoriality of the landscape by reconstructing the major habitation patterns while simultaneously creating a study model that integrated various approaches to help detect the Neolithic settlements in the future. All this was achieved and their research model contribution is just one of the many that have been made by researchers in the fields of GIS and archaeology.

1.5.2 The Detection of Archaeological Features
One of the simplest means of identifying areas of archaeological significance from aerial view imagery is by using soil or crop marks that appear in the surficial soil or vegetation. Soil marks represent the changes of colour and texture visible in the image and are usually caused by the presence of shallow or surface features that affect the homogeneity of the soil (Lasaponara and Masini, 2011). Crop marks differ from soil marks in representing archaeological features by changes in the surface vegetation rather than changes in soil homogeneity. As Lasaponara and Masini (2011) describe, these changes usually appear by differences in plant colour and height and are caused by the variances of stress in the vegetation. the chemical composition of the soil and depth at which the roots of the vegetation can extend. Lasaponara and Masini (2011) also indicate that crop marks are most
easily identifiable in Spring and only from an aerial viewpoint. Archaeological features may also be detectable by the presence of shadow marks and the less common “frost marks” (Kipfer, 2000, p. 198). Shadow marks are simply what their name implies; shadows seen in the image because of variances in elevations due to buried features. Frost marks may also represent the presence of buried archaeological features by the varying retention of frost in hollows and other features. See Figure 1 for examples of shadow, soil and crop marks detectable in aerial view photographs and how each is formed.

Figure 1. Examples of shadow (A), soil (B) and crop (C) marks visible in oblique aerial photography (left), and the formation of each mark type (right). (Adapted from Drewett, 1999).

1.5.3 Visual Analyses

A visual analysis can be described as the visual detection of features present in an image and the subsequent digitization of them. Visual interpretation involves the recognition of the physical attributes of a feature. According to Pavlidis (2005), archaeological visual interpretation is based on tone, texture, shape, size, spatial patterns, orientation, shadows and spatial relationships. This imagery interpretation is most easily performed within a GIS where the marked features can be managed in a database-type system with dynamic attributes assigned to them (Kaimaris et al., 2010). The attributes can then be updated or changed without the implication of affecting other features recorded in the GIS. Visual interpretation facilitates a comparison of the researcher’s remotely sensed data to the features that he or she was able to identify before any automatic detection was performed. De Laet et al. (2007), for example, first performed a visual interpretation on their Ikonos-2 image, digitizing the supposed archaeological structures (based on shape and tone etc.), to evaluate how well the automatic
extraction they later performed contributed to the extraction of the features compared to their own extraction. This presented satisfactory results for De Laet et al. (2007), consequently allowing them to make the suggestion that a visual interpretation should be conducted before any automatic extraction is performed.

1.5.4 Image Classification
Using the elements of visual interpretation, images can be classified with pixel-based or object-based techniques that try to comprehensively classify everything represented in the image (De Laet et al., 2007). The main objective of image classification is to assign every pixel in the raster image to a specific class representing a certain feature or land cover type on the Earth’s surface: forest, shrub or open land, water, buildings, and archaeological features for example. In a supervised classification, by using the different bands and manipulating the appearance of an image or specifying the parameters for the object’s physical attributes, the researcher can identify what classes should be made for the classification process. An unsupervised classification is performed by the computer application (such as ERDAS) by processing various clustering algorithms or image segmentations that can distinguish between the naturally occurring spectral or spatial differences within the image and then groups them depending on their similarities (De Laet et al., 2007).

1.5.5 Remote Sensing Data for Aerial Archaeology
The remote sensing data from various platforms is becoming increasingly available from many different data sources. Some examples of the imagery available which are commonly used in archaeological studies are: Quickbird and IKONOS from DigitalGlobe (IKONOS was formerly provided from Geo-Eye); Corona from USGS; ASTER and BlueMarble from NASA; Landsat from NASA and USGS; and SPOT imagery from SPOT Image (Wilkinson, 2009). Imagery provided by sources such as DigitalGlobe is offered in panchromatic and multispectral images with the highest photographic spatial resolutions available (46 cm to 65 cm panchromatic and 1.8 m to 2.62 m multispectral) and can be delivered fully georeferenced, making it fairly GIS ready (Masini and Lasaponara, 2007; WorldView Global Alliance, 2013). These Earth observing satellites also collect data such as RADAR and LiDAR that can be used for aerial archaeology studies (e.g. Alexakis et al., 2010; Garrison et al., 2011). Digital elevation and terrain models (DEM and DTM) are also common data types used in aerial archaeology that provide detailed information about the differences in elevation within or surrounding a site with an accuracy that usually depends on the pixel sizes and extrapolation methods chosen by the researcher (Lasaponara and Masini, 2011).

1.6 Study Area
The Bridge River archaeological site is a large pit house village situated on a terrace along the lower Bridge River valley of the Mid-Fraser area in south-central British Columbia, Canada. It is located about 11 km North-West from the city of Lillooet and is just one of the many pit house villages in the area (Figure 2).
consists of 73 pit house depressions between 5 m to 20 m in diameter, making up what once was a large winter pit house village that was first established roughly 1900 to 1800 years before present (B.P.), being abandoned after 1200 B.P., and then briefly reoccupied between 400 to 200 B.P. (Prentiss, Smith, Reininghaus, Schirack, Wanzenried and Ward, 2009).

Today the pit houses are identifiable as clusters of depressions in the ground, though they were originally built as semi-buried shelters with a dug out floor about a meter deep, with roof beams supported by a frame built from sturdy posts in the center of the pit (Figure 3). These houses were typically used in the winter and likely housed up to thirty people each. It is believed that the houses could be used for up to ten to twenty years before any refurbishment was needed. As described by Prentiss and Kuijt (2012), if the house did need rebuilding the process started off by salvaging the reusable materials and then burning down the remaining materials of the house. Afterwards, the debris was either removed from the pit or new sediments were brought in to cover it, creating a new floor (as was the case in Bridge River). As a final step the roof was then rebuilt. The rims around each pit house, called middens, accumulated over the years with the disposal of

Figure 2. Pit house village sites in the area surrounding Lillooet, British Columbia, (Prentiss and Kuijt, 2012). This figure is reprinted with permission of the Publisher from People of the Middle Fraser Canyon by Anna Marie Prentiss and Ian Kuijt © University of British Columbia Press 2012. All rights reserved by the Publisher.
debris and waste, which resulted in raised rims around each pit house - valuable for the archaeological research conducted later (Prentiss and Kuijt, 2012). Inside the pit houses were areas for sleeping, cooking, tool making and storing food. Remnants of hearths and storage pits, in particular, can be fairly easily identified with some reconnaissance methods such as ground based remote sensing (Prentiss and Kuijt, 2012).

![Figure 3. A cross section of the pit house structure (Prentiss and Kuijt, 2012, with permission from Illustrator Eric S. Carlson).](image)

### 1.6.1 Previous archaeological and geophysical investigations

The intention for the previous research carried out on the village was to comprehensively understand the evolution and organization of the site, all while developing a better understanding of the processes of any socio-economic inequality present within the population living there (Prentiss et al., 2009). One of the first tasks of the archaeological investigation led by Anna Prentiss from the University of Montana, which started in June 2003, was to extensively map the site. Later on a geophysical investigation was undertaken producing high resolution surface and subsurface maps derived from various magnetic, electromagnetic, resistivity and ground penetrating technologies (Cross, 2009). This mapping helped in digitally representing the features present within each pit house at the site.

### 2 Methods

The methodology was collected from parts of the literature to determine what aerial archaeology techniques could be deemed suitable for the type of study at hand. The methodology described here has been adapted from those outlined by De Laet et al. (2007), Ciminale et al. (2009), and Alexakis et al. (2010) in their various archaeological studies to detect sub-surficial features with remote sensing techniques with very high resolution satellite imagery and geographic information systems.
2.1 Data Collection
With permission granted from the Xwisten Band (Bridge River Indian Band), the site map (Figure 4) along with its datum point coordinates for the archaeological investigations from 2003 were provided by Dr. Anna Prentiss and used for this study. The site map was then georeferenced and scaled to match the projection system in the GIS created for the study. The Worldview-2 satellite image (Figure 5) of the study site was purchased from DigitalGlobe through European Space Imaging. It was captured on the 25<sup>th</sup> of March 2012, and is a 4-band multi-spectral, pan-sharpened image with a resolution of 50cm by 50cm. Other data collected for the study included aerial imagery and shapefiles of existing archaeological and heritage sites provided from the Government of Canada in 2013 to use as a means of orientation and reference within the GIS. Additional imagery and topographic base maps available in ArcMap 10.1 and provided by ESRI were also added to the GIS for extra help in rectification and reference of all the collected data.

Figure 4. Bridge River site map provided by archaeologist Dr. Anna Prentiss from the University of Montana from the 2003 archaeological investigation.
2.2 Pre-Processing
Pre-processing of the original satellite image included pan-sharpening, clipping and geographical rectification of the image (De Laet et al., 2007; Alexakis et al., 2010). As the Worldview-2 imagery was already provided pan-sharpened to 50cm resolution the pre-processing procedure could start straight from ensuring the correct georectification of the image and clipping the raster to the study area. Though DigitalGlobe offers fairly high accuracy in the geolocation of their satellite imagery (up to 23m for Quickbird and less than 5m for WorldView) the imagery was not positioned exactly the same as the georeferenced site map from Dr. Anna Prentiss based on the datum point provided. The projection system for all the data in the project was set to the 1984 World Geodetic System for UTM Zone 10 North (or WGS_84_UTM_Zone_10N), and once the satellite imagery was rectified it was clipped to the extent of the site.

2.3 Visual Analyses
A visual interpretation was completed to identify what features were identifiable just using the RGB band image (Figure 6, left) and the NIR band image (Figure 6, right) and digitizing the visible features. A set of polygons were digitized (see results in Figure 7) around the features that were easily identified from the RGB image and another set for those additionally identified using the NIR image. Other features that potentially represented archaeological features were also identified and digitized.
2.4 Pit House Feature Extraction

The extraction methods described in this section were outlined by De Laet et al. (2007) in their study on archaeological feature extraction from high resolution Ikonos-2 imagery for an archaeological site in Turkey. Their site consisted of many surficial and sub-surficial archaeological features (mainly walls) and the methods were implemented to identify which features could be automatically detected using remote sensing aerial archaeological methods.

![Image of RGB and NIR bands](image.png)

*Figure 6. The RGB (left) and NIR (right) bands from the georeferenced and clipped image that was used for the initial visual interpretation.*

2.4.1 GIS-Based Feature Extraction

Using various property settings in ArcMap 10.1 is a simple way to manipulate the image to become an ‘enhanced’ image. The settings for contrast, brightness, resampling and stretch-type can all be defined by the user which then results in the image displayed in various ways, helping drastically in image interpretation. Using *Image Analysis* in ArcMap 10.1 also provides useful tools to create enhanced images by changing display options and applying various processing techniques. *Image Analysis* was used in this study to produce sharpened images for the RGB (Figure 1.1 in Appendix I) and NIR bands (Figure 1.2 in Appendix I) as well as for a false-colour composite (Figure 1.3 in Appendix I). With each of these images subsequent visual analyses were used to evaluate how many more features could be identified.

2.4.2 Pixel-Based Feature Extraction

A pixel-based extraction (or classification) was performed within ArcMap 10.1 and ERDAS in this study. The reason for the use of both applications was to evaluate which of them produces the best results of unsupervised and supervised classifications. An unsupervised ISODATA classification was performed in ERDAS; set to 7 classes, using a maximum of 24 iterations. In the supervised classification, using training sets for features based on the spectral values, the software classified each pixel using the defined maximum likelihood method for classification. The
tools available in ArcMap 10.1 and ERDAS were used to create a database-type system for storing the spectral information of each training area defined by Areas of Interest (AOIs). Classes were set to Compacted soil, Trees, Shadow, Grassy or Open, Dense vegetation, Midden, Pit and Pit shadow.

2.4.3 Object-Based Feature Extraction
As De Laet et al. (2007, p. 835) discuss: “Very often pixel-based techniques do not work very well as a pixel is not related to the characteristics of an object or an area as a whole”. Object-based techniques are therefore useful when the shape and other physical characteristics of an object are easily identifiable in an image. An object-based extraction method was performed on the image using the Trimble software eCognition. The developer’s trial of eCognition is freely available from Trimble and was used to first segment the image based on a multi-resolution segmentation that takes into account the pixel values, scale, shape and compactness defined for the objects. The segmentation was set so that object size was fairly small (at a scale of 5), and the parameter weights of shape and compactness set to 0.9 and 0.01 respectively (Figure 2.1 in Appendix II). A second spectral difference segmentation (Figure 2.2 in Appendix II) was also tested to create larger objects of similar properties, but it was decided that leaving the object sizes smaller would be more beneficial in the classification. Various “features” or tools that help identify differences between objects within eCognition were also evaluated to see whether any produced discernable differences that could be used as classification parameters (see Figure 2.3 in Appendix II). These “features” were later discarded too as it was decided that a simpler classification method was going to be used. By simply selecting “samples” (much like ERDAS’s AOIs or ArcMap 10.1’s training areas, Figure 2.4 in Appendix II), and assigning each to a defined class, a supervised classification was then performed. As the Developer’s Trial version of eCognition does not allow exporting the results straight into GIS applications, a simple screen shot was used to bring the image into ArcMap 10.1 to be rectified and compared with the site map.

2.5 Accuracy comparisons
After the archaeological features were extracted from the satellite imagery using the three extraction methods an evaluation was performed to evaluate how accurate these results were. This was performed by comparing them to the site map created from the previous archaeological investigations within a GIS. By integrating everything in the GIS and ensuring all rectification was correct, the results could be digitized and then compared to the overlapping site map, allowing evaluation of how many identifiable features existed.

3 Results

3.1 Pre-processing
The satellite image was clipped and georeferenced using the archaeological site map to ensure that the following analyses were performed in the highest possible
positional accuracy. Figure 5 on Page 12 shows the final result of the preprocessed satellite image.

3.2 Visual Analysis and Accuracy Comparison

Visual analysis as a first step in archaeological remote sensing allows for the researcher to analyse how apparent features present themselves in the image before additional image analyses are conducted. The visual analysis in this study was done to quantify how well the features could be correctly identified, or detected, in the image. The initial visual analysis was performed on the RGB and NIR bands separately, and resulted in 78 visible and potential features identified, see Figure 7 and Figure 8 for a visual representation of these results.

Using the RGB-composite in ArcMap 10.1; 27 pit features were identified based on the obvious shape or on the visible shadow created by some of the rims around the pit. By displaying the NIR band of the image in ArcMap 10.1, an additional 14 pit features and 37 external pit features were identified; totalling 51 additional features identified in the NIR visual analysis. So, with the initial visual analysis, 78 potential archaeological features in total were identified. The next step was now to perform an accuracy comparison to find how accurately these results represented the real archaeological features at the site. As a side note, an additional two potential path-like features were also identified in the visual analysis based on their colour and location in between the pit houses. These two features were not included in the accuracy comparison as they were not identified in the archaeological map provided by Dr. Anna Prentiss (Figure 4).

![Visual Analysis Results](image)

*Figure 7. Initial Visual Analysis Results.*

There are a total of 138 features present at the site: 73 pit houses and 65 external pit features. Of the 78 potential features identified in the visual analysis - a total of 61 features were identified correctly when compared to the map of features provided by Dr. Anna Prentiss (Figure 4). To break these results down farther, of
the features identified in the RGB-composite image; 26 of the 27 features were correctly identified. And of the 51 features identified using the NIR band, 35 features were found to be correct too. Correctly identifying 78 of the 138 features at the site offers an accuracy rate of only 44 percent for the visual analysis. As presented by the results shown in Figure 8 a visual analysis can be useful for familiarizing oneself to the site and to what can be expected from the other extraction methods, but it can not be fully depended on as the only means for detecting every archaeological feature at the site.

Figure 8. Results of the visual interpretation in RGB and NIR, with those incorrectly identified highlighted in yellow.
3.3 Feature Extraction

3.3.1 GIS-Based Feature Extraction
GIS-based feature extraction involves enhancing the image to create higher definition in the features visible and then recording those that are easier to identify. The contrast, brightness, stretch and sharpen enhancements for the RGB and NIR bands produced images that were all used to evaluate if more features could be identified. In Figure 9 the additional features identified for the enhanced RGB images are represented in red, and the features identified in the NIR image are represented in green. This map also shows the comparison of the GIS-based results to the initial visual interpretation and to those features previously mapped in the archaeological investigation.

Figure 9. Results from the GIS-based feature extraction in comparison to the visual analysis and original site map.
3.3.2 Pixel-Based Feature Extraction

The following three figures (Figures 10, 11, and 12) show the results for the three pixel-based classification methods undertaken. Figure 10 is the result from the unsupervised classification performed within ERDAS Imagine 2011 along with the previously mapped pits to help with visualization. The software was able to classify each pixel into one of the seven classes. However, due to the homogeneity within the image from the limited range of reflectance values between grassland, dense vegetation and pit shadows, no features were fully identifiable. This classification on the other hand was successful at distinguishing between compacted soil (orange) and the more vegetated areas (red and pink). The roads were classed correctly and even the potential path and some pit centers were classified into this category. Pit shadows (red) were classified fairly conclusively for each pit, though, the denser vegetation surrounding the site (which is represented in similar reflectance values in the satellite image) was classified the same.

![Figure 10. The result from the unsupervised classification performed within ERDAS along with the previously mapped features for better visualization.](image-url)
The supervised classification (Figure 11) was performed in ERDAS Imagine 2011 using a training set that represented each of the classes sought for. These were: pit shadow and dense vegetation (red), pit rims and grass (pink), and compacted soil (orange) and grassy or open areas, trees and tree shadows (white). This classification was fairly successful in distinguishing between pit rims and pit shadows and grassy areas, though similar to what happened in the unsupervised classification, the pit shadows were incorrectly assigned to the surrounding areas with dense vegetation, and the grassy areas were not fully distinguished from the pit rims within the site. This is also due to the similarity of the pit rims and grassy areas in terms of reflectance. Pit rims were also identified in this classification surrounding each tree around the site. This is also due to the close similarities in reflectance for the pit rims and tree rims.

Figure 11. The result from the supervised classification within ERDAS.
The supervised classification within ArcMap 10.1 can be seen in Figure 12. Here, the Spatial Analyst extension was utilized to classify the image based on the training areas for pit shadows and dense vegetation (red), pit rims and grass (pink), compacted soil (orange) and grassy or open areas, trees and tree shadows (white). This classification was also able to distinguish the pit shadows fairly well but also it had the issue of separating the more densely vegetated areas around the site as well as the pit rims classified around each tree.

Figure 12. The result of the supervised classification within ArcMap 10.1.

3.3.3 Object-Based Feature Extraction

The result from the object-based supervised classification (Figure 13) within eCognition proved remarkably similar to the pixel-based classifications performed
earlier. The segmentation process created many separate objects based on the heterogeneity within the image and the subsequent clustering of the pixels into objects (Figure 2.1 in Appendix II). The sample objects used for the classification represented pit shadows and dense vegetation (red), pit rims and grass (pink), compacted soil (orange), grassy or open areas, trees, and tree shadows (white). This classification did well at identifying pit shadows for almost all of the pits at the site, as well as identifying areas of compacted soil. Denser vegetation was better classified here too; however, the distinction between pit shadows and pit rims with the dense vegetation in the surrounding areas was not well defined. Object-based classification can be done in various levels of detail within eCognition, this simple classification method was chosen as it was most similar to the previous types of classifications performed and allowed for a better comparison between the performances of each.

Figure 13. The result of the object-based classification performed within eCognition.
3.4 Accuracy Comparison
As presented in the figures in the results section, the positional accuracy of the
identified features differs slightly from method to method. The most accurate
feature identification comes from being able to fully recognize a feature in the
image and this proves difficult when the results are represented in classified
images like the pixel-based and object-based results in this study. The accuracy of
the results presented in the classified images was determined by overlaying the
archaeological site map on the images and then judging how many of the classified
features corresponded to actual features present at the site (see figures in
Appendix III). In doing so it was decided that of the three methods that the object-
based classification proved the best for accurately detecting the features based on
the number of pit shadows classified and those actually visible in the image.

4 Discussion
Although there has been an increasing interest and advancement in technologies in
aerial archaeology in the last few years, there has been limited development of
specific methodologies and new perspectives of data handling for a detailed
method of fully extracting and understanding the information provided from
remote sensing datasets (Kaimaris et al., 2010; Lasaponara and Masini, 2011).
Integrating remotely sensed data and archaeology has proved to be an important
method for gathering information about a site. Aerial archaeology is important in
the detection, prospection, and furthermore, the preservation and conservation of
archaeological information. As Chen et al. (2013) discuss, aerial archaeology can be
an incredibly important tool for identifying and preserving archaeological sites
before they are destroyed. They continue by saying that archaeological sites are
unique sources of knowledge, linking modern and past humans in history, culture
and natural contexts. And even in a scientific sense, Chen et al. (2013, p. 2) argue
that past settlements provide valuable information on the “patterns of biological
variations among humans and their ancestors, human achievements and linguistic
origins”.

The methodology of this study was applied to evaluate how well aerial archaeology
techniques perform in identifying pit house features in very high resolution
imagery. It was also applied to assess whether it could be utilized in future pit
house archaeology in North America. The main use of applying aerial archaeology
techniques in studies such as these is to find the best way to uncover the anomalies
over surfaces that correspond to real archaeological features, ensuring all
archaeological excavations are worthwhile when it comes to physically uncovering
the buried features.

Manipulating the image within ArcMap 10.1 for the GIS-based feature extraction
proved very useful in improving the definition of features and contrasts within the
image. The combined efforts of the visual analysis and the GIS-based extraction
resulted in the highest number of features identified; suggesting that initial visual interpretation cannot be fully replaced by classification methods for feature extraction from high resolution imagery. The pixel-based feature extractions were mildly successful in feature detection though did not offer much detail about the features. Some areas like the tree rims and dense vegetation around the site were incorrectly classed due to the high similarity in reflectance values throughout the image. Using imagery with more bands could help in overcoming issues such as this as more contrasts between earth features increases with each band (Verhoeven and Schmitt, 2010). Object-based classifications offer many possibilities in remote sensing and aerial archaeology studies. Results presented here for the object-based classification, though, were not as successful as they could have been. Performing a more detailed classification with even more detailed imagery and better understanding of eCognition and optimal training sets and parameters would offer more satisfactorily conclusive results for archaeological object-based feature extraction. To further a study such as this, using this methodology on imagery over a larger area could potentially identify sites previously unknown and could also eventually lead into the creation of predictive models suitable for semi-automatic to fully-automatic detection of sites throughout North America.

4.1 Limitations

As with most studies, there were a few limitations faced during the research process. The following are some of the most important considerations recommended during future studies relevant to this one.

Classification of images can be quite a long process if highly detailed results are sought for. Be sure to manage time and data wisely, it is best to have a basic knowledge of the archaeological site before conclusive results are drawn and enough testing of the application and the parameters set is completed. Field visits and/or trusted information sources should be incorporated in the study.

As Lasaponara and Masini (2011) discuss, it is best to acquire imagery that was collected/captured at a time where optimal contrast detection can be made. This is usually during spring and summer months where moisture can be retained or present within the site.

For aerial archaeological evaluation where previous research is limited, great care should be taken when it comes to positioning, rectifying and georeferencing all images and datasets. Using Google Earth to extract positional data could be an option for areas insufficiently mapped.

A potentially prominent fallback of this research is when it is applied to areas with many trees. Results of this study proved fairly unsatisfactory and more research should go into distinguishing sites that might be near or situated under tree cover.
Canopy-penetrating technologies exist (such as AIRSAR/RADAR) that have previously been used in archaeological settlement detection in the Maya Lowlands of South America (Garrison et al., 2011). Radar imagery was not acquired in this study due to the limited availability and aerial coverage over the area.

The problem of homogeneity over a surface is one that most researchers run into in aerial archaeology (De Laet et al., 2007). Very often the archaeological features were constructed out of the same surrounding material, making detection and especially classification of some features very difficult due to the similarities in reflections and composition (De Laet et al., 2007). Using very high resolution imagery with more bands such as thermal, ultraviolet, and microwave along with detailed elevation data can help overcome problems such as this (Verhoeven and Schmitt, 2010).

5 Conclusion
Archaeological sites are an important link between the past and present human civilizations. Methods of detecting, prospecting and conserving archaeological sites with the least detrimental methods are necessary to develop to ensure the possibility to fully understand past civilizations. As Bescoby (2006, p. 1) states, “[t]he use of remotely sensed images and aerial photographs, in particular, has become an essential part of archaeological landscape studies”. Although using remote sensing techniques in archaeological investigations is a fairly recent practice, many studies integrating the two have been conducted and prove that useful information related to archaeological research can be produced (Alexakis et al., 2010).

Rewarding results come from interpreting the imagery with the use of visual analyses, image classifications based on pixel values or object segmentation, and even more so when all are related to one another in a GIS platform where spatial analyses and relationships can be performed. This thesis presented a basic methodology that can be used for aerial pit house archaeology, results of which can be further incorporated into predictive models that could automatically detect similar sites in the future.
References


Contreras, D.A. and Brodie, N., 2010. The utility of publicly-available satellite imagery for investigating looting of archaeological sites in Jordan. *Journal of Field


Appendix I: GIS-Based Feature Extraction
This appendix shows the image manipulations created and used within GIS-based feature extraction portion of the study as described in section 2.4.1.

Figure 1.1. The original RGB satellite image (left), the stretched RGB image (middle), and the sharpened stretched RBG image (right).

Figure 1.2. The original settings for the NIR image (left), the stretched image (middle), and the sharpened image (right).

Figure 1.3. The original RGB image (left), the stretch BGR image (middle), and the sharpened BGR image (right).
Appendix II: Object-Based Feature Extraction
Appendix II shows the images created from the object-based analysis using Trimble eCognition software as described in section 2.4.3.

Figure 2.1. The multi-resolution segmentation; scale of 5, shape and compactness weights of 0.9 and 0.01 respectively.

Figure 2.2. The spectral difference segmentation with a scale of 12.
Figure 2.3. An example of one of the features created in eCognition that was evaluated to find differences that could be used as classification parameters. This particular feature is a vegetation ratio (NIR – Red).

Figure 2.4. The samples selected and assigned to the different classes for the classification within eCognition.
Appendix III: Accuracy Comparisons of the Classified Images

Here are the accuracy comparison results for each of the classified images. The highlight polygons represent those that corresponded well with the pit shadow class, which was decided was the most important tell-tale sign of a feature being present.

Figure 3.1. ERDAS unsupervised classification.

Figure 3.2. ERDAS supervised classification.

Figure 3.3. ArcMap 10.1 supervised classification.

Figure 3.4. Object-based classification.