THE POTENTIAL OF PREDICTIVE MODELING OF
ARCHAEOLOGICAL RESOURCES USING HIGH RESOLUTION
MULTISPECTRAL GEOEYE-1 IMAGERY
AT THE MANN SITE, POSEY COUNTY, INDIANA

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ABSTRACT

THESIS: The potential of predictive modeling of archaeological resources using high resolution multispectral GeoEye-1 Imagery at the Mann site, Posey County, Indiana

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I explore the viability of using geographic information systems and satellite-based remote sensing to predict locations of archaeological resources in the Midwestern United States. The study area used for this investigation is the Mann site in Posey County, Indiana (12Po2) and the primary remote sensing data used is GeoEye-1 satellite imagery obtained on October 14, 2010. The GeoEye-1 satellite offers affordable imagery that has a relatively high spatial resolution. The resolution of this imagery is high enough to detect variations in the spatial and spectral signatures of these resources to allow for predictive modeling of their locations. Anomalies have been detected at the site and in the adjacent landscape that could be undiscovered archaeological resources.
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CHAPTER 1: AN INTRODUCTION TO ARCHAEOLOGICAL PROSPECTION

Introduction

Archaeological prospection is the process of locating cultural material remains in a landscape, and it is a major component of contemporary cultural resource management. Current primary methods of prospection rely on a mix of aerial and satellite imagery analysis, pedestrian surveys, and geophysical and geochemical testing (Clark 2003). Over the past decade tremendous technological enhancements have taken place in the areas of geographic information systems and remote sensing. In this study, I apply these new technological enhancements as a means to improve current methods for archaeological resource prospection.

Geographic Information Systems (GIS) are computer systems that are designed to manipulate, analyze, and visualize spatial data. Remote Sensing (RS) is the gathering of information about an object from a distance (Jensen 1996:1). Geographic Information Systems use remote sensing data for visualization purposes.

Through the use of airborne and spaceborne sensors in conjunction with GIS software, I identified methods for quickly and accurately identifying two categories of archaeological resources in the Midwestern United States via a case study at the Middle Woodland Mann site earthwork complex. The first resource category of “relief resources” included archaeological resources in the landscape that still have a height dimension that sets them apart from the adjacent landscape. Relief resources consist of mounds and earthworks that can still be found throughout much of the Midwestern United States, which can be identified via pedestrian and/or topographic surveys. The second resource category of “planar resources” included those resources that once existed as relief resources on the landscape that have now been plowed down or eroded to the point that they no longer have a height dimension that differentiates them from
the adjacent landscape. These resources are currently identified through the use of historic maps, aerial photography, archaeological excavation, or in situ geophysical methods.

It is important at the outset to quickly define a number of terms that will be used repeatedly throughout this thesis. Since my research focuses on remote sensing I will first define the two primary types of sensors used in remote sensing; passive and active. Passive remote sensing systems capture electromagnetic radiation that is emitted by the sun, reflected off of the earth’s surface, and captured by the sensor (Jensen 1996:3). Multiple forms of passive remote sensing systems exist, but they can be broken down into three primary subcategories. The first subcategory is panchromatic sensors. These sensors record electromagnetic radiation using the entire visible portion of the electromagnetic spectrum and produce a black and white image. The second subtype is multispectral sensors, which record electromagnetic radiation in individual bands of the electromagnetic spectrum. These sensors at a minimum usually record information in the blue, green, red, and near-infrared bands and can be displayed in true or false color format. The final subtype, hyperspectral sensors, can record tens to hundreds of very narrow bands of the electromagnetic spectrum whereas multispectral systems can only record around ten broad bands of the electromagnetic spectrum. These bands can range from the ultraviolet wavelengths to the thermal and far-infrared regions (Liang et al. 2012:8).

In contrast to passive sensors, active remote sensing systems emit and record their own type of electromagnetic radiation. Two primary types of active remote sensors are LIDAR and RADAR. LIDAR, which stands for Light Detection And Ranging, is a sensor that emits its own amplified light signals and records the backscattered response from the terrain. RADAR sensors, or Radio Detection And Ranging, emit and record microwaves to obtain information regarding the ground surface, land cover, or subsurface features (Liang et al. 2012:8).
The electromagnetic radiation that is recorded is referred to as spectral information. This spectral information can also be discussed in terms of resolution. Spectral resolution refers to how sensitive a particular sensor is to different wavelengths of the electromagnetic spectrum. Spectral resolution corresponds to the number of recording bands as well as bandwidths. Remote sensing sensors vary greatly in the number of bands they record, with each band corresponding to a range of electromagnetic radiation. Sensors that can detect multiple bands, each with a narrow width, have a higher spectral resolution than those that can only record information in a few bands with a wide width (Jensen 1996:3). Another form of resolution that should be noted is spatial resolution, which refers to the size of a pixel in an image. The smaller the pixel dimensions, the higher the spatial resolution. This is because a smaller pixel size allows for smaller objects to be resolved in an image (Jensen 1996:4). The final type of resolution that requires discussions is radiometric resolution. Radiometric resolution refers to a sensor’s sensitivity to variations in electromagnetic radiation signal strength. This sensitivity is measured in bits and corresponds to the range of unique strength values that the sensors can record. The standard today is eight bits, which allows a sensor to record 256 individual values, although some newer sensors can record up to 12 bits, or 4096 values (Jensen 1996:7).

Two common types of files are used in remote sensing and both have unique terms associated with them. Raster is the term used for an image that consists of individual cells or pixels arranged into rows and columns. Each pixel in a raster has at a minimum two-dimensional values corresponding to the X and Y position of the pixel in the data set. Rasters can also contain additional values such as pixel brightness or elevation values for each cell. Vector is the term used for files that consists of a series of nodes or vertices that represent spatial information. Vector files can be in the form of point, line, or polygons (Campbell and Wynne 2011:111).
The preceding terminology encompasses decades of work in the fields of GIS and remote sensing, and archaeological prospection has had its place in these fields since their inception. Archaeological prospection in the United States can be traced back to the 18th century and likely existed well before. Perhaps one of the most famous archaeological prospectors is Thomas Jefferson, the third President of the United States. Jefferson conducted and documented excavations on his own property and also commissioned others to prospect for archaeological resources via ground survey and excavation as President of the American Philosophical Society in 1799 (Wiley and Sabloff 1974). This type of antiquarian inquiry would continue to gain momentum for the next century up until a new technology was to emerge, aerial photography.

**Aerial Photography**

Aerial photography was the forerunner of today’s advanced systems and began with the photographing of a small village in eastern France in the mid-19th century from a hot air balloon. It was not until a half a century later that the first aerial image of an archaeological site was captured in England. The photographing of Stonehenge in 1906 marked the beginning of a new wave of archaeological prospection (Estes et al. 1977). By the early 1920s, O.G.S. Crawford realized that subsurface archaeological resources could be detected using this new method (Giardino and Haley 2006:48). Although this method is the oldest of all airborne archaeological prospection tools, it is still a very viable and widely used means of locating cultural resources. Aerial photography is at its most basic level a panchromatic recording of information throughout the visible portion of the electromagnetic spectrum (Giardino and Haley 2006:49). Aerial photography has improved considerably since its inception in the early 1900s. Currently, archaeologists have a choice between aircraft-based (airborne) aerial photography and satellite-based (spaceborne) panchromatic imagery, both offering very high-resolution imagery of a specific area of interest (AOI). Satellite-based panchromatic recording methods are widely used
by archaeologists across the globe, especially in areas where it is difficult or unsafe to access by plane due to current military operations or extremely adverse environmental conditions.

Additionally, the use of panchromatic imagery in archaeological prospection allows for the comparison of imagery over several decades due to declassified military airborne and spaceborne imagery. The use of historic aerial photography is especially useful in detecting buried archaeological features that have been destroyed or covered up by urban development or agricultural practices (Anderson 2001; Bruder et al. 1975; Burks and Cook 2011; Cox 1992; Estes et al 1977; Matheny 1962; Nichols 1988; Parrington 1979; Solecki 1957; Reeves 1936; Verhoeven 2012). A major downfall of both aerial photography and panchromatic imagery is that they are not able to be manipulated or enhanced to the degree that other types of data allow. Nonetheless, both types of data provide a means for detecting buried archaeological features through the identification of crop and soil marks.

Prehistoric human activity, either in the form of settlements, middens, cemeteries, or other instances of human alterations of the landscape, causes chemical changes to occur in the soil. Over time these changes in the landscape are covered over with the addition of new soils; however, the chemical change still exists buried in the subsoil. Plants are able to absorb these chemicals through the water that is leached by their roots from the subsoil. These chemical changes can be detected through variations in crop growth or biomass production in aerial photos and panchromatic imagery (Parcak 2009).

An eighteen-year campaign using aerial photographic recording of Bohemia was able to locate over 1,000 archaeological sites by noting the crop marks in agricultural fields. Additionally, the researchers were able to determine that based on the plant phenology, crop marks were most accurately identified in cereal crops (Gojda and Hejcman 2012). Crop marks can either be in the form of positive marks (i.e., increases in growth or biomass production) or
negative marks (i.e., restriction in growth or biomass production characteristics when compared to adjacent crop growth patterns). The researchers found that the location of positive crop marks was highly correlated with the existence of subsurface archaeological features (Gojda and Hejcman 2012:1659). Even now, nearly a century after aerial photography was introduced, it is still widely used to prospect for archaeological resources either as a primary or supplementary method. A portion of this widespread use of this technology can be attributed to software such as Google Earth™, which provides free viewing of high-resolution aerial photography and multispectral imagery of the entire globe.

Google Earth™, which was released in 2005, provides access to an immense database of global imagery (Ur 2006). However, it only enables a user to view the imagery and not manipulate it; therefore, it does not represent a true geographic information system (Kaimaris et al. 2011). The imagery that Google Earth™ provides ranges in spatial resolution from 0.6 to 30 meters depending on the area of interest. The multispectral imagery that is available for viewing through Google Earth™ is only available in the visible spectrum. The Google Earth™ software does allow for the addition, or overlay, of other datasets and layers as well as the inputting or exporting of Global Positioning System (GPS) coordinates and distance calculation (Parcak 2009). In recent years Google Earth™ has become more of a tool for research than simple visualization. In a project aimed at identifying known and unknown sites in a large survey area of Afghanistan, researchers were able to locate over 470 previously unknown archaeological sites using the high-resolution imagery available on Google Earth™. The spatial resolution of the imagery was high enough to allow the researchers to accurately type the sites into dwellings, hamlets, or camps (Thomas et al. 2008). During the research timeframe, the area under study was largely inaccessible due to military operations, but the use of spaceborne imagery allowed for the research to be carried out nonetheless (Thomas et al. 2008).
The viability of Google Earth™ imagery for archaeological prospection has been demonstrated by multiple researchers in various landscapes. Another study conducted in 2011 examined the plain of Philippi (Eastern Macedonia, Greece) for signs of a historical road connecting Amphipolis to Philippi with a total study area of $500\text{km}^2$ (Kaimaris et al. 2011). The researchers developed a method to prospect for new archaeological sites in this region using Google Earth™ but their research found that the imagery Google Earth™ provided was not of high enough resolution to be able to successfully and repeatedly locate already known archaeological sites. Nonetheless, Google Earth™ is a useful and cost-effective tool for understanding the general landscape with reasonable accuracy (Kaimaris et al. 2011). The use of Google Earth™, for archaeological prospection is only limited by the resolution of the data (Ur 2006). One problem that Google Earth™ poses for archaeological prospection is that the free access and high-resolution imagery makes it possible for looters to find unknown sites and destroy them before they can be studied or protected (Kaimaris et al. 2011).

**Multispectral Sensors**

Multispectral imagery is another tool for prospection which has received a large amount of attention in recent years for its archaeological research potential. High resolution multispectral imagery provides a low cost solution to obtain imagery which can be processed to aid in the detection of buried archaeological features. Multispectral satellite sensors with resolution capabilities of one meter or better increase the potential for the detection of minor archaeological features in the landscape. A case study in the Northern Lagoon of Venice combined current high resolution satellite imagery with historical imagery, excavation data, and pedestrian survey data, along with topographic, environmental, and hydrologic maps into a GIS to understand the complexity of the landscape (Traviglia and Cottica 2011). The high resolution satellite imagery (IKONOS™ and Quickbird™ sensors) was processed using various techniques.
in an attempt to resolve buried structural features. Preliminary results of the processing have resulted in positive identification of a portion of the underlying features in the landscape (Traviglia and Cottica 2011).

In another study focusing on San Giovenale in Northern Lazio, Italy, researchers used an array of remote sensing platforms to prospect for Etruscan features in the landscape. The researchers approached archaeological prospection in this manner to combat the large degree of variation in vegetation types that were covering the surface of the site (Lasaponara et al. 2012). Additionally, the site had been occupied for several hundreds of years, and the marks left by different types of structures and habitation areas within the larger site varied greatly. In order to identify the smaller and larger features, varying high-resolution active and passive sensors were used along with a combination of historical maps. Through the use of high-resolution aerial and satellite-based multispectral sensors, which included near infrared and thermal infrared bands as well as LIDAR and aerial photographs, the researchers identified the remains of various archaeological features such as cemeteries, housing structures, roads, tombs, and wells (Lasaponara et al. 2012).

_Hyperspectral Sensors_

A relatively new development in the field of remote sensing and archaeological prospection is the use of hyperspectral remote sensing systems. Hyperspectral data provides a means to precisely examine spectral reflectance values from the landscape to more accurately search for archaeological sites. However, hyperspectral imagery does have a notable disadvantage. Since the data are so diverse, it is highly susceptible to atmospheric and ground-cover conditions that can create many false positives in the imagery. Therefore, hyperspectral data are best used when multiple image acquisitions can occur and can be corrected with _in situ_ spectral measurements (Parcak 2009). This can be illustrated with a case study that was
conducted in eastern Crete using multispectral, hyperspectral, aerial photography, and LIDAR imagery to study an archaeological site. The study found that the multisensory approach is best pursued when prospecting for archaeological sites to combat both the spatial and spectral resolution shortcomings of each sensor (Rowlands and Sarris 2007).

A similar study, conducted in Scotland, found that hyperspectral data were more useful in areas that were less likely to exhibit crop marks pertaining to buried archaeological features due to variations in soil moisture content. The single hyperspectral-based prospecting mission identified all of the previously located sites found via aerial photos and located others that had not been previously known. The major downfall was low spatial resolution of the hyperspectral data compared to aerial photography (Aqquus et al. 2008). However, over time this issue will solve itself as technology improves.

LIDAR

One of the most widely used active remote sensing systems is LIDAR. LIDAR has rapidly grown in popularity, and its use in the past few years has yielded very promising results (Burks and Cook 2011; Chase et al. 2011; Crons and Shaw 2009; Harmon et al. 2006; Johnson and Ouijum 2014; Parcak 2009; Riley and Tiffany 2014; Romain and Burks 2008; Štular et al. 2012). LIDAR data come in the form of a point cloud, and they are most often used to generate bare earth digital elevation models (DEM). LIDAR provides a means to obtain high-resolution imagery of obscured archaeological resources features based on the ability of LIDAR to penetrate vegetation canopies and a small amount of soil by obtaining multiple returns per image. Each return can be processed from the point cloud to obtain a different level of penetration information. Furthermore, airborne LIDAR sensors can obtain pixel size resolution of three centimeters, providing an astounding level of detail for archaeological prospecting (Parcak 2009).
Investigations into areas of archaeological interest in the United Kingdom have found that LIDAR is able to detect archaeological features where soil marks are not present on the ground (Parcak 2009). In northeastern Italy, researchers used airborne LIDAR data on the karstic plateau to prospect for potential archaeological features. The researchers decided to use LIDAR for prospection because the archaeological features they were interested in locating were prehistoric and protohistoric structures (Bernardini et al. 2012). When initially built these structures would have stood out from the landscape but over time they were gradually consumed by it. However, portions of them can still be detectable by looking at variations in relief against the background of the rest of the landscape. LIDAR is able to detect these variations in relief very well, especially at the high resolutions obtainable with airborne sensors. Through the use of high resolution LIDAR imagery and freeware processing software, the researchers detected superimposed structures that ranged from prehistoric Copper Age structural remains to protohistoric fortified Roman camps. Their findings greatly surpassed those of several years of ground-based archaeological reconnaissance that had been previously conducted in the region (Bernardini et al. 2012).

**RADAR**

The other primary active remote sensing system used in archaeological prospection is RADAR. RADAR sensors have the ability to “peer through” vegetation cover and arid soils to allow for the detection of buried archaeological features such as roads and structures, similar to LIDAR. The penetration capabilities of active remote sensing systems are limited by ground-cover type, soil particle size, and moisture content (Parcak 2009). However, RADAR sensors have the ability to see through cloud cover, and they are unaffected by atmospheric conditions or the time of day when data are collected (Campbell and Wynne 2011:205). RADAR based
systems have been especially useful in identifying archaeological resources in areas of dense vegetal cover (Lasaponara and Masini 2013).

The successful use of RADAR based archaeological prospection can be seen in multiple studies that have used historic Shuttle Imaging Radar A (SIR-A) and Shuttle Imaging Radar B (SIR-B) sensors as well as more modern RADAR sensor packages (Gaber et al. 2013; Garrison et al. 2011; Holcomb 2001; McHugh et al. 1988; Wendorf et al. 1987). These sensors were used to successfully locate archaeological sites and features in arid environments. RADAR-based sensors have also enabled the creation of high resolution DEMs that have been useful for the identification and mapping of larger archaeological features such as mounds and geometric earthworks (Lasaponara and Masini 2013). RADAR sensors can be directly credited for the discovery of the lost city of Ubar in Oman in the late 1990s (Blom et al. 1997:1). Ubar was a legendary city known for its frankincense trade in prehistory and was thought to have been lost forever. The suspected location of where Ubar once existed was in “the Empty Quarter of Arabia, one of the most inhospitable places on earth” (Blom et al. 1997:1). Through the use of historical records, SIR-A, multispectral, and aerial imagery researchers successfully located the site in Oman. The SIR-A imagery allowed the researchers to "see through" the sand and locate old river channels and archaeological sites that had been covered by years of windblown sand (Blom et al. 1997:1).

It is important to note that sensors only provide one piece of the puzzle for archaeological research. The majority of these data are useless without the ability to process, analyze, and visualize the captured data. This is where geographic information systems come into play. GIS allow for the combining of various forms of data and the manipulation of these data through spatial analysis techniques.
**Geographic Information Systems**

“GIS is about evaluating, analyzing, comparing, and contrasting layers of imported data” (Parcak 2009:106). Geographic information systems allow for the combining of multiple forms of data about an archaeological site into a model that can aid in prediction of unknown sites. This combination allows for forecast modeling of site location and temporal variation that can aid in prediction of where other sites are likely to occur. Datasets that have been used in previous GIS-based prospecting models include soil information such as slope and erosion, topography, and hydrology (Egeland 2010; Espa et al. 2006; Harrower 2010; Jones 2006). Additional data that can be combined in a GIS include historic maps, ground-sensed data (e.g., magnetic susceptibility), and ground-penetrating radar results (Nolan 2014; Parcak 2009). All of these data sources allow for spatial and attribute pattern analysis and modeling and prediction of site location (Connolly and Lake 2006).

All of the case studies discussed above employed GIS software to analyze and visualize the remotely sensed data. GIS systems also allow for environmental modeling, which is highly useful in archaeological prospection. An excellent example of this is the discovery of two Mayan ceremonial centers in the Petén Jungle of Guatemala. Researchers utilized the predictive capabilities of GIS to analyze least-cost paths through the landscape based on a digital elevation model. This analysis led to the discovery of these two ceremonial centers deep in the jungle (Estrada-Belli and Koch 2007). There are numerous GIS software packages and applications available for use in archaeological prospection. However, there is not one GIS that is a panacea, and like remote sensing systems, each GIS has its strengths and weaknesses. Deciding on which one to use is dictated by the research question and the types of data a project will utilize. The success of a project relies on the accurate selection of the remote sensing data and the GIS software. This is a primary reason why the majority of the studies reviewed have taken a multisensor approach to this type of research. These studies have also helped to lay the foundation for this research agenda.
CHAPTER 2: MANN SITE HISTORY

Site Background

The site chosen for this investigation is the Mann site (12Po2), which is located in southwestern Indiana along the Ohio River. The site has a long history of habitation but a sparse history of investigation and excavation. Archaeological resources that have been found at the site range from the Paleoindian period (ca. 10,000 B.C.E.) all the way to the Late Woodland Period (ca. 500-1000 C.E.). However, the majority of the artifacts found at the site date to the Middle Woodland period ca. 1-500 C.E. and are characteristically Hopewell (Ruby 1997). Only a handful of individuals have recorded information about this very large and extremely complex earthwork site over the past 150 years. The first recorded information that has been discovered regarding the site is the work of Joel W. Hiatt. Hiatt's manuscript was written during the late 19th century when he was a resident of Mount Vernon, Indiana. His manuscript details the location and excavation of conical mounds that border the eastern edge of the site along with the discovery of classic Hopewell trade goods that include copper ear spools and bear canines. Later in the 19th century a collector by the name of Otto Laval reported finding copper ear spools and a copper deer effigy headdress that originated from the same group of mounds on the eastern border of the site (Laval 1923).

Approximately 50 years later, a collector by the name of Joseph J. Geringer composed a map of the mounds and earthworks that were still present at the site (Geringer 1949). In 1949, the site was documented by archaeologist William Adams in his report on archaeological resources in Posey County, Indiana. Adams' manuscript details local collector findings at the site along with the location of mounds and earthworks. Shortly after Adams' report J. C. Householder conducted a low-level aerial reconnaissance of the site and was able to identify large geometric earthworks that had previously been undiscovered. During the next 30 years,
Charlie Lacer, Jr., extensively surface-collected nearly the entire site on a regular basis and also conducted small excavations into the mounds. His 30-year endeavor is documented in a 1000-plus page manuscript detailing his findings. His massive surface collection has provided invaluable data to archaeologists over the past 20 years, which has helped to increase the understanding of the site dynamics. During the 1960s and 1970s while Lacer was extensively collecting the site, Dr. James Kellar of Indiana University conducted excavations at the Mann site focusing on the habitation areas. The most recent investigation of the site occurred in the early 1990s with Bret Ruby's investigation and synthesis of all previous Mann site materials and cultural information culminating in his doctoral dissertation (Ruby 1997).

*Site Topography*

The Mann site is located on a high terrace overlooking the Ohio River in the Wabash Lowlands. The known range of the site covers an expanse of over 175 hectares and contained a minimum of 16 mounds and earthworks. These mounds and earthworks are shown on the map below (Figure 2.1), which has been adapted from Ruby's dissertation (Ruby 1997:42). The mound and earthwork dimensions were culled from Ruby's work on the Mann site in 1997 and his numbering system has been kept for consistency. The mound and earthwork dimensions are a combination of measurements based on aerial imagery, ground estimations, and excavation dimensions collected by Ruby, Keller, Lacer, and Hiatt's independent works (Ruby 1997:319).
IU1 is a large oblong mound located on the southwestern portion of the site in the center of a large partial rectangular earthwork (IU2). The dimensions of the mound as recorded by Ruby in the early 1990s were 135 meters long by 55 meters wide by 4.5 meters high. IU1 is the most intact mound at the site as it has been spared the decades of cultivation that the other earthworks have seen. However, very little is known about this mound as it has not been professionally investigated (Ruby 1997:321).

IU2 is the partial rectangular earthwork surrounding IU1 and it has been completely obliterated by cultivation. The earthwork was first identified by J C. Householder's aerial reconnaissance of the site in the 1950s, and consists of four wall sections encompassing an area of approximately 14 hectares. The earthwork measurements were estimated by James Kellar in
1979 and are as follows: the west wall measures 175 meter long, the longer east wall measures 300 meter long, and the northern wall is broken up into two sections measuring 290 meters long and 275 meters long with a 25 meter gap in between (Kellar 1979:101). Due to the complete obliteration of these earthworks, it is speculated that they were only approximately one meter in height during their original construction, similar to the rectangular Ohio earthworks (Ruby 1997:322).

IU3 is another smaller earthwork that is located just north of IU2. IU3 has also been completely obliterated by cultivation, however, Ruby was able to estimate the size of this square earthwork based on Householder's images. Each side of this earthwork is approximately 310 meters long with breaks at the corners and midpoints of each side of roughly 15 meters (Ruby 1997:323).

IU4 is an earthwork located just to the east of IU2. IU4 consists of a series of four smaller earthen embankments composing a hook-like configuration. Very little is also known about these embankments as their identification was only via aerial photographs analyzed by Kellar in the 1970s. The base of the hook-like configuration is approximately 275 meter long with the top segment measuring approximately 50 meters long (Ruby 1997: 324).

IU5 was also identified via aerial photography and has been speculated to be the remnant of a mound that has been completely cultivated. The approximate measurement of this mound is 20 meters in diameter (Ruby 1997:325).

IU6 is a large mound located near the center of the site. The measurements of the mound in the late 1990s taken by Ruby were 90 meters in length, 45 meters in width, and 3.5 meters in height. This large mound has not been excavated, but two surface finds at the site were recorded by Lacer, which consist of an eagle pipe and a panther pipe (Ruby 1997:325).
IU7 is the smaller of two c-shaped embankments found at the site. The earthwork has been destroyed by cultivation, however, this earthwork was also recorded via historic aerial photographs. The approximate measurement of this earthwork is 35 meters in diameter (Ruby 1997:325).

IU8 is a mound located due south of IU6 and measured 125 meters long by 80 meters wide by 2 meters high in the early 1990s. No additional information is known about this mound (Ruby 1997:326).

IU9 is the largest mound located at the site, which can be found just east of IU8. The measurements of IU9 as recorded by Ruby in the early 1990s were 150 meters long, 75 meters wide, and 4 meters high. This mound has been excavated on multiple occasions and the archaeological resources found within it have attributed the mound to the Middle Woodland time period (Ruby 1997:326).

IU10 is a linear earthwork that once stretched over 700 meters in length and was approximately five meters wide. The earthwork was first identified by Hiatt but has been subsequently used as road fill and has been destroyed (Ruby 1997:333).

IU11 is a small, conical mound that measured 35 meters in diameter and just over one meter in height in the early 1990s. IU11 has been speculated to be directly associated with IU10 due to its location directly south of a bend in the IU10 embankment.

IU12 was the largest of the easternmost mounds at the site. Based on Hiatt's manuscript, IU12 was over six meters high until a road was put through the center of it. During the road construction Lacer noted that a copper and antler headdress was discovered. In the 1990s, Ruby noted the dimensions of this now bisected mound as 45 meters by 40 meters (Ruby 1997:337).

IU13 is another conical mound located on the far eastern portion of the site. Hiatt recorded the dimensions of the mound as approximately 3 meters high and 45 meters in
diameter. This mound was excavated on multiple occasions by both Hiatt and Lacer, and a total of 44 burials were recovered along with an extensive collection of Hopewell grave goods (Ruby 1997:338).

IU14 is a conical mound located to the northeast of IU13, which was recorded by Hiatt to be approximately 3 meters high. No other dimensions were recorded for this mound, although it was excavated by Lacer, who identified burials and Hopewellian grave goods within it (Ruby 1997:347).

IU15 is a conical mound located to the north of IU14. The dimensions of the mound were recorded by Hiatt as approximately 2.4 meters high and 16 meters in diameter. This mound was also excavated by Hiatt and was found to contain burials and Hopewellian grave goods (Ruby 1997:349).

IU16 is a small circular depression located in the far southeastern portion of the site. This anomaly was noted by Ruby but nothing is known about this feature (Ruby 1997:351). It can be speculated that due to its small size and remote location that perhaps it was the remnants of a borrow pit used for earthwork construction.

IU17 is the larger of the two c-shaped embankments at the site, which is located just to the east of the smaller one, IU7. The measurements of the embankment were estimated to be 75 meters in diameter based on 1950 aerial imagery (Ruby 1997:351).

The mounds and earthworks listed above are currently the only ones known to exist. However, the possibility of undiscovered mounds and earthworks is very high due to the low level of intensive investigations that have taken place in this area. Additionally, throughout the history of the site when at-the-time sophisticated prospecting techniques were used new resources were discovered. This is part of the reason why I chose this particular site. The other primary reason is the documented existence of relief and planar resources that allowed for both
investigational methods to be tested. In order to verify that relief and planar resources were present at the Mann site, ground reconnaissance was performed on March 14, 2014. The relief resources that were located via ground reconnaissance are shown below in Figure 2.2 and included IU1, IU6, IU8, IU9, IU12, IU13, and IU14.

Figure 2.2: The Mann Site Relief Resources (DigitalGlobe 2011; ESRI 2014).

The Mann site has a much larger number of known planar resources than relief resources. Figure 2.3 shows the location of all of the planar resources based on Ruby's map. These resources were not identified via ground reconnaissance and include IU2, IU3, IU4, IU5, IU7, IU10, IU11, IU15, IU16, and IU17.
In general, Hopewell is the term used to define a complex series of social networks that existed during the Middle Woodland period. These networks were characterized by the sharing of exotic (non-local) goods and mortuary rituals (Seeman 1979). The original term Hopewell was coined by Warren K. Moorehead in the first quarter of the 1900s to describe the distinctive archaeological materials that were excavated on the farm of Mordecai C. Hopewell in Chillicothe, Ohio (Moorehead 1922:80). Initially, the term Hopewell was used to classify a set of material remains that had specific stylistic characteristics. Later, however, the term Hopewell was extrapolated to describe a region-wide culture based on the occurrence of material remains with these specific characteristics. This Hopewell manifestation proliferated to a greater extent
throughout the entire Midwest from the Great Lakes to the Gulf coast and from Kansas all the way to western New York (Seeman 1979).

In the late 1960s and 1970s, the Hopewell culture saw a great increase in scholarly research and began to be defined in several different ways. In this time of reconceptualizing Hopewell, archaeologists began to describe Hopewell based on an economic model or a shared ideological model of interaction. Hopewell was termed a shared set of social ties based on similarities in settlement structure but differences in material goods (Kay 1979). It was also termed a “complex” based on the subsistence, site structure, and artifact variance found throughout the region (Prufer 1977). Hopewell was called a type of logistics network that consisted of the movement of raw materials, finished goods, and the sharing of a common ideology and symbolic status markers (Struever 1977; Struever and Houart 1972). In similar terms, it was called a system of interregional exchange that exhibited a high level of intraregional variation (Seeman 1979), or interregional exchange on multiple levels between differing core areas (Jeske 2006). Hopewell was also discussed as a cultural horizon (sensu Willey and Phillips 1958) as a way to understand its variance in the region (Dancey 2005). Today, the way that Hopewell is most commonly conceptualized is as a series of interaction spheres based on a shared religion and mortuary practices (Caldwell 1964).

A comparison of the regional distribution of exotic raw materials and finished artifacts found that Hopewell was indeed a prehistoric system of trade and exchange (Seeman 1979). However, not all Hopewell sites are seen as equal. Certain areas are characterized by an extremely high volume of exotic goods and well-defined mortuary practices, while other Hopewell sites only exhibit one of these features in lesser degrees. The sites that typify these manifestations are found primarily in Ohio. However, a few sites have been located in Illinois and Indiana that have a large volume of Hopewellian exotic goods comparable to Ohio (Seeman
Throughout the past several decades, Hopewell has been a focal point of Midwestern archaeological studies due to on-going debate as to what Hopewell actually was and how to understand and interpret the exotic Hopewellian artifacts. These exotic artifacts include elaborate mica cutouts, platform and effigy pipes, large obsidian blades and bifaces, bear canines, copper ear spools, and copper headdresses (Seeman 1979).

With various existing ideas about the social complexity, shared ideology, and symbolic meanings of Hopewellian artifact data, settlement patterns, and method of subsistence, what exactly is Hopewell? The notion of Hopewell as a single cultural system is problematic due to the variability present during the time period. Hopewell consisted of a diverse network of groups of hunter-gatherers who also practiced small-scale horticulture (Johnson 1976; Pacheco and Dancey 2006; Struever 1977). Studies into Hopewell subsistence have also shown that their diets were characterized by a high level of diversity. Food selection methods appear to have been driven by opportunity and taste rather than access (Ford 1979; Wymer 1996). They were highly dispersed across the landscape and did not utilize nucleated villages, but they did possess a level of residential stability based on hamlets and short-term extractive camps (Abrams 2009; Dancey and Pacheco 1997; Griffin 1996; Lepper 2010; Pacheco 1996; Prufer 1977).

In essence, Hopewell is a generalized term used to capture elements of regional cultural similarity. Since it is an idealized type, it is important to recognize the no such pan-regional culture ever truly existed. However, the sites that fall under this umbrella are often characterized by the construction of mounds and elaborate earthworks representing their ideological principles and mortuary practices. These ideologies and corresponding mortuary practices have left a distinctive signature on the landscape, and it is these signatures that I will attempt to locate.
Hopewell Mound and Earthwork Construction

The Mann site is an extremely large and complex Hopewell site. In general, Hopewell mounds and earthworks have been subjected to intensive research that has allowed archeologists to understand the construction process along with mound and earthwork inclusions. This research has revealed two primary factors that will affect the spectral reflectance values for these resources. The first factor recognized by excavation data is that the majority of Hopewell earthworks and mounds were built using various types of soil. Soil reflectance signatures are affected by both the mineral and organic composition of the soil, as well as the soil particle size and moisture content. The mineral and organic composition of the soil has a larger influence on the hue of the soil. Iron oxides, for example, make the soil darker whereas calcium carbonates make the soil lighter (Gomarasca 2009:438).

It is believed that the soils that were used for mound construction were ritually important, and therefore specifically selected for their color and texture (Mainfort 2013:102). Some archaeologists assert that the process of mound and earthwork construction itself was ritualized, making the selection and transportation a ritualized process as well. Based on geoarchaeological analysis of the soils, it has been found that some of them were local, others were transported from large distances, and still others were created specifically for the mound construction by combining various soils and minerals together prior to construction (Sherwood and Kidder 2011). The soils used in the construction process appear to have been selected for their highly contrasting colors. Embankments that have revealed this type of soil construction include the Hopeton square embankment, the Fairground Circle at Newark, the High Banks Great Circle, the Seip square embankment, the square embankment at Anderson mounds, Brown Mound (Bernardini 2004:340; Brown and Porter 1966; Seig 2005; Sherwood and Kidder 2011). Other Hopewellian mounds and earthworks were composed in the form of sod blocks that were cultivated specifically for mound wall construction. These materials were not present in any of
the areas adjacent to the mounds and were allowed to form under specific conditions. Therefore, mound building was a process that took several years of preparation and planning in soil preparation alone (Van Nest et al. 2001).

The second factor is the type and level of inclusions found in Hopewellian mounds and earthworks. A large number of Hopewellian mounds were burial mounds for ancestors. The inclusion of human remains in a mound increases the possibility of the release of calcium carbonates into the soil via diagenesis. As diagenesis occurs, the calcium stored in the bones is leached into the adjacent soils thereby increasing calcium carbonate levels (Hedges 2002). Mound and earthwork fill has also been found to contain large deposits of wood ash generated by multiple burning episodes followed by a rapid covering of the ash while it was still hot (Bernardini 2004:344). In trapping the ash in the soil, it also altered the soil color due to the thermal change. Soils that have been burned or have been mixed with large amounts of wood ash exhibit changes in their spectral reflectance values (Chuvieco 2008:126). The burning of wood creates ash that is approximately twenty percent calcium carbonate (Ohno and Erich 1990). Calcium carbonate, unlike many other minerals, is not easily leached from the soil (Ulery et al. 1993).

Lastly, the fill in Hopewell mounds and earthworks has been found to contain animal bones, charcoal, and shells, all of which can alter the chemical properties of the soil (Birmingham and Eisenberg 2000). The inclusion of shells in mounds can also affect the calcium carbonate levels in the soil based on the type of shell and the physical properties of the soil (Faulkner 2011). As the shells break down, calcium is released into the soil and it has a direct impact on its spectral signature (Steponaitis 1986). These two factors have the potential to produce a change in the spectral signature between archaeological resources and non-archaeological. The remaining questions is whether the currently available spaceborne sensors have a high enough spectral resolution to detect these differences.
CHAPTER 3: RESEARCH METHODS

Google Earth Exploration

The first signatures that this research identifies are those that correspond to archaeological relief resources. To reiterate, relief resources are those resources that can still be identified as relief features in the terrain. The first step was to test whether or not the relief resources that were located via ground reconnaissance were easily discernible using contemporary GIS systems. The initial imagery that was used was from the freeware Google Earth™. A total of 16 historic images were available for this study area ranging from April 16th, 1993 up to September 22nd, 2013. In addition to investigating the Google Earth™ imagery, Bret Ruby's initial map of the Mann site archaeological resources was georectified so that it could be used as an overlay for accurately locating the known resources. Georectification is the process of aligning a map of unknown spatial reference to a base map that has a spatial reference component through the use of ground control points (Jensen 1996:124). The newly georectified image provided a solid reference map for the approximate locations of all the known archaeological resources. Using Google Earth™ imagery as the first step was necessary in order to determine the viability of free imagery for archaeological prospection. If all of the resources noted on the historic maps were accurately located in free imagery, then it would negate the need for more complex manipulations to visualize these resources.

Geographic Information System Manipulations

A series of image manipulations were then used to visualize relief resources. I experimented with multiple tools that are currently available in most GIS software platforms using freely available data. The platform that I selected was Environmental Systems Research Institute's (ESRI) ArcMap 10.2. The data sets that I chose to work with were digital elevation models (DEM), with a spatial resolution of five feet, which are free through United States
Geological Survey (USGS) and the Indiana Spatial Data Portal (ISDP). The only requirement to obtain this data is to set up a free account with their service. The USGS has an excellent website and interactive map called EarthExplorer which allows the user to select an area of interest (AOI) and download multiple forms of imagery. This imagery can be obtained from http://earthexplorer.usgs.gov. The imagery used for this research was obtained from the Indiana Spatial Data Portal at http://gis.iu.edu/downloadData/index.php, which is managed by Indiana University. Each pixel in the DEM has two-dimensional values corresponding to the X and Y position of the pixel in the data set and an additional dimensional value labeled the Z value that corresponds to the elevation of each pixel above sea level. This Z value is useful for identifying relief resources since these resources will have a larger Z value than the adjacent landscape. Figure 3.1 shows a single DEM raster obtained from ISDP symbolized based on elevation values. In this raster the locations of IU8 and IU9 have been highlighted. The areas corresponding to IU8 and IU9 have a brighter pixel value than the adjacent landscape due to their higher elevation.

Figure 3.1: Single Elevation Raster (ISDP 2014, ESRI 2014).
The study area covers over 1,500 hectares but a single DEM only covers approximately 150 hectares. Additionally, due to the pattern in which the DEMs were generated, it takes a total of 12 DEMs to capture the total area of the site. To solve this problem once the 12 individual DEMs were obtained from the ISDP it was necessary to mosaic all 12 together to create a single DEM. This was accomplished using the mosaic dataset tool found in ArcGIS 10.2, which creates a new image where each individual DEM is plotted based on their spatial relationship to each other. This new dataset can then be exported to a single DEM that combines all of the original DEMs together. The resulting image consists of 3200 columns of pixels and 2400 rows of pixels, with a spatial resolution of five feet. This new image provided the base for the relief resource location GIS processes and is shown in Figure 3.2. The elevation imagery visualized in its raw format does not provide any advantage over the standard imagery. In fact, it obscures the view of a majority of the relief resources and only the location of IU1, IU6, IU8, and IU9 are discernible. However, the software offers an array of tools that can help to visualize relief resources.

Figure 3.2: Mosaic Elevation Dataset (ISDP 2014, ESRI 2014).
Once the DEM was generated, the first image manipulation geoprocessing tool that was used was the Slope function. This function, which is common to most basic GIS software, creates a new raster that shows the slope of the terrain based on the input elevation file. The slope function calculates the rate of change of elevation from pixel to pixel based on a three by three pixel cubic neighborhood (De Smith et al. 2007:259). The slope function was chosen for its ability to visualize rate of change in elevation. Relief archaeological resources will have a slope signature and should be detectable in a slope raster. The limitation will only be on the spatial resolution of the imagery and if the resources have a slope that is great enough to differentiate from the adjacent landscape.

Next an aspect raster was created from the base elevation raster. The aspect raster is very similar to a slope raster except that the aspect raster shows the compass direction of the downslope. This function is calculated using a three by three pixel neighborhood and identifies the maximum rate of change in this neighborhood and its direction (ESRI 2014). The aspect function was chosen because mounds in particular should have a very unique aspect signature. Since the majority of mounds are characterized by an increase in elevation from the adjacent landscape with sides that slope up in all directions to a round, conical, or flat top; then all of the compass down slope directions should be represented in a relatively small area. This factor brings up an interesting point as to whether or not these specific signatures could be isolated in the imagery to make them stand out even more.

Mound Signature Isolation

In an attempt to isolate these unique aspect signatures it was necessary to reclassify the aspect values into a number that is more manageable. I chose to use a total of 12 classes, each encompassing 30 degrees of variation within each class. Additionally, new values were associated with each of the 12 classes and are provided in Table 3.1. Raster aspect values
ranging from 0 to 179 were given new values ranging from one to six, aspect values ranging from 180 to 359 were given new values ranging from negative one to negative six. The rationale behind this reclassification is that if a mound signature has all of the compass directions represented within a small area, and if neighborhood statistics are calculated based on these new values, then mound resources should approximate zero. The reclassification function is a simple tool whereby the only required information is the original image and a reclassification table (ESRI 2014).

<table>
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<th>TO</th>
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</thead>
<tbody>
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<td>29.9999</td>
<td>1</td>
<td>ValueToValue</td>
</tr>
<tr>
<td>2</td>
<td>30</td>
<td>59.9999</td>
<td>2</td>
<td>ValueToValue</td>
</tr>
<tr>
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<td>89.9999</td>
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<tr>
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<td>119.9999</td>
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<td>ValueToValue</td>
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<td>12</td>
<td>330</td>
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<td>-1</td>
<td>ValueToValue</td>
</tr>
</tbody>
</table>

Table 3.1: Aspect Reclassification Table.

The second part of the isolation procedure was to calculate focal statistics for this newly reclassified raster. Focal statistics calculate descriptive statistics based on a user-defined parameter, for example, mean, sum, or difference for a given neighborhood of cells. This neighborhood can be adjusted based on number of cells or neighborhood type. The neighborhood type refers to the shape of the neighborhood used to gather the specified number of cell values. These neighborhood shapes include such selections as circular, rectangular, annulus, or wedge (ESRI 2014). A conditional function was then run to eliminate all values except those ranging from -500 to 500. Again, mound features should approximate zero when they are summed since the entire range of values should be equally represented within a small area.
Multispectral Data Acquisition

The second series of archaeological prospection methods employed in this research focused on identifying the signatures of planar archaeological resources. Again, planar resources are resources that are no longer visible in relief, thus requiring a different approach. To identify the spectral differences between archaeological and non-archaeological resources, multispectral imagery had to be obtained of the site. However, a question immediately arises when the inquiry turns from spatially focused to spectrally focused, which is: would there be a spectral difference between archaeological resources and non-archaeological resources? The answer to this question is yes, there should be a spectral difference between these resources since spectral reflectance values vary for each type of material that composes the earth's surface.

Current multispectral imagery is available from an array of sensors in many different spatial and spectral resolutions ranging from hundreds to thousands of dollars per image. Two basic parameters dictated what data would be used to answer this question. The first parameter was that the imagery needed to be recently acquired and of moderately high spatial and spectral resolution. The majority of the imagery that is freely accessible for download does not contain all of the spectral information that is recorded by a sensor and cannot be spectrally enhanced or adjusted. The second parameter was that the imagery needed to be moderately affordable, less than $500. Given these parameters the imagery chosen for this research was multispectral imagery obtained from the GeoEye-1 satellite sensor.

The GeoEye-1 sensor provides one of the highest spatial resolution images commercially available to date. The spatial resolution of this sensor is 0.41 meters in the panchromatic spectrum (adjusted to 0.5 meters due to government regulation) and 1.65 meters at Nadir for the multispectral bands (adjusted to 2.0 meters due to government regulation). The sensor collects data in four bands with a spectral range of 450-520nm (Blue), 520-600nm (Green), 625-695nm
(Red), and 760-900nm (Near Infrared) (Parcak 2009). The cost associated with this sensor varies depending on what band/image combination is selected. The total cost of the image used for this investigation was $400 based on a rate of $16.00/km$^2$ with a minimum required image size of 25km$^2$. The image package, with a collection date of October 14th, 2010, included a 4-band multispectral image with 2.0 meter resolution, a panchromatic image with 0.5 meter resolution and the associated metadata. The full multispectral image is shown below in Figure 3.3 in true color format.

![Image](image.png)

Figure 3.3: Original GeoEye-1 Multispectral Image (DigitalGlobe 2011; ESRI 2014).

*Radiometric Correction*

The first process performed was to radiometrically correct the Geoeye-1 imagery obtained from Apollo Mapping. This process was done using a program developed by Exelis Visual Information Solutions called Environment for Visualizing Images version 5.1 (ENVI). In a perfect situation the amount of electromagnetic radiation recorded by the sensor is the same amount that is reflected or emitted from the resource of interest. However, this is almost never
The amount of electromagnetic radiation that is recorded can be affected by uncalibrated sensors or from atmospheric attenuation. Atmospheric attenuation occurs through the scattering and absorption of the electromagnetic radiation as it passes through the atmosphere and interacts with various gasses and aerosols. This difference or error is referred to as noise. Radiometric correction is necessary to correct for any noise that is recorded during the data collection process (Jensen 1996:107-111).

There are two types of radiometric correction, absolute and relative. Absolute radiometric correction relies on the assumption that the electromagnetic radiation recorded by the sensor is an absolute function and converts pixel brightness values to reflectance values based on a transformation equation. Relative radiometric correction normalizes the spectral properties of an image based on another or multiple other images that have been corrected using the absolute method (Jensen 1996:110). Absolute radiometric correction was chosen for this image since no previously existing corrected images were available for calibration. In order to properly calibrate the image the header information for the image needed to be input. This included inputting the data regarding the satellite's recording wavelengths, as well as the offset and gain values. These values were included in the metadata of the original imagery and are included in Appendix A.

**Pansharpening**

Pansharpening is a specific type of image fusion technique often used in remote sensing to increase the visual interpretability of an image. Pansharpening is a technique that relies on a user-defined transformation that fuses a panchromatic image of high spatial resolution and a multispectral image of lower spatial resolution together, producing a new multispectral image with a spatial resolution equal to the panchromatic image. As mentioned above, the GeoEye-1 sensor records multispectral (4-band) data with a spatial resolution of 2.0 meters and a panchromatic (1-band) image with a spatial resolution of 0.5 meters. When these images are
fused through pansharpening, the output is a multispectral (4-band) image with a spatial resolution of 0.5 meters. The original panchromatic image obtained from the Apollo Mapping is shown below in Figure 3.4.

![Original GeoEye-1 Panchromatic Image](image)

Figure 3.4: Original GeoEye-1 Panchromatic Image (DigitalGlobe 2011; ESRI 201).

Multiple transformations exist that can be used to fuse the image, and they are either based on color transformations, Brovey and Intensity Hue Saturation (IHS), wavelet transformations, or statistical methods such as Principle Component Analysis (PCA) (Ayhan and Atay 2012:379). The Brovey transformation uses a multiplicative approach based on panchromatic pixel intensity and each multispectral pixel value. The Brovey transformation is used to increase the contrast of the features that correspond to the tails of the image histograms. However, it also affects the radiometric information and should not be used if this information needs to be preserved for additional image processing (Nikolakopoulos 2008: 648). The Intensity Hue Saturation fusion technique transforms a three-band color composite into IHS
color space based on a three-dimensional color cube. The intensity portion refers to the brightness of the color, the hue corresponds to the shade of the color, and the saturation corresponds to the whiteness of the color. This transformation increases the resolution of the imagery; however, it also affects the histograms of each band. Therefore, additional image enhancements must take this adjustment into account (Ayhan and Atay 2012:380; Nikolakopoulos 658:2008).

Due to the limitations of the software package license I was using, I was unable to use any wavelet-based transformations. However, I was able to test two statistically-based orthogonal transformations: Principle Components Analysis (PCA) and the Gram-Schmidt. PCA "is a statistical technique that transforms a multivariate dataset of correlated variables into a dataset of uncorrelated linear combinations of the original variables" (Ayhan and Atay 2012:380). PCA is used to reduce the dimensionality of a dataset allowing for the majority of the variance between all of the bands to be view in a single image (Jensen 1998:172). In a comparative test, PCA transformations provided the best improvement in image spatial detail and for this reason, it was used as a pansharpening method for this investigation. The Gram-Schmidt orthonormalization technique, which is based on weighted band averages that are decorrelated to produce orthogonal band vectors, was also used in this investigation (Maurer 2013).

**Color Composites**

The first visualization technique that was used after radiometric correction was altering band display values, or band display combinations, to try and resolve the features of interest. The GeoEye-1 image contains data on four different spectral bands. However, only three of these bands can be viewed at a time. These bands are displayed using red, green, and blue (RGB) color configuration. Figure 3.3 shown above is displayed in a RGB combination
corresponding to bands 3, 2, and 1 (RGB=321). This is known as a true color composite because each band is assigned and displayed using its true color value. Therefore, the spectral information in band one with a spectral range of 450-520 nanometers (nm), which corresponds to the blue region of the visible portion of the electromagnetic spectrum, is displayed as blue in color. Band two, with a spectral range of 520-600 nm, corresponds to the green region and is displayed as green in color, and, band three, with a spectral range is 625-695 nm, corresponds to the red region and is displayed as red in color. This combination does not use any of the data recorded about band four, with a spectral range of 760-900 nm, which corresponds to the near infrared region of the electromagnetic spectrum. However, altering which bands are assigned to a color can help to visualize information that cannot be detected by the human eye. The near infrared region is just beyond the visible light range, so this wavelength is too long for our eyes to detect (Jensen 1996). Despite this, GIS software allows the user to assign it to a specific color, either red, green, or blue, which allows us to visualize this data in a false color composite format. Figure 3.5 illustrates where the visible range falls in the electromagnetic spectrum.

Figure 3.5: Electromagnetic Spectrum (Lambert 2013).
Image Enhancement

Image enhancement techniques rely on algorithms to transform the information contained in the imagery in such a manner that it is more easily interpreted. In terms of image enhancement algorithms, there is no panacea as these algorithms only change the appearance of the data and are deemed successful or unsuccessful based on the individual's ability to interpret them, making this a highly subjective method (Jensen 1996:139). Image enhancement techniques are focused on two different methods, the point and the local. Point methods focus on changing or altering the brightness value of each pixel in the image independently without regard for the neighboring pixel values. Local methods rely on spatial neighborhood analysis and take into consideration the surrounding pixel brightness values when adjusting each individual pixel in the image (Jensen 1996:139).

One of the primary types of image enhancement methods is contrast enhancement. The basic premise behind contrast enhancement is to increase the ability to differentiate various biophysical materials in the imagery. Of concern to this study is the ability to differentiate soils that once composed earthworks from soils that did not. Contrast enhancement is a way to exaggerate the difference in brightness values between different biophysical materials to make their identification easier. However, the majority of biophysical materials that make up the Earth’s surface are not pure in form, reflecting very similar amounts of electromagnetic radiation through the majority of the electromagnetic spectrum. This situation results in very low contrast differences between these materials, making them difficult to identify. This problem is compounded by cultural use and mixing of these materials into other materials making their signatures even more similar (Jensen 1998:145).

A primary method of contrast enhancement is contrast stretching. The majority of sensors that are used currently have a radiometric resolution of at least 8 bits. This allows for the
sensor to record a total of 256 colors, or 256 individual brightness values for each pixel. Each bit refers to the binary coding of the number, and the total number of recorded values for an 8-bit sensor is $2^8$ or 256. However, this corresponds to pixels values of only 0-255. Most of the initial data that is captured by sensor consists of brightness values in the range of 0-100. Therefore, contrast stretching stretches the histogram for the image from 0-100 to 0-255 thereby making the contrast more distinct (Jensen 1996:145). Additionally, two types of contrast stretching are commonly used in remote sensing, linear and nonlinear stretching. Linear enhancements are only effective if applied to images that are composed of pixel values that have near normal distribution (Jensen 1996:147). The histograms for each band are provided below in Figure 3.6, and the computed statistics for each band are provided in Table 3.2.

![Image](image.png)

Figure 3.6: Band Histograms (DigitalGlobe 2011, Exelis 2014).
Multiple methods of linear contrast enhancement exist, but they are useful only to the extent that they increase the interpretability of the data. The Minimum-Maximum contrast stretch method simply stretches the histogram from the original $X_{\text{min}}$ and $X_{\text{max}}$ values to the maximum $X_{\text{min}}$ and $X_{\text{max}}$ values based on the number of bits. The Minimum-Maximum contrast stretching is seldom useful for most interpretations as it does not greatly increase the contrast of the image and in most instances produces a lower contrast image.

Another method of linear contrast enhancement is to use a percentage-based linear contrast stretch. This method relies on the analyst selecting $X_{\text{min}}$ and $X_{\text{max}}$ values that lay a certain percentage away from the mean of the histogram. This eliminates the very high and very low brightness values creating a high contrast between brightness values that fall closer to the mean. A method similar to the percentage stretch and also very useful is the standard deviation stretch. The standard deviation method stretches the histogram of the image based on a chosen number of standard deviations. For example, if three standard deviations is chosen then the minimum brightness value that falls three standard deviations below the mean will be the minimum value and the brightness value that falls three standard deviations above the mean will

---

Table 3.2: Band Statistics.

<table>
<thead>
<tr>
<th>Statistics</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Band 1</td>
<td>4.177839</td>
<td>51.209801</td>
<td>6.725787</td>
<td>1.325212</td>
</tr>
<tr>
<td>Band 2</td>
<td>2.57745</td>
<td>35.173603</td>
<td>6.052378</td>
<td>1.558322</td>
</tr>
<tr>
<td>Band 3</td>
<td>1.054044</td>
<td>56.779686</td>
<td>5.846455</td>
<td>2.309303</td>
</tr>
<tr>
<td>Band 4</td>
<td>0.498836</td>
<td>19.636871</td>
<td>5.920898</td>
<td>1.904429</td>
</tr>
</tbody>
</table>
be the maximum value. This type of stretch often provides the most viable image enhancement results, which can greatly increase image interpretability (Jensen 1998:147).

The other primary method of contrast enhancement is based on non-linear histogram transformations. One of the most useful and most implemented is histogram equalization. The histogram equalization algorithm computes a probability based on the number of pixels and the average brightness value, and then assigns each pixel a new brightness value based on this probability. This transformation applies the greatest contrast enhancement to the areas that fall near the mean of the data while reducing contrast in areas that fall far from the mean (Jensen 1996: 151). This process is different from the linear methods discussed above because it redistributes similar brightness values along the histogram thereby flattening the kurtosis of the histogram. This non-linear function actually changes the dataset because of the redistributing of brightness values so any additional enhancements that are performed on a histogram-equalized image can produce inaccurate results (Jensen 1996:151).

Another very popular technique is the application of filters to images to increase contrast with one of the most common being the high-pass filter. High-pass filtering is used to enhance local variations in the imagery by dramatically increasing the contrast in the regions of slight brightness value variation (Jensen 1998:158). A high pass filter uses a specified neighborhood size to recalculate and emphasize the differences in brightness values. The neighborhood size chosen was a basic three-by-three pixel neighborhood, however others were also tried. In a three-by-three high-pass filter the algorithm recalculates each pixel value based on the surrounding eight pixels. This produces edge enhancements between biophysical materials by removing minor variations in brightness values (Nag and Kudrat 1998).
Image Classification

The two primary methods of multispectral image classification that are used to transform data into information are hard classification and soft classification. Hard classification methods assign each pixel in an image to a single class based on the results from the selected classification algorithm. Soft classification methods assigns each pixel a membership value based on all the classes to which it could belong. The higher the class membership value, the more likely it is mathematically calculated to belong to that class. Soft classification methods are good for identifying mixed pixels in the imagery, however since the imagery used in this analysis is very high spatial resolution and the features of interest are relatively large, sub pixel classification was not necessary (Jensen 1996:197-201). Therefore, hard classification methods were only utilized in the supervised and unsupervised approaches.

Unsupervised classification relies on a spectral clustering algorithm. This algorithm automatically groups pixels together based on statistically-determined criteria (Jensen 1998:197). The only real parameter that is required for this type of classification is to define the number of clusters for the algorithm to identify (Conolly and Lake 2006:147). The clustering method used for this investigation was the Iterative Self-Organizing Data Analysis Technique (ISODAT) clustering method. The ISODAT runs multiple iterations through the data in order to properly group spectral clusters. During the first iteration, the algorithm randomly assigns clusters then calculates the minimum distance to the center of each cluster and calculates the mean and standard deviation of each cluster. In the next iteration, these clusters are adjusted in order to reach smaller standard deviation values. The algorithm continues to iterate through the dataset until either the maximum number of iterations is met or an acceptable level of variance is achieved in each cluster. These parameters can be adjusted by the user before running the algorithm to increase the accuracy of the output (Jensen 1998:236-237).
Supervised classification is a much more intensive process than unsupervised classification because it relies on prior knowledge of the identity and the location of land cover in a given image. This is a necessary component as these areas are then used to train the classification algorithm in order for it to accurately locate similar biophysical materials. Furthermore, the user also decides on the number of training areas to use for each class. If too few training areas are used, or pixels are mixed between what is selected in the image and what actually exists in the real world, then the resulting image could classify these resources improperly. In this regard there are two primary types of error that are common in classification methods. The first type is error of commission, in which a pixel is assigned to a class to which it does not belong. The second type is error of omission in which a pixel is not assigned to a class to which it belongs (Jensen 1998:218). Once these training areas are selected a chosen algorithm calculates multivariate statistical parameters for each training site.

Multiple supervised classification algorithms exist and four were tested in this research. The following supervised classification methods utilized the same training area data and were generated using ENVI 5.1. A total of seven training classes were used with a minimum of 30 training pixels selected for each class. The training classes were linear earthworks, c-shaped earthworks, mounds, vegetation, water, developed, and fallow. The training areas for the linear earthworks, c-shaped earthworks, and mounds were chosen based on Ruby's map. The training areas for vegetation, water, developed, and fallow land were chosen based on my knowledge of the area. The developed class included contemporary manmade structures such as buildings and roads. The fallow land class consisted of farmland that is adjacent to mounds and earthworks that is not known to contain archeological resources.

The first method, the Parallelepiped classification, is based on simple Boolean logic and uses the upper and lower bounds of each spectral dimension to create a multidimensional
parallelepiped. The dimensions of the pipeds are based on a measurement of pixel values contained within each training set, using either the mean, or the minimum and maximum (Wilkie and Finn 1996:200). If untrained pixel values fall within a class’s piped region, they are then assigned to that class (Richards 2012:269-271). The second method, the Maximum Likelihood algorithm, assumes a multivariate normal distribution of pixels and each class and builds a discriminate function. The algorithm then calculates the probability of a pixel belonging to a specific class by taking into account the mean and covariance of the training set. The pixel is then assigned to the class that it has the highest probability of existing in (Conolly and Lake 2006:148; Jensen 1998: 197). The third method, the Minimum Distance classification algorithm, calculates the Euclidean distance to each mean vector from each unknown pixel in the image. The pixels with the shortest mean distance from the training class data are grouped into that specific class. The final method, the Mahalanobis distance classification algorithm, is similar to the Maximum Likelihood except that it is sensitive to vector direction, uses a simplified Euclidean distance measurement, and assumes that the covariance measurement between all classes is equal (Richards 2012:271).

**Anomaly Detection**

Anomaly detection is a workflow that is provided in ENVI 5.1 software that can detect and extract features that are spectrally different from the adjacent surroundings. Anomaly detection focuses on locating unknown targets and is commonly used in surveillance operations. This workflow allows for the calculation and identification of these targets using three different methods. The first method uses the Reed-Xiaoli Detector (RXD) algorithm to identify spectral color differences between pixels. The RXD method performs a transformation that is the inverse of principle component analysis. RXD generates a new component image with exaggerated
brightness values for those targets that have a very low probability of being present in the image, thereby identifying anomalous targets (Exelis 2014).

The second anomaly detection method used was the Uniform Target Detector (UTD) algorithm. The UTD is exactly the same as the RXD method except for one component. The RXD method uses a vector extracted from the imagery in its calculations whereas the UTD method uses a unit-based vector. See Reed and Yu (1990) for a detailed discussion of this algorithm. The final anomaly detection method used was a hybrid subtraction method that uses both RXD and UTD algorithms to create a new component. This hybrid method was the best bet for the detection of the planar resources since their pixel brightness values are only slightly different than those of the adjacent area (Exelis 2014).

In situ Data Collection

All of the previous methods have been strictly limited to manipulating the data that I was able to extract from the original GeoEye-1 imagery. Other possible image enhancement methods existed but they required in situ data to be collected in order to calibrate and spectrally map the image based on precise field measurements. Obtaining accurate in situ measurements was coordinated and conducted during the relief reconnaissance site visit discussed previously. A few steps had to be taken prior to the site visit to ensure accurate data capture. The first step was to map landowner parcels to the site in order to identify which areas I would have direct access to. Since the majority of the site is still private property, it was necessary to obtain permission from the landowners. Through coordination with Michele Greenan, Director of Archaeology at the Indiana State Museum, permission was obtained for the parcels below highlighted in blue and shown in Figure 3.7. Permission was not obtained for some of the primary areas of interest; however, I was still able to access and collect data for multiple planar resources including the geometric earthworks IU2 and IU4, the c-shaped earthwork IU17, the linear embankment IU10, and two of the cultivated mounds IU12 and IU13.
The next step was to create a vector file to map the earthworks and data collection points that I would have access to. After these areas were mapped the initial plan was to use ArcPad 10 to navigate to these sites while in the field and then obtain reflectance values from the center of each. However, ArcPad 10 would not function as initially planned during a test run navigation trial so this method was discarded and Universal Transverse Mercator (UTM) coordinates were obtained from the approximate center of each resource. These coordinates were then loaded into a Handheld Trimble Geo XT 6000 with TerraSync software. This method proved much more reliable in a test run and therefore was used in the field to navigate to each point. The coordinates are provided in the Table 3.3, and Figure 3.8 shows the location of each point at the site.
Table 3.3: UTM Coordinates for Reflectance Collection.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Northing</th>
<th>Easting</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mound 2</td>
<td>4196713.82</td>
<td>426862.16</td>
</tr>
<tr>
<td>Mound 3</td>
<td>4196653.24</td>
<td>426818.24</td>
</tr>
<tr>
<td>Shell Road 1</td>
<td>4196801.66</td>
<td>426823.56</td>
</tr>
<tr>
<td>Shell Road 2</td>
<td>4196805.65</td>
<td>426842.19</td>
</tr>
<tr>
<td>C Shaped Embankment 2</td>
<td>4196614.01</td>
<td>426178.62</td>
</tr>
<tr>
<td>C Shaped Embankment 1</td>
<td>4196660.59</td>
<td>426161.32</td>
</tr>
<tr>
<td>Rectangular Earthwork 1</td>
<td>4196885.5</td>
<td>425590.68</td>
</tr>
<tr>
<td>Rectangular Earthwork 2</td>
<td>4196751.09</td>
<td>425631.63</td>
</tr>
<tr>
<td>Rectangular Earthwork 3</td>
<td>4196785.69</td>
<td>425708.82</td>
</tr>
<tr>
<td>Rectangular Earthwork 4</td>
<td>4196657.93</td>
<td>425599.69</td>
</tr>
</tbody>
</table>

Figure 3.8: *In Situ* Data Collection Points (DigitalGlobe 2011, ESRI 2014).
The *in situ* reflectance values were collected using an Analytical Spectral Devices, Inc. FieldSpec Handheld spectroradiometer and their RS³ data collection software package. Upon arrival at the site, the spectroradiometer was allowed to warm up for 30 minutes prior to any data collection to equalize any variations due to changes in ambient temperature. Once the spectroradiometer was prepped, I began navigating to the first point for data collection using the TerraSync software and the preprogrammed UTM coordinates. Once I had arrived at a point, the spectroradiometer was set up on a tripod and elevated to 60 inches off the ground and directed down to the point at a 45 degree angle. This process was followed for every single data point. When the sensor was set in position, the RS³ software was initialized. Upon initializing the software, a white reference panel was held directly in front of the sensor at an angle complementary to the ground to calibrate the sensor. While the sensor was pointed at this panel, the software ran through an optimization process to calibrate the sensors to the light source and temperature. Once the optimization process was completed, a white reference measurement was taken to zero the sensor. At that point, fifteen reflectance measurements were taken at an interval of less than one second each. This process was followed exactly at each data collection point for a total of ten separate data points. This data collection process is outlined in the literature provided for the FieldSpec spectroradiometer (Hatchell 1999).

**Processing in situ Data**

The next step after collecting the *in situ* measurements was to process the recorded transmitted electromagnetic radiation values into reflectance values. This was performed using the ViewSpec Pro software that was included with the spectroradiometer. The ViewSpec Pro software allows the user to view and calibrate *in situ* data into several different formats; however, for this investigation reflectance was the only calibration needed. The initial transmittance *in situ* wavelength readings are shown in Figure 3.9 before calibration to reflectance values.
The electromagnetic radiation emitted from the sun is affected as it travels through Earth's atmosphere. These effects are in the form of scattering and absorption by atmospheric particles. This absorption can be seen on the initial wavelength readings above which is very high around the 760nm range. These readings correspond to the normal atmospheric absorption effects that are illustrated below Figure 3.10. The figure shows a much longer region of the electromagnetic spectrum, but the sudden absorption of electromagnetic radiation in the near-infrared region can be seen.
Once this data was converted into reflectance wavelength values, it could then be used by the remote sensing software to calibrate and compare spectral reflectance values in the GeoEye-1 imagery. The calibrated reflectance values are provided in Figure 3.11 after post-processing had been performed. After all of the *in situ* measurements were processed, I could then return to the remote sensing software to begin further processing the data and compare it with the data recorded by the GeoEye-1 satellite.

Figure 3.10: Electromagnetic Atmospheric Absorption (Jensen 1996, Figure 6.3).

Figure 3.11: Calibrated Reflectance Measurements (ViewSpec Pro 2014).
Spectral Information Divergence

The spectral processing method that was used to identify these specific reflectance wavelength signatures in the imagery was the Spectral Information Divergence (SID) function offered in ENVI 5.1 (Exelis 2014). The SID works by locating and identifying spectrally pure features in the imagery and allows for sub-pixel feature detection. The SID uses a pixel value deviation measure to identify and classify image pixels to in situ reflectance measurements. The smaller the deviation in value between an in situ value and an image value, the higher the probability that the pixels are composed of similar biophysical materials. If the deviation value is too high, then the pixels is not classified and given a zero value (Du et al. 2004). Once the in situ measurements were loaded and plotted into the SID, shown in Figure 3.12, image spectra were then matched based on the level of divergence to reference spectra in n-dimensions.

Figure 3.12: SID Spectral Measurement Plots (DigitalGlobe 2011; Exelis 2014).
CHAPTER 4: RESEARCH RESULTS

Google Earth Exploration

The investigation of the 16 historic images of the Mann site available via Google Earth™ provided many significant results. One of the primary benefits of Google Earth™ is that it offers relatively recently acquired imagery along with several historical images spanning back 20 years in some areas. Through a comparison of Bret Ruby's map to each of the historic images, multiple archaeological relief resources were accurately identified. Figure 4.1 shows Ruby's georectified map overlaid onto the GeoEye-1 imagery.

![Figure 4.1: GeoEye-1 Image and Ruby's Overlay Map (DigitalGlobe 2011; Ruby 1997; ESRI 2014).](image)

The most recent image available on Google Earth™ that had the highest number of archaeological resources discernible was captured on August 12, 2007. In this image a total of nine resources were discernible, which included all of the relief resources IU1, IU6, IU8, IU9, IU12, IU13, and IU14. Two planar resource signatures were also identified and these were IU2, the large rectangular earthwork, and IU10, a portion of the shell road. Figure 4.2 shows the
location of these resources. The relief resources are designated by blue leaders and the planar resources by green leaders. Some of these resources are easier to identify than the others however they all stand out enough to enable their detection. Just this first image holds very promising results for the remainder of this investigation.

Figure 4.2: Google Earth™ Imagery August 12, 2007, accessed on July 3, 2014.

In the next image, Figure 4.3, with a collection date of April 5 1998, multiple relief and planar resources were located as well as some anomalies. The relief resources include IU1, IU8, IU9, and IU6; the planar resources include IU2, IU3, and IU4. A total of five anomalies were picked out in this image and are designated by red leaders. Four of the anomalies appear to be mound signatures. One of these anomalies is just to the west of IU6 while another two are directly west of IU9, and a fourth one is north of the site, across the road. The last anomaly appears to be a type of earthwork in the shape of the number seven and can be seen in the far west portion of the site.
Using these two historic images, I was able to identify various relief and planar resources at the site along with a few anomalies. However, even though each image provided information about the site resources, they did not provide the same information. This issue is one of the focal points of this research – how to identify a method to extract all information regarding the location of both relief and planar resources from a single image. To illustrate the problem even better, I have included an additional image obtained from Google Earth™ (Figure 4.4). This third image was collected on September 22, 2013, and due to the current land cover, only IU1, IU6, IU8, and IU9 are identifiable. However, the earthwork anomaly that was present in the previous image is also identifiable in this one as well.
Returning to the initial question, can contemporary GIS simplify the process of locating relief resources in the Midwest? It appears that even freely available imagery is able to supplement archaeological resource location of relief and planar resources. A better question is whether or not contemporary GIS can improve and standardize the process of locating these resources. The identification of these resources had been serendipitous based on the image acquisition date and time along with prior knowledge of the site. I proceeded in my research by manipulating this spatial data with the goal of discovering a methodology to standardize identification of their spatial signatures.
**Geographic Information System Manipulations**

Using the DEM rasters, a slope raster was generated to aid in the visualization of the rate of change in elevation from one pixel to the next. As discussed previously, archaeological relief resources have a degree of slope and therefore should be detectable in a slope raster. However, this is highly dependent on the surrounding terrain. If the surrounding terrain is very rugged, then this obscures their signatures. However, since this site is heavily tilled and relatively flat, relief resources stand out rather well. Figure 4.5 shows the resulting slope raster for the Mann site. Relief resources including IU1, IU6, IU8, and IU9 are clearly identified in the imagery. IU12, IU13, and IU14 signatures are present, but they are much harder to locate. Additionally, two anomalies were identified at the southern portion of the site that appear to form a circular pattern with IU8 and IU9. However, I had not located these signatures, which were very close to the signatures left by IU6, IU12, and IU8.

![Figure 4.5: Slope Raster (ISDP 2014; ESRI 2014).](image)
The aspect raster provides a visualization of the compass direction of the downslope, not just the rate of change as does the standard slope raster. Figure 4.6 shows the generated aspect raster for the area encompassing the Mann site. Each color represented in the image illustrates a different downslope direction. Similar to the slope raster, the aspect raster visualizes multiple relief resources rather well. These resources include IU1, IU6, IU8, IU9, and IU12. The aspect raster, however, was not able to provide a good visualization of IU13 or IU14, but it did allow for the identification of three anomalies. Two anomalies to the south of IU8 and IU9 were also identified in the slope raster as well as an anomaly to the north of the site. This northern anomaly is not the same as the one identified in Figure 4.3, therefore two possible anomalies have been identified to the north of the site and multiple in the site itself. Since the slope and aspect rasters have provided new information on possible anomalies, and have been able to identify multiple relief resources, the next question is whether or not these two tools can be used to isolate these signatures from the rest of the landscape, thereby producing an output raster of just these resources.

Figure 4.6: Aspect Raster (ISDP 2014; ESRI 2014).
Mound Signature Isolation

The mound signature isolation was a series of functions that were combined together in order to achieve the goal of signature isolation. The first in the series was to reclassify the aspect raster so the values could be used to calculate focal statistics for the entire area. I wanted a series of values that could be used in neighborhood focal statistic calculations, which when summed together would approximate a zero value for those areas where mounds occur. The compass downslope direction values were reclassified as shown below in Figure 4.7.

![Figure 4.7: Reclassified Aspect Raster (ISDP 2014; ESRI 2014).](image)

The second step of the isolation procedure was to calculate focal statistics for this newly reclassified raster. Numerous permutations were tried by adjusting neighborhood size and neighborhood type while returning a summed value. However, the best output was generated by using a circular neighborhood of 15 cells based on the size of the known relief resources. The resulting focal statistic raster is shown below in Figure 4.8. The locations of IU1, IU6, IU8, and IU9 have been shown in this raster to illustrate the focal statistics recalculation of these areas.
The focal statistics output raster values ranged from negative 4238 to 4183. Therefore, I ran a conditional function to isolate values ranging from negative 500 to 500. Again, mound features should approximate zero when they are summed since the entire range of values should be equally represented within a small area. The output conditional raster is shown below in Figure 4.9 overlaid onto a hillshade raster. Hillshading produces a three-dimensional (3D) image based on pixel elevation and provides shading based on a user-defined sun azimuth and latitude (ESRI 2014). All of the red signatures in the imagery show areas where the calculated value ranges between negative 500 and 500. A few of the relief resources were identified by the process, including IU1, IU6, IU8, and IU9. However, a very large number of anomalies were also identified to the degree that it is apparent that there is a large percentage of error in method. This method was not able to isolate the signatures of relief resources any better than the slope or aspect rasters alone. That is not to say that a process similar to this cannot isolate these signatures, it is just that the parameters and methodology of this particular one could not.
Radiometric Correction

The first process performed was to radiometrically correct the Geoeye-1 imagery to ensure that the reflectance values recorded in the image was as accurate as possible. The initial GeoEye-1 imagery is shown directly below in Figure 4.10 in true color format. The high spatial and spectral resolution of this imagery provides a great amount of detail regarding site resources. In this raw imagery alone, all seven relief resources can be identified along with two planar resources, IU2 and IU10. Additionally, multiple anomalies were detected in the south and east portions of the site. A long linear area of discoloration is present in the southern portion of the site. A mound signature anomaly is located just below IU9, in a similar location to the anomaly found in the slope and aspect rasters. Another linear anomaly is found on the eastern portion of the site running northeast from IU12 at a length of well over 500 meters and a width of approximately 20 meters. The linear section cuts back sharply to the west near the 500 meter mark and another portion dissipates as it continues farther northeast until it is no longer visible.
The GeoEye-1 image that had been radiometrically corrected also provided an excellent level of detail regarding site resources. Figure 4.11 shows this image in true color format with the multiple resources and anomalies that were identified in it as well. One anomaly not apparent in the original imagery is found, which appears to be a mound signature between IU6 and IU9. There is a significant difference between the two images as radiometrically correcting the image greatly increased the contrast and brightness of the imagery by converting the recorded reflectance values into actual radiance values. Interestingly, neither of these images displayed the anomalies that had been apparent in the northern portion of the site using the slope and aspect functions. The value alone of having access to high spatial resolution imagery for archaeological prospecting is readily apparent in these two GeoEye-1 images.
Pansharpening

Having seen the potential that high spatial resolution imagery alone can have for archaeological prospection, the next step was to begin processing the imagery to extract more information to aid in the identification of relief and planar resources. The first process I used was pansharpening. Pansharpening fuses a panchromatic image of high spatial resolution and a multispectral image of lower spatial resolution together, producing a new multispectral image with a spatial resolution equal to the panchromatic image. As discussed previously, multiple methods exist, and were utilized, to pansharpen the GeoEye-1 imagery. Figure 4.12 shows the four resulting images from the pansharpening transformations. The top left image shows the Brovey transformation, the top right image shows the IHS transformation, the bottom left image shows the Gram-Schmidt transformation, and the bottom right image shows the PCA
transformation. In this instance, none of the pansharpening techniques greatly enhanced the ability to resolve planar or relief resources, nor did it uncover any new anomalies. Each image only revealed the same resources and anomalies that were found in the radiometrically corrected image. This is likely because the spatial resolution of the multispectral bands of the GeoEye-1 image that was used in this research was already high enough. The archaeological resources that I attempted to locate were all much larger than the two-meter resolution of the multispectral range, therefore increasing the resolution to 0.5 meters had no effect. This is a positive finding as it shows that satellite imagery technology is currently able to acquire data with high enough spatial resolution to be particularly useful for archaeological prospecting in the Midwest.

Figure 4.12: GeoEye-1 Pansharpened Images (DigitalGlobe 2011; ESRI 2014; Exelis 2014).
Color Composites

Displaying the image using different band combinations in no way changes the information in the imagery. The only purpose of this technique is to aid in visualization of resources and land cover types. All of the possible false color composite band combinations were attempted but only a few results are shown below in Figure 4.13. Again, band 1 corresponds to the blue portion of the electromagnetic spectrum that was collected by the sensor. Band 2 corresponds to the green portion, band 3 the red portion, and band 4 the near infrared portion. The top left image shows the GeoEye-1 imagery in RGB = 321, the top right image is displayed in RGB = 213, the bottom left image is RGB = 432, and the bottom right image is RGB = 342. The majority of the combinations simply provided redundant results, but some of the images did sharpen the appearance of the anomalies, particularly RGB = 432, and RGB = 342. These two combinations include the near infrared band in the image composite along with two visible spectrum bands. Overall, displaying the data in false color composite format did not aid in identifying these resources in the landscape any better than the true color format radiometrically corrected image and therefore should not be a sole method used to identify relief and planar resources.
Image Enhancement

The series of image enhancement techniques I used in this research consisted of multiple contrast stretching algorithms. The first image enhancement technique applied to the radiometrically corrected imagery was the minimum-maximum contrast stretch (Figure 4.14.) This linear form of stretching expands the histogram from the original Xmin and Xmax values to the maximum Xmin and Xmax values based on the radiometric resolution. Minimum-Maximum contrast stretching produced an image that was much darker than the original display method of standard deviation stretching. Enhancing the image using this method only produced an image that provides less visual detail and therefore is not useful.
Figure 4.14: Minimum-Maximum Linear Enhancement (DigitalGlobe 2011, ESRI 2014).

The second linear-based contrast enhancement method applied to the imagery was to use a percent clip. The percent clip stretches the histogram to a user-defined set of values that lays a certain percentage away from the mean of the histogram. This eliminates the very high and very low brightness values that provide a higher contrast between those values that fall close to the mean. Figure 4.15 provided below shows the radiometrically corrected image with a three percent clip contrast stretch applied. Multiple percentages were tested and the three percent clip produced the highest level of contrast for the resources of interest. Figure 4.15 shows the location of IU2 very well and provides enough contrast to locate IU10 as well. All of the relief resources can also be identified along with the anomalies that have been present thus far in the southern portion of the site. However, this type of enhancement was not able to locate either of the two anomalies that were previously noted to the north of the site.
Since this form of stretching did not provide any better results than the standard deviation stretching method, I had reached the limits of linear contrast enhancements. For that reason, I turned to non-linear contrast enhancement methods, specifically histogram equalization (Figure 4.16). After applying the histogram equalization stretch to the imagery, I was able to identify all relief recourses as well as the three planar resources, IU2, IU4, and IU10, rather well. Multiple anomalies were also located in the center and eastern portions of the site. Three anomalies in the center appear to be mound signatures and the anomalies in the south and eastern portions appear to be earthwork signatures. This nonlinear form of contrast enhancement provided the best results in regards to image enhancement techniques for archeological prospection thus far.
Multiple other forms of image enhancement techniques exist and were applied to the imagery, specifically high pass filtering. The results of the high pass filtering produced images that were less visually interpretable than the other forms of contrast enhancement. Figure 4.17 below shows the results of a three-by-three high pass filter applied to the radiometrically corrected image. The three-by-three high pass filter along with all of the other filters applied to the radiometrically corrected image only blurred the imagery to the extent that only a few resources were detectable. In this image, the location of IU1 and IU9 have been provided for reference only since they were no longer detectable in the imagery. However, I was still able to identify the two linear anomalies in the filtered images. At that point I had exhausted the limits of the software in terms of contrast enhancement methods. The histogram equalization method by far produced the best results in terms of archaeological prospection.
Image Classification

The two types of hard classification approaches that were used included unsupervised and supervised approaches. Unsupervised classification relies on minimal user input, in which the only real parameter is to define the number of classes, thus making it ideal for archaeological prospection since no training data is needed. The ISODAT clustering method was used in this research and multiple class numbers were attempted, from three classes to twenty classes. The purpose of classification is to group like biophysical materials together. In an ideal scenario, the ISODAT algorithm would pick up on archaeological resources and group them into a single class. Figure 4.18 shows four of the eighteen output rasters from the ISODAT unsupervised training process. The top left image shows the four ISODAT classes, the top right image shows eight ISODAT classes, the bottom left image shows 12 ISODAT classes, and the bottom right image shows 16 ISODAT classes. None of the resulting rasters were able to isolate either the
relief or the planar resources into a single class. It appears that in the GeoEye-1 imagery, the spectral signatures of archaeological resources are either not unique enough to be isolated due to the wavelengths recorded by the sensor, or the ISODAT clustering algorithm is the problem. However, some anomalies were classified as different from the adjacent landscape, providing evidence that this type of image manipulation could be more successful with a different dataset or in a different study area.

Figure 4.18: Unsupervised ISODAT Classification (DigitalGlobe 2011, ESRI 2014, Exelis 2014).
To test whether or not the ISODAT clustering algorithm was the problem, a supervised classification approach was used. A total of four different supervised classification algorithms were used in order to test the overall viability of this approach and to determine whether this was a spectral problem related to the sensor or mathematical problem related to the algorithm used. The parallelepiped classification was able to accurately pick up the locations of the c-shaped earthworks near the center of the site as shown in Figure 4.19. The area inside of IU2 was also assigned this same class value; however, numerous other instances of this class value were also found throughout the image, thus diminishing any value that it had. Additionally, none of the other classes could be isolated using the parallelepiped method.

Figure 4.19: Parallelepiped Classification (DigitalGlobe 2011, ESRI 2014, Exelis 2014).
The next method, the maximum likelihood method shown in Figure 4.20, also produced very interesting results in the identification of planar resources. This method was able to isolate nearly the entire northern portion of IU2. Additionally, the area just to the east of IU2, where IU4 was located, was assigned the same class value. However, this method also produced numerous false positives and was not able to isolate any class completely.

![Figure 4.20: Maximum Likelihood Classification (DigitalGlobe 2011, ESRI 2014, Exelis 2014).](image)

The final two methods, the minimum distance and the Mahalanobis distance are similar in computation and produced nearly identical results as shown in Figure 4.21. The minimum distance classification raster is shown on the left and the Mahalanobis distance on the right. Neither of these classification algorithms was able to isolate any of the class signatures based on the training data used. The multiple tests that I ran using both supervised and unsupervised algorithms demonstrated that the limiting factor in this method is not the classification
algorithms, but the ability of the GeoEye-1 sensor to detect these differences to a high enough degree, thus not enabling the algorithm to isolate them from the adjacent landscape.

Figure 4.21: Minimum Distance and Mahalanobis Distance Classification (DigitalGlobe 2011, ESRI 2014, Exelis 2014).

Anomaly Detection

The first anomaly detection method used, the RXD method, exaggerated brightness values for those targets that had a very low probability of being present in the image. The RXD method was applied to the radiometrically corrected GeoEye-1 image and is shown below in Figure 4.22. The RXD method was able to visualize the location of planar resource IU2 and relief resources IU6 and IU9. This method also picked up several regions within the center portion of the site that could possibly be mound signatures from currently unknown planar resources. The anomalies to the southern portion of the site as well as to the eastern portion of the site that had been identified previously also showed up using the RXD method.
The second anomaly detection method, the UTD method, produced very different results compared to the RXD method. The same anomalies were found in the center portion of the site near the mound group, along with the anomalies to the south and eastern portion of the site. However, the UTD method also detected an anomaly group within the bounds of IU2 and a large group of anomalies to the north of the site. Previous mound anomalies were detected in this area using spatial methods, but to this point no spectral method identified a concentration of anomalies to this degree in the north as shown in Figure 4.23.
The final anomaly detection method, the hybrid RXD-UTD method, provided very interesting results in terms of the identification of planar resources and anomalies at the site as shown in Figure 4.24. This method was able to detect planar resource IU2 as well as the group of anomalies that are contained by this earthwork. In the center portion of the site, a group of four mound signatures were located running at a 45-degree angle pointing to the northeast. Additionally, a linear earthwork signature was detected directly above that running at a 330 degree angle pointing to the southeast. Two single mound signatures were also located one to the northeast of IU9, and one due east of IU9 above the long linear anomaly in the south. The large group of anomalies to the north was also identified very well using this method.
Overall, the anomaly detection methods have provided the most interesting results in terms of identifying spectral anomalies at the site. They were not able to resolve all of the planar resources at the site, but all of them easily detected IU2. With this in mind, interpreting these anomalies in the image as positive signs of archaeological resources has to be approached with caution. Nonetheless, these results are very promising in terms of archaeological prospection, even if just a small portion of these are in fact unknown planar resources.

Spectral Information Divergence

The SID mapping method was employed in an attempt to locate all known planar resources and mounds at the site. The SID method, which is based on *in situ* measurements of known resources, was only able to accurately identify IU2 in the imagery. However, several areas were classified as belonging to IU10's spectral signature category. The image did not
isolate IU10, but it begs the question as to whether these areas are higher in calcium deposits than the surrounding areas. Since IU10 was the shell road, the likelihood of its signature being unique due to increased calcium levels is very likely. The highest number of pixels in the imagery were not classified which is a positive outcome. The IU17 category encompassed the majority of the classified pixels in the imagery, which suggests two possibilities. The first is that the spectral signature of IU17 has deteriorated to the point that it is no longer unique enough from the adjacent landscape to be identified, or that the GeoEye-1 sensor records wavelength ranges that are too broad. Since the SID was able to accurately locate IU2, I believe that it is the range of the sensor that is the inhibiting factor preventing this method, and all previously executed spectral methods, from obtaining a high level of accuracy in identifying planar resources.

Figure 4.25: Spectral Information Divergence (DigitalGlobe 2011, Exelis 2014, ESRI 2014).
CHAPTER 5: SUMMARY AND CONCLUSIONS

Site Anomalies

No single method employed in this research was able to identify all relief or planar resources at the Mann site. Nonetheless, a few of the methods did identify several of the resources accurately while also identifying some anomalies. Here I discuss the anomalies that were detected using some of the methods as well as their implications for understanding the site.

The first instance where anomalies were detected in this research was during the investigation of the Google Earth™ imagery, specifically Figure 4.3 with an imagery acquisition date of April 5, 1998. An anomaly appears to the north of the site, and based on the spectral signatures of IU6 and IU8 it appears to be a mound anomaly. Another mound signature anomaly also appeared in the center portion of the site between IU6 and IU9 and two more adjacent to each other near the southern portion of the site. In this image, a large linear anomaly at the eastern edge of the site began to appear. In Figure 4.11, the radiometrically corrected GeoEye-1 image, this linear anomaly became clearer, and it appeared to extend across the entire eastern edge of the site and cross the southern edge of the site south of IU9. In Figure 4.16, the histogram equalized image, two additional mound signature anomalies appeared in the center portion of the site, one to the southeast of IU6 and another to the northeast of IU9. Finally, in Figure 4.24, the RXD-UTD anomaly detection raster, a few more mound signatures were identified in the southern portion of the site along with a very large group to the north. In addition, two linear anomalies were also detected in the center portion of the site, one just to the north of IU6, and the other due north of IU17. Figure 5.1 below shows the location of all of the detected anomalies along with the location of the known relief and planar resources.
This research identified multiple mound signature anomalies especially in the northern portion of the site. With the inclusion of these anomalies and the original relief and planar resources culled from Ruby's survey map, it appears that a semicircle of mounds may have been present near the center portion of the site. Additionally, it shows that a high level of activity also occurred to the north of the site beyond the current site boundary. The only way to truly know if these anomalies are actually mound signatures would be to conduct geophysical surveys or excavations in these areas. However, if even just half of these mound anomalies in the central portion of the site are actual mounds it creates a much different picture of how the site once looked.
The linear anomaly that runs from the northeast edge of the site to the southern portion of the site is very likely an anomaly caused by soil erosion. Based on elevation maps and ground reconnaissance, this area has a steep down-sloping nature and hard rains and flooding could easily have caused organic material to be leached from this soil causing a higher density of minerals to be present in this area giving it a higher reflectance value. Also due to the size of this anomaly, nearly 1700 meters long and over 20 meters wide it is likely a result of water drainage. To illustrate this point better, Figure 5.2 shows a slope raster with the original radiometrically corrected GeoEye-1 image overlaid onto it. As you can see in this image, the steep downslope, designated by the areas in red, directly corresponds to the areas exhibiting this spectral anomaly.

Figure 5.2: Large Linear Anomaly (DigitalGlobe 2011; ESRI 2014).
The smaller linear anomalies detected in the central portion of the site could have been an earthwork similar to either IU2, IU3, or IU4. The northern linear anomaly corresponds to the same direction as the northern wall of IU2 does. Perhaps other earthworks existed in this central region that have long been destroyed. Nonetheless, these results are very interesting in terms of what else could exist at this site and how these methods could be applied to other areas.

Lastly, some very interesting findings came out of this research. The majority of the figures do not show the full extent of the GeoEye-1 imagery that was purchased for this investigation as I focused specifically on the areas composing the site and directly adjacent. In examining Figure 3.3 closely, a series of very strong mound signatures becomes apparent in the far northeastern portion of the image. These signatures were detectable in a majority of the spectral methods that were applied to the imagery and these signatures are shown below in the radiometrically corrected image (Figure 5.3). After further research and discussions with the Indiana State Museum, no mounds are known to exist in this area (Michele Greenan, personal communication). These mound signatures are the most exciting finds as they are the closest to resembling the signatures of other mounds such as IU6 and IU9 and are in an area where no resources are known to have existed.
Conclusions

The primary goal of this research was to test the viability of using current GIS techniques and remote sensing technology to affordably locate relief and planar archaeological resources to aid in cultural resource management. Currently available, as well as historic, panchromatic and multispectral imagery was shown to be very useful in locating relief resources and in some circumstances planar resources in raw format. Numerous image enhancement and manipulation techniques were applied on up-to-date remote sensing data to improve identification precision with mixed results. Over half of the image manipulations (i.e., pansharpening, linear contrast enhancements, high pass filtering, ISODAT classification, and mound signature isolation) techniques were largely unsuccessful. However, techniques such as non-linear contrast enhancement via histogram equalization, maximum likelihood and parallelepiped classification algorithms, RXD-UTD anomaly detection, and spectral information divergence showed promising results in terms of locating planar resources and identifying other planar anomalies.
This split in results leads me to believe that it is the spectral resolution of the data that is the inhibiting factor and not the methods. Given that some of the methods were able to detect these spectral differences in the imagery provides evidence that spectral differences do exist between archaeological and non-archaeological resources. Therefore, if the GeoEye-1 imagery was more sensitive to spectral differences, by recording more bands or recording smaller band widths, these resources could be detected with a higher level of precision.

As discussed previously, the GeoEye-1 sensor collects four spectral bands; 450-520nm (Blue), 520-600nm (Green), 625-695nm (Red), and 760-900nm (Near Infrared). This is a relatively broad spectral range for each band. The Worldview-3 satellite sensor, which was launched in August of 2014, may be a viable candidate for an affordable solution to the GeoEye-1's shortcomings. This new super-spectral satellite can produce multispectral imagery with resolutions of 1.24 meters in the multispectral range and 0.31 meters in the panchromatic. Furthermore, this sensor will be able to collect 16 total bands of electromagnetic radiation; eight in the visible and near infrared regions and eight in the short-wave infrared region (DigitalGlobe 2014). The eight bands that will be included in the multispectral range are shown in Table 5.1.

<table>
<thead>
<tr>
<th>Spectral Range</th>
<th>Color</th>
</tr>
</thead>
<tbody>
<tr>
<td>400-452nm</td>
<td>Costal</td>
</tr>
<tr>
<td>448-510nm</td>
<td>Blue</td>
</tr>
<tr>
<td>518-586nm</td>
<td>Green</td>
</tr>
<tr>
<td>590-630nm</td>
<td>Yellow</td>
</tr>
<tr>
<td>632-692nm</td>
<td>Red</td>
</tr>
<tr>
<td>706-746nm</td>
<td>Red Edge</td>
</tr>
<tr>
<td>772-890nm</td>
<td>Near Infrared Region 1</td>
</tr>
<tr>
<td>886-945nm</td>
<td>Near Infrared Region 2</td>
</tr>
</tbody>
</table>

Table 5.1: Worldview-3 Sensor Bands (DigitalGlobe 2014)
This change in spectral band number and range could be enough to provide the additional information needed to be able to detect these resources in the landscape. Another route is through the use of hyperspectral sensors to identify these resources. Hyperspectral sensors, such as the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) developed by NASA, collects 224 individual spectral bands in the range of 0.4-2.45nm with an individual band resolution of 9.4nm (Gupta 2003:301). This type of sensor offers a massive amount of data that enables the detection of extremely slight variations in biophysical spectral reflectance values. Since the aim of this research is to detect variance in soil reflectance values, this type of sensor may provide the answer. However, the current cost inhibits this from being a viable method applicable to archaeological prospection in general. This will not always be the case as technology has been improving at an exponential rate since the 1960s, and the cost is continually being driven down. In a few years, spaceborne remote sensing technology could have reached a state where archaeologists could affordably use it to rapidly locate, identify, and protect archaeological resources.

At the heart of any research is not only the results but also the methods used. These methods are what can be adjusted, explored, and applied to different problems to find new solutions. The methods explored here are far more important than the results that were obtained. The current state of affordable remote sensing data was the factor limiting the precision of the results, not the methods employed. Researchers all across the globe are currently exploring spaceborne archaeological prospection with some amazing results in terms of locating previously unidentified resources. This continued trend in developing methods for processing remotely sensed data for archaeological prospection will lead to a point in the future when GIS and remote sensing data will be the primary means of archaeological prospection. The methods used to process, visualize, and interpret these data are the archaeological toolkit of the future.
The methodology implemented here has wide-reaching implications in terms of identifying new sites and uncovering additional resources at currently known sites. The total study area used in this research was 25km$^2$. Not only were these methods able to identify new anomalies within the currently known site boundaries, but anomalies were also identified in two additional areas where new resources are likely to exist. If these methods are used along with higher spectral resolution imagery at other large Hopewell sites, then it is likely that new resources and anomalies may be detected. Additionally, these methods are not just confined to Hopewell sites. As the spectral sensitivity of these images improves, any type of anthropogenic disturbance to the landscape could be detected, allowing researchers to investigate sites from a very large temporal and functional range. Furthermore, this type of investigation allows research to be conducted in areas that are not easily accessible by other means for various reasons such as harsh climate, rough terrain, or endemic warfare. This helps to tremendously cut the costs associated with archaeological prospection in these areas and also makes prospection possible in others.

It must be noted that passive spaceborne remote sensing is not a panacea for all problems in archaeological prospection. Ground-based geophysical methods reveal much more information about resources that lay beneath the soil. Aerial-based methods active remote sensors such as LiDAR and RADAR are not powerful enough to produce the detail that Ground Penetrating Radar (GPR) and magnetics can. Nevertheless, these methods are very useful in areas with a high level of vegetation ground cover. These active remote sensors have the ability to penetrate vegetation canopy and obtain data about the ground surface within these areas. Passive remote sensors are not able to obtain surface reflectance values in these areas because of land cover conditions, therefore active remote sensors are a very important part of the prospection process given the survey area. GPR and magnetic surveys are much more time-
consuming survey methods and also require direct access to the site. Surveying 25km² of land using these methods would take months or years to complete at a very high cost. However, the use of active and passive remote sensing in conjunction with GPR and magnetic surveys could help to drive down the cost by focusing ground-based surveys to specific areas. This multisensor approach to archaeological prospection is one of the most widely used and produces the best results. In terms of surveying large areas for new sites, there is currently no more cost effective method than using aerial or spaceborne remote-sensing techniques. The focus of future research is to employ ground-based methods to verify anomalies identified by spaceborne methods and use these findings to refine and improve the prospection process.
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APPENDIX A

GeoEye-1 Metadata
==================================================================
Version Number: 2.6
==================================================================

Company Information
    DigitalGlobe
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    Customer Service Phone (U.S.A.): 1.800.232.9037
    Customer Service Phone (World Wide): 1.703.480.5670
    Customer Service Fax (World Wide): 1.703.450.9570
    Customer Service Email: info4@digitalglobe.com
    Customer Service Center hours of operation:
        Monday - Friday, 6:00 - 18:00 Eastern Standard Time

Product Order Metadata
Creation Date: 01/23/14
Product Work Order Number: SG00091941_001_002128639
Product Order Number: 1451672
Customer Project Name: Imagery
Ground Station ID: PGS
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    Longitude: -87.8722991943 degrees
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    Coordinate: 3
    Latitude: 37.9000015259 degrees
    Longitude: -87.8115005493 degrees
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    Latitude: 37.9000015259 degrees
    Longitude: -87.8722000122 degrees

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    Map Y (Northing): 4199871.6420151759 meters
    Coordinate: 2
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Map Y (Northing): 4199823.3715926809 meters
Coordinate: 3
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Map Y (Northing): 4195030.4498022292 meters
Coordinate: 4
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Map Y (Northing): 4195078.6202056212 meters

Sensor Type: Satellite
Sensor Name: GeoEye-1
Product Line: Geo
Processing Level: Standard Geometrically Corrected
Image Type: PAN/MSI
Interpolation Method: Cubic Convolution
Multispectral Algorithm: None
Stereo: Mono
Mosaic: No
Map Projection: Universal Transverse Mercator
   UTM Specific Parameters
       Hemisphere: N
       Zone Number: 16
Datum: WGS84
Product Order Pixel Size: 0.5000000000 meters
Product Order Map Units: meters
MTFC Applied: Yes
DRA Applied: No
Media: Electronic
Product Media Format: Electronic
File Format: GeoTIFF
   TIFF Tiled: No
   Compressed: No
   Bits per Pixel per Band: 11 bits per pixel
Multispectral Files: BGRN

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Product Image ID: 000
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   Pan Along Scan: 0.4323743880 meters
   MS Cross Scan: 1.8113982677 meters
   MS Along Scan: 1.7294975519 meters
Scan Azimuth: 270.4130736761 degrees
Scan Direction: Reverse
Panchromatic TDI Mode: 16
Multispectral TDI Mode 13: 6
Multispectral TDI Mode 24: 6
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Ancillary Cal Creation DateTime: 2010-11-02 17:46:32 GMT
Gain Cal Creation DateTime: 2009-09-18 21:17:47 GMT
Dark Offset Cal Creation DateTime: 2009-09-21 15:01:37 GMT
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Ancillary Cal Effective DateTime: 2010-09-12 00:00:00 GMT
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- Blue: Gain: 0.025017, Offset: 0.000
- Green: Gain: 0.017183, Offset: 0.000
- Red: Gain: 0.027738, Offset: 0.000
- Near Infrared: Gain: 0.009593, Offset: 0.000

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Nominal Collection Elevation: 73.58443 degrees
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Acquisition Date/Time: 2010-10-14 16:42 GMT
Percent Cloud Cover: 0

Product Space Metadata
Number of Image Components: 1
X Components: 1
Y Components: 1

Product MBR Geographic Coordinates
Number of Coordinates: 4
- Coordinate 1: Latitude: 37.9431992869 degrees, Longitude: -87.8727168533 degrees
- Coordinate 2: Latitude: 37.9436374469 degrees, Longitude: -87.8114986987 degrees
- Coordinate 3: Latitude: 37.8999872706 degrees, Longitude: -87.8110191614 degrees
- Coordinate 4: Latitude: 37.8995497943 degrees, Longitude: -87.8722011513 degrees

Product Map Coordinates (in Map Units)
UL Map X (Easting): 423318.0000000000 meters
UL Map Y (Northing): 4199872.0000000000 meters
Pixel Size X: 0.5000000000 meters
Pixel Size Y: 0.5000000000 meters
Product Order Map Units: meters
Columns: 10760 pixels
Rows: 9688 pixels
Reference Height: 78.6396179199 meters

Product Component Metadata
Number of Components: 1
Component ID: 0000000
Product Image ID: 000
Component File Name: po_1451672_pan_0000000.tif po_1451672_bgrn_0000000.tif
Thumbnail File Name: po_1451672_rgb_0000000_ovr.jpg
Country Code: US

Component Geographic Corner Coordinates
Number of Coordinates: 4
  Coordinate: 1
    Latitude: 37.9431992869 degrees
    Longitude: -87.8727168533 degrees
  Coordinate: 2
    Latitude: 37.9436374469 degrees
    Longitude: -87.8114986987 degrees
  Coordinate: 3
    Latitude: 37.9000052949 degrees
    Longitude: -87.8110193592 degrees
  Coordinate: 4
    Latitude: 37.8995678183 degrees
    Longitude: -87.8722013640 degrees

Component Map Coordinates (in Map Units)
  UL Map X (Easting): 423318.0000000000 meters
  UL Map Y (Northing): 4199872.0000000000 meters
Pixel Size X: 0.5000000000 meters
Pixel Size Y: 0.5000000000 meters
Product Order Map Units: meters
Columns: 10760 pixels
Rows: 9684 pixels
Percent Component Cloud Cover: 0