COMPARING LANDSAT7 ETM+ AND NAIP IMAGERY FOR PRECISION AGRICULTURE APPLICATION IN SMALL SCALE FARMING: A CASE STUDY IN THE SOUTH EASTERN PART OF PITTSYLVANIA COUNTY, VA

by

Robert Kevin Bohon Jr.

A Thesis Presented to the
FACULTY OF THE USC GRADUATE SCHOOL
UNIVERSITY OF SOUTHERN CALIFORNIA
In Partial Fulfillment of the
Requirements for the Degree
MASTER OF SCIENCE
(GEOGRAPHIC INFORMATION SCIENCE AND TECHNOLOGY)

June 2014

DEDICATION

This is dedicated to my wife Lindsey, and my family for supporting me.

ACKNOWLEDGMENTS

I would like acknowledge all those who have helped me with research and data analysis: Ryan Jensen, Dan Mertz, Rich Curran, and Charles Nickerson. I would also like to thank the USC faculty for their direction throughout the GIST program, especially my advisor Dr. Flora Paganelli and committee members Dr. Su Jin Lee and Dr. Darren Ruddell.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF EQUATIONS

LIST OF ABBREVIATIONS

AAG	Association of American Geographers
GIST	Geographic Information Science and Technology
JEP	Joint Educational Project
SSI	Spatial Sciences Institute
USC	University of Southern California
RS	Remote Sensing
VI	Vegetation Index
PA	Precision Agriculture
NAIP	National Agriculture Imagery Program
USGS	United States Geological Survey
USDA	United States Department of Agriculture
FSA	Farm Service Agency
NRCS	Natural Resources Conservation Service
DOQQ	Digital Orthophoto Quarter Quads
NDVI	Normalized Difference Vegetation Index
GNDVI	Green Normalized Difference Vegetation Index
RVI	Ration Vegetation Index
SAVI	Soil Adjusted Vegetation Index
ROI	Return on Investment
PE	Percent Error
VRT	Variable Rate Technology

ABSTRACT

Small scale farming identify farms with less than 300 acres of agricultural land and represent a large population of producers in the US, thus the interest in procedures such as Precision Agriculture Application in productivity cycles. This study compares publically available Landsat7 ETM+ imagery, at nominal 30 meters pixel resolution, and National Agricultural Imagery Program's (NAIP) imagery, at nominal 1 meter pixel resolution, to evaluate their use in Precision Agriculture (PA) applications for small-scale farming. The selected study area was determined based on crop characterization and land size criteria identified in the South Eastern part of Pittsylvania County, VA. The selected agricultural fields within the study area, 14 in total, were of varying shapes, ranging from 7.5 to 150 acres in size, and characterized by a specific crop type such as non-alfalfa hay.

The methodology for this study consisted in the computation and analysis of four vegetation indices (VIs) to evaluate the effect of imagery resolution to depict vegetation maturity in the selected 14 sites. The VIs used consisted of: Ratio Vegetation Index (RVI), Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI), and Soil-Adjusted Vegetation Index (SAVI). In addition to the Vis analysis, a pixel Percent Error estimate was derived from the low- and high-resolution VIs products to evaluate the amount of variance between Landsat7 ETM+ and NAIP data.

As expected, NAIP's VIs results provided more detail about the study sites compared to the Landsat7 ETM+ VIs products. This was evident as NAIP's ability to locate and visualize vegetation and non-vegetation features within the study sites, which is of particular importance for PA applications. In contrast, Landsat7 ETM+ imagery

were not able to provide adequate identification and monitoring capabilities when used in limited areal extent, specifically required for small scale farming PA applications. Spectral mixing of land features smaller than the 30 meters pixel resolution imagery were causing vegetation differences to be diluted across the fields rather than being isolated and identifiable like in the NAIP's VIs results.

Results from the PE analysis confirm the VI results and show a great difference between VI values derived from the low resolution Landsat7 ETM+ and high resolution NAIP imagery. The majority of the sites contain a high percentage of pixels error above the acceptable percentage, which outline that VI values derived from low resolution imagery do not provide results comparable to the high resolution imagery. Moreover, the size of the sites do have an effect on the amount of acceptable PE within each field, with larger fields containing higher percentages of Acceptable PE than smaller sites. Therefore, due to the use of reduced size fields in small scale farming, the use of low resolution imagery might not be appropriate to adequately represent the actual ground conditions necessary for reliable PA use.

CHAPTER 1: INTRODUCTION AND LITERATURE REVIEW

While there are still tractors, harvesters, combines and other typical machines involved, those machines and their operators are now equipped with GPS units, various environmental sensors, and other forms of technology such as the sue of satellite and airborne imagery, commonly identified as Remote Sensing (RS), that help monitor and track almost every element of traditional farming. The leap into a new generation of small scale agricultural technology, defined as Precision Agriculture (PA), is made possible through the use of RS and its innovations. PA has its benefits, however, it brings to farmers some difficult choices due to the implementation of a new technology, which has its challenges and costs. Implementing PA requires startup costs for training, hardware, and software that could intimidate potential new users. As with all new technology, there is an inherent amount of risk associated, especially in terms of cost. Identifying cost effective methods with new technology can be a trying process.

Small scale farming accounts for around 92% of farms within the US (Poole, 2004) and the majority fall in the low producing section of that category where the farm produces barely enough to cover the costs of maintaining a working farm. The other 8% are large family or commercial farming outfits that produce over $250,000 in revenue. In a study conducted in 2010 throughout the state of Ohio, of 3,000 farmers surveyed, 38.7% stated that they had adopted 1 or more elements of PA. This percentage identified farms of the largest size and highest gross income (Diekmann & Batte, 2010). Unfortunately this trend is not limited only to Ohio but it is common across the United

States, as stated in the USDA's National Institute of Food and Agriculture (NIFA) website (USDA National Institute of Food and Agriculture 2009):

> "Small and medium sized producers have a distinct disadvantage over large producers. In high-volume agriculture, economies of scale and narrow profit margins provide an economic advantage to large producers. Furthermore, large producers tend to have more education and are less wary of technology than smaller producers. These characteristics of production agriculture suggest that most technological advances, including site-specific management, are not scale neutral."

1.1 Introduction to Precision Agriculture (PA)

While there is a noted disadvantage, there are some areas where PA applications can be utilized by small scale operations. PA contains a variety of technology, therefore individual elements can be implemented over time at a more manageable level rather than purchasing multiple elements at one time. PA by definition refers to:

> "a management system that is information and technology based, is site specific and uses one or more of the following sources of data: soils, crops, nutrients, pests, moisture, or yield, for optimum profitability, sustainability, and protection of the environment" (McLoud & Gronwald 2007).

The information and technology used include a host of hardware (GPS Units, vehicle mounted sensors, auto-steering, etc.) and software (GIS software, recordkeeping, sampling collection, etc.) which drive the management styles and processes of farms. While it is not as efficient to pick and choose which elements to use, cost savings and increased revenue from PA over time could eventually lead to increased implementation.

Modern PA can trace its history back to when emerging technology became available to the public. Early uses of GPS for precision agriculture began in the early 1990's with the availability of NAVSTAR GPS (Sturdevant 2007). Variable rate dispersion of fertilizers and pesticides, yield mapping, and isolating field damage from weather related events were the first of many adoptions of modern PA through the availability of GPS technology. Early estimations in 1994 predicted that only 5% of farmers were utilizing the new GPS enabled PA, yet this was considered ‘booming’ for the time (Sturdevant 2007).

Implementation of PA in agriculture since the early adoptions has increased, but not across the entire spectrum of PA. The Agricultural Resource Management Survey (ARMS) analyzed data from 2001 to 2010 of corn, winter wheat, and soybeans to try to understand the adoption rates of PA. In the study, it found that while the PA technology is becoming more readily available, it is still developing, and the adoption rates reflect this. Easier forms of PA, such as Yield Monitoring, are first to be implemented, with Yield Monitoring adoption rate of 45% for soybeans, 42% for corn producers, and 35% for winter wheat (Schimmelpfennig 2011). Other forms, such as Variable Rate Technology (VRT), which require more sophisticated analyses and technology, are less likely to be utilized. VRT rates for soybeans was 8%, corn was higher at 12% and winter wheat topped at 14% and is steadily increasing (Schimmelpfennig 2011).

PA utilizes RS as a source of data used to create products that can be used across a wide range of practices. Table 1 contains a listing of RS products and suggested uses developed by the Missouri Precision Agriculture Center (Casady & Palm, 2002). A wealth of information is available through RS, which directly assists with the day to day management of farming operations.

RS products differ in temporal availability, spatial resolutions, and spectral resolution. These factors require evaluation and the pros and cons of the different RS products need to be determined for best use in each individual PA application, whether large scale or small.

Table 1: RS products and suggested uses.

RS Product	Use in PA
Soil Brightness	Construct soil maps or direct soil sampling
Crop Vigor or Health	Various uses including replanting, fertilizer use, pesticide use, and yield predictions
Vegetation Cover	Replant decisions
Chlorophyll Content	Nitrogen management
Yield Predictions	General management
Weed Escapes	Weed management
Stress due to Canopy	Irrigation management moisture deficits
Crop Residue	Evidence of compliance with erosion prevention guidelines

Source: Casady & Palm, 2002

Farming is critical to the livelihood of civilization, the best available technology and practices needs to be utilized to operate at peak efficiency. As previously mentioned in the Ohio study (Diekmann & Batte, 2010), only 38.7% of the Ohio farmers surveyed were using PA. Thus, the motivation for this study stems from the lack of widespread use of PA within the farming community. Technology evolves and advances as time progresses, and so it is necessary that adoption rates of technology follow suit. New tools and processes are being developed to modernize and streamline processes that are currently being used. The goal is to be more efficient with resources and increase output, essentially do more with less. Unless these new practices and technology are used, these goals will not be met. Spreading the word and educating potential users about how PA can be implemented needs to go hand in hand with the development of new technology.

Small farms are an important part of American agriculture. In the 1998 National Commission on Small Farms, a renewed dedication to the improvement of small farms was created (Volkmer et al., 1998). The purpose of this commission was to develop goals and strategies for small farms to succeed in a very competitive economy. As stated in the report (USDA National Commission on Small Farms 1998):

> "Small farms have been the foundation of our Nation, rooted in the ideals of Thomas Jefferson and recognized as such in core agricultural policies. It is with this recognition of our Nation's historical commitment to small farms that we renew our dedication to the prominence of small farms in the renewal of American communities in the 21st century."

The importance of small farms stretches far beyond the production of crops. Communities benefit from the presence of small farms in terms of divers types of owners, cropping systems, landscapes, biological organizations, culture, and tradition (Volkmer et al., 1998). These small farms are a source of employment for the rural communities they reside in. Farms can be a great learning environment for children, where they can learn about responsibility and the fruits of hard work. Additionally, with the majority of farming across the Nation being small scale, the ecological and environmental management are more personal and results with more involvement of farmers and their environment. The benefit of small scale farming is shaping the rural parts of the country and needs to be protected. With new technology and modern farming practices, these small farms can continue to operate and have the ability to increase production and revenue.

Education is critical to changing the minds of those that are unfamiliar about how PA can be used on a farm. The more familiar PA is to potential users, the greater the chances of implementation. There is a substantial amount of academic research articles and journals aimed at agricultural developments, most of which are written for a technical audience.

1.2 Review of Remote Sensing in Precision Agriculture studies

The point of view of a farmer looking at their crops is very limited, and the more they can see, the more they can understand and act on. Remotely sensed images can be used to identify nutrient deficiencies, diseases, water deficiency or surplus, weed infestations, insect damage, hail damage, wind damage, herbicide damage, and plant populations, to name a few (Nowatzki, Andres, & Kyllo, 2004). In Figure 1 is shown a very simplified sequence of the main elements of a complete remote sensing system, from beginning to end, of remote sensing of vegetation and use for PA purposes. .There are many elements that are required, which encompass acquisition, processing, analysis, and interpretation of RS imagery.

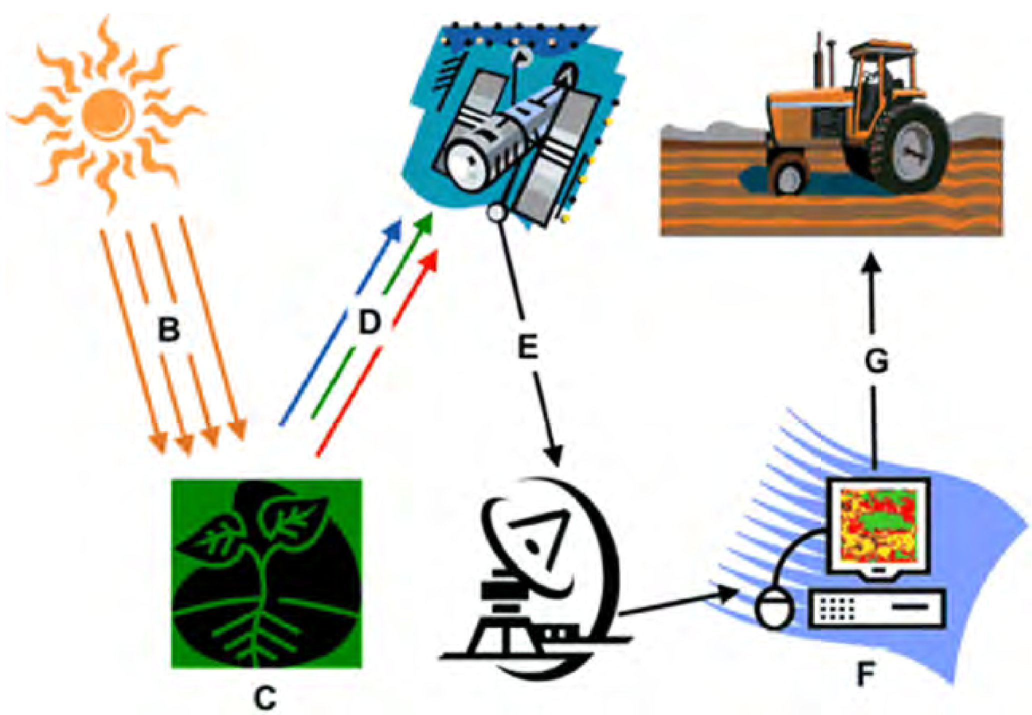

Figure 1. Remote Sensing in Precision Agriculture: The sun (A) emits electromagnetic energy (B) to plants (C). A portion of the electromagnetic energy is transmitted through the leaves. The sensor on the satellite detects the reflected energy (D). The data is then transmitted to the ground station (E). The data is analysed (F) and displayed on field maps (G) and then used in the field (Nowatzki et al., 2004).

Agricultural RS applications can trace their roots back as early as the 1920's. In 1927 aerial photography was used to differentiate the difference between healthy and diseased cotton plants (Neblette, 1927). This is a very early successful instance of using remotely sensed information for agricultural purposes. After aerial photography came the use of satellites for remote sensing. Crop imagery began to be obtained by Landsat in 1978 (Tenkorang & Lowenberg-DoBoer, 2008). Since then many different satellite constellations have been launched and cover the entire earth, such as the ASTER, IKONOS, GEOEYE, QuickBird, RapidEye, and SPOT systems. Each has their own specialties that range from high resolution to different scanners, which include thermal and panchromatic bands. In addition to satellite based sensors, low altitude sensors provide another method for collecting RS data. Airplanes, helicopters, and unmanned aerial vehicles (UAVs) provide a great service when satellite platforms are not an option.

Remote sensing in general has many advantages, and those advantages translate well toward agriculture. Remote sensing technology is a non-destructive method of data collection, it is systematically collected over large geographical areas, can reveal data about places inaccessible by humans, the systematic nature of data collection can remove sampling bias, provides biophysical information usable by other sciences, and remote sensing data is independent from other mapping sciences such as cartography or GIS (Jensen, 1996). Of these advantages, we can see how useful remote sensing is. Systematic collection of data that is unbiased can eliminate a majority of field work previously performed by individuals with in situ surveying (Liaghat, 2010), as well as monitoring distant areas of a large scale farming installation.

1.2.1 Remote Sensing of Vegetation

Remote sensing of vegetation requires knowledge of the structure and function of vegetation itself and how its energy is recorded through sensors. This allows a user to better understand what is being seen through the data that has been collected and apply that data to real life plant identification or condition. Plant life differs between species and their chemical composition is what is reflected in the data. Vegetation Indices (VI) are derived from the reflectance properties of plants and are used to identify characteristics of plant life. These properties correspond to data points that are measured in the electromagnetic spectrum, particularly in the visible, near-infrared and infrared portions. In the case of using RS for agricultural purposes, the focus is directed to the energy reflected from plant foliage.

The most important parts of plant foliage that are indicated through RS data is pigments, water content, carbon content, and nitrogen content (Exelis, 2013). These components all contribute to the spectral characteristics of each plant. Figure 2 below contains a reflectance graph showing portions of the electromagnetic spectrum and the respective plant components. Each part of the plan affects the reflectance values. This is a major factor when utilizing RS data for PA applications. Spectral profiles like Figure 2 tell us a great deal about the condition of vegetation.

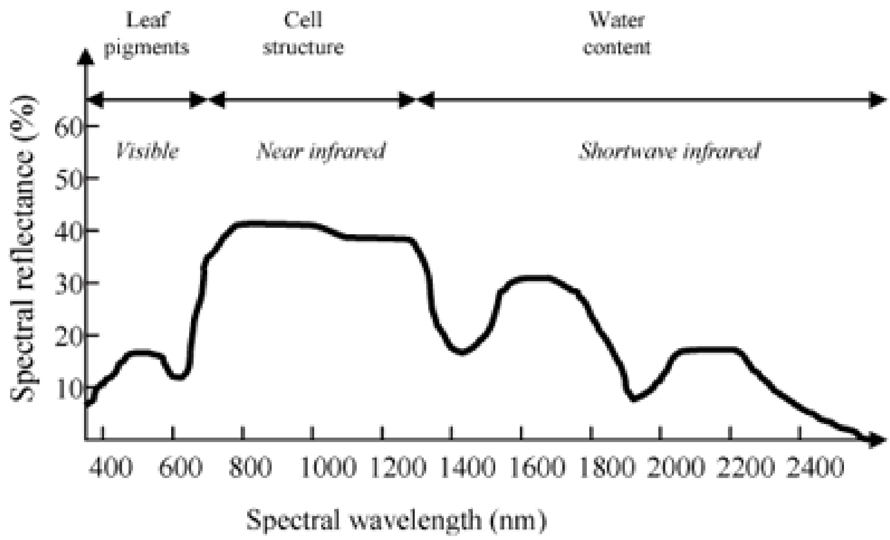

Figure 2. Plant Spectral Profile: Typical reflectance sensitivities as controlled by leaf pigments, cell structure, and water content. Crop health and other plant characteristics can be identified based on the specific values returned in a spectral profile. The variation of spectral values tells the story of the plant and gives a molecular breakdown of what is happening inside (Exelis, 2013).

Pigments within the plant include chlorophyll, carotenoids, and anthocyanins (Exelis, 2013). Each of these components that are found within a plant responds differently depending on the health and condition of the plant. Chlorophyll is commonly known for giving the green color to plants and helps see the general health of the plant. Plants registering with high levels of chlorophyll are healthy and have high rates of photosynthesis, meaning that they are well nourished and are able to sustain themselves. The presence of high levels of carotenoids generally indicates stress, which can be caused by low moisture content or disease, but can also indicate death of the plant. Identifying carotenoid content can be very beneficial early on in the growing season to help identify crop diseases and failures in irrigation systems. The last pigment compound is anthocyanins, which shows changes in the foliage. This lends itself to identifying plants undergoing senescence. All of these pigments within a plant are represented through RS imagery.

The water content within a plant helps facilitate many processes that are necessary for the plant to survive and sustain itself. Nutrients and minerals are transported throughout the plant by water, and without water, the plant could not survive. Measuring water content through RS is performed using the water content found within the leaves using the near-infrared and shortwave infrared regions of the electromagnetic spectrum. The values associated in this portion of the spectrum can then be used to identify the water content of the plant and whether it has an appropriate amount and can survive or if there is a lack of sufficient water.

Plants need carbon to survive, as it is the main requirement to perform photosynthesis. Plants use carbon in forms as sugar, starch, cellulose, and lignin. Cellulose and lignin are used in cell structure and have spectral characteristics that appear in the shortwave infrared range of the electromagnetic spectrum. In addition to carbon, nitrogen is also found in plants and has spectral characteristics that affect VIs that measure plant pigments. Nitrogen can be found in plant leaves, contained in chlorophyll, proteins and other molecules.

1.2.2 Vegetation Indices

Vegetation indices use a combination of two or more wavelengths of spectral values into a single value, which can identify and highlight functional characteristics of vegetation (Department of Ocean Earth and Atmospheric Sciences, ODU, 2003). Because of the different chemical compositions of vegetation, these reflectance values change plant to plant, including different stages of growth and during times of plant stress. In addition to identifying plant characteristics, VIs can also be used as mapping tools. Image classification, such as land use can be identified through the use of VIs that is specifically tailored toward plant identification. Other uses include canopy mapping, and tracking deforestation.

The use of VIs requires the same knowledge of plant physiology as using RS. With over 150 different VIs present today, the desired output and land conditions will determine the type of VI used. Some of the most popular and widely used VIs developed over the years includes Normalized Difference Vegetative Index (NDVI), Soil Adjusted Vegetation Index (SAVI), and Ratio Vegetative Index (RVI). Each of these VIs uses the same basic ratio based approach, but there are advantages to use one over the other.

1.2.2.1 Type of Vegetation Indices and their use

Ratio Vegetation Index (RVI)

The Ratio Vegetation Index (RVI)_is the simplest VI as it is a basic ratio of near infrared and red bands (Birth and McVey 1968). The use for this is a general view of vegetation in a given scene. The equation (1) for calculating RVI is as follows:

$$RVI = NIR / RED \quad (1)$$

Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI)_calculates the different between the near infrared and red reflectance values divided by their sum (Tucker 1979, Hunt and Yilmaz 2007). The equation (2) produces a value ranging from -1 to 1, where positive values generally denote vegetation and values approaching 0 and below are devoid of vegetation, such as barren rock and snow. The example in Figure 3 shows the difference of NDVI values for healthy and unhealthy vegetation.

$$NDVI = (NIR - RED)/(NIR + RED) \quad (2)$$

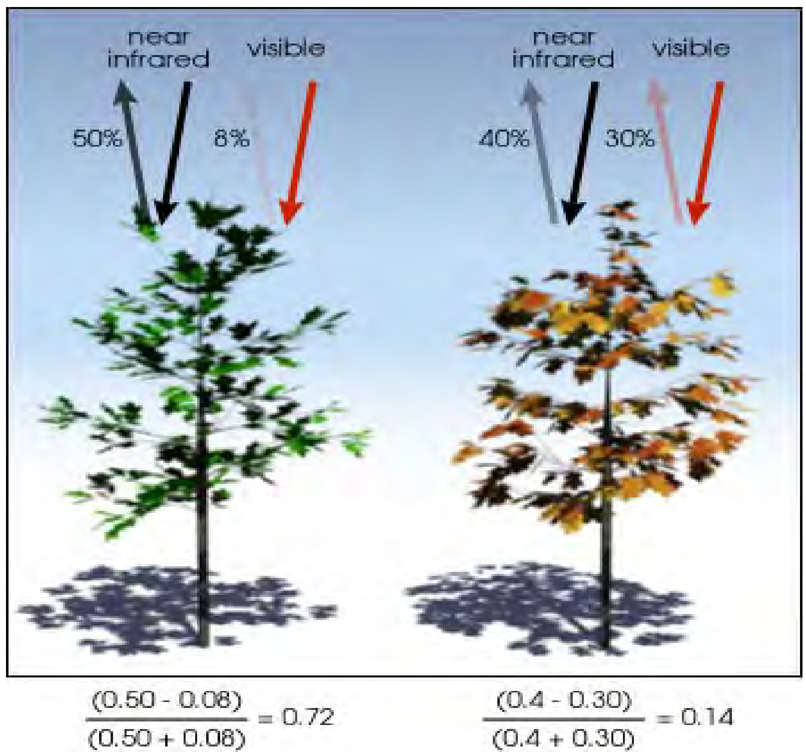

Figure 3. NDVI Calculation: NDVI is calculated from the visible and near-infrared light reflected by vegetation. Healthy vegetation (left) absorbs most of the visible light that hits it, and reflects a large portion of the near-infrared light. Unhealthy or sparse vegetation (right) reflects more visible light and less near-infrared light. The numbers on the figure above are representative of actual values, but real vegetation is much more varied (NASA Earth Observatory, 2013).

Green Normalized Difference Vegetation Index (GNDVI)

A variation of NDVI has been developed (Hunt et al. 2007) that uses the green band portion of the electromagnetic spectrum rather than the red band. This is referred to Green Normalized Difference Vegetation Index (GNDVI). This is calculated using the same equation (3) as NDVI, but with green band substituted for Red:

$$GNDVI = (NIR - GREEN) / (NIR + GREEN) \quad (3)$$

The benefit of GNDVI over NDVI is that the green band can cover a broader range of chlorophyll in plants than the red band. This applies to mature plants, and can be useful for crop yield monitoring late in the growing season. NDVI's use of the visible red band works well for young, adolescent vegetation and is suitable for general greenness and growth monitoring.

Soil Adjusted Vegetation Index (SAVI)

The Soil Adjusted Vegetation Index (SAVI) uses the same band as NDVI (red) but introduces a constant to account for the present of soil in the data (Huete 1988). The equation (4) for calculating SAVI is as follows:

$$SAVI = \quad ((NIR - RED)x(1 + L))/(NIR + RED + L) \quad (4)$$

The L value is the constant for soil brightness and produces values that are independent of background noise (soil reflection). The L value ranges from 0 to infinity, but Huete suggested that a value range be determined for vegetation density (Qi et al., 1994). The value range suggested is L=1 for low vegetation, L=0.5 for intermediate vegetation and L=0.25 for high vegetation. Note that when L=0 the output would equal NDVI. This would be appropriate to use early on in the growing season where there is an abundance of bare soil while seedlings are growing, or other situations where there is a large amount of soil present when taking imagery.

1.2.2.2 Data Output from Vegetation indices

Once the calculations of VIs have been performed, the resultant data can be visually examined. One of the advantages of using RS imagery is the ability to isolate individual spectral bands and perform false color composite images. This process alters the natural color scheme of what is seen by the eye to highlight a specific feature or collection of features that cannot be seen by the naked eye. Figure below shows part of the City of Ukiah, California. NDVI was calculated using 1 meter resolution imagery and a false color composite color ramp is shown ranging from brown (unhealthy vegetation), to red to green (healthy vegetation). Agricultural fields can be seen with lots of green present, and surrounding neighborhoods and roads are represented with darker browns and reds.

Figure 4. False Color Composite: NDVI calculated Ukiah, CA, using NAIP 2010 1-meter resolution NDVI imagery. False color composite images allow a different view where subtle differences can be identified. In a true color image, green grass would be visible and dominant, but with this alternate view, all rooftops and other features that would be camouflaged by their colors stand out and can be easily seen. In this image green tones depict healthy vegetation, yellow tones a mix of vegetation and soil, and red tones bare soil or manmade infrastructures.
Source: ArcGIS Online, 2014

1.2.3 Benefits of Precision Agriculture

The benefits of PA derive from streamlined processes and added monitoring ability. The results of efficient processes and monitoring include reducing the amount of wasted resources, increased ability to monitor soil and crop conditions, and the potential for increased yield with enhanced crop management. In a Cornell Precision Agriculture case study, the farm of Elmer Richards and Sons was used as a test sight. The Richards farm is a dairy farm that grows 1,300 acres of corn and 1,000 acres of wheat, along with their 800 cow dairy operation. In 1997 a yield monitor was purchased to assist with identifying problem areas and to create field maps. As stated in the study, it was an additional 10 hours of work for the entire year to manage data with an additional hour to calibrate the sensor as needed, both of which is considered minimal (Kahabka, Staehr, Hanchar, & Knoblaunch, 2000). Through their use of the yield monitor, crop maps were produced utilizing yield data combined with GPS data. Based on the information gained from implementing one PA element, numerous changes in crop selection were made as a result of having accurate data available when making decisions.

Additional benefits of PA present opportunities that do not apply the farmer's bottom line; there are environmental advantages and benefits of using PA. Utilizing advanced resource management, the amount of farm related pollution and erosion can be lessened. Through targeting specific areas with a predetermined amount of pesticides, fertilizers, or any other additives, runoff can be curbed to reduce ground water contamination.

Erosion is another source of water contamination and removes valuable topsoil. Monitoring key areas through PA can prevent many practices such as over irrigation on sloped fields and unnecessary field and crop treatments. In addition, with the capability to track farm equipment using GPS, high traffic areas can be identified and addressed to reduce unnecessary traffic and movement on and around sensitive areas that are prone to erosion.

1.3 Research question and Objectives

Small scale farms rely heavily on the success of their crops as it is generally the only source of income. Because of the limitations of available capital, any potential addition to current operations is a financial risk. In addition to financial risks, new technology brings new challenges that include hardware, software, and the technical capabilities of the user. The uncertainty about new technology and financial risks are factors that keep potential users from considering using.

The research topic for this case study is comparing low and high resolution RS products for use in PA applications for small scale farming. Due to the limited land and resources available with small scale farming, utilizing RS data needs to be as efficient as possible. Resolution differs between RS sensors and sources, and cost is influenced by resolution. This comparison used publicly available Landsat7 ETM+ low resolution data, 30 meters nominal resolution, and efficient NAIP high resolution data, 1 meter nominal resolution, to achieve the following measurable objectives:

- quantify the amount of error between Landsat7 ETM+ and NAIP data through the use of VI and PE analyses
- quantitative comparison of Landsat7 ETM+ vs. NAIP,

The predicted outcome is that there will be a large amount of difference between the two based on the large difference in pixel size, so much so that the low resolution imagery will not provide the optimal results. Small scale farming fields are small and low resolution pixels are large and cannot collect the same level of detail and information compared to their high resolution counterpart.

Alternately, high resolution imagery provides a large amount of data, which could actually be in excess of the amount of needed information. If the larger pixel size can produce results comparable to the high resolution, then the use of low resolution imagery can be considered optimal. Even with this as a possibility, the expected outcome is that the low resolution imagery is not optimal for small scale farming.

The following chapters of this thesis discuss and explain the process that took place to achieve the thesis objectives. Chapter 2 discusses the study site selection process, with details related to the site selection criteria. Chapter 3 provide details on the data selection and methodology used for the vegetation indices extraction, statistical analysis, and values quantification and comparison. Chapter 4 lists the results and chapter 5 presents the conclusions and potential future work.

CHAPTER 2: STUDY AREA

Precision Agriculture's use of imagery provides a data driven view of a specific area. RS imagery provides the spectral vegetation values for a field and after further analysis (such as a vegetation index calculation or false color composite image) a crop health map is derived that allows a farmer to understand the general health their field.

The accuracy of this data depends on several factors, which include the characteristics of the field. Agricultural fields come in various shapes and sizes, terrains, climates, locations, and other characteristics that will affect the RS imagery and resultant data. These variations occur both naturally and manmade, which needs to be taken into account when gathering data. To present the best possible study locations, several factors were selected and included in the site selection process.

Small scale faming exists throughout the country and across a wide variety of land types. To be able to represent small scale farms for this comparison, features and characteristics of small scale farms were used that can be applied to most small farms in one way or another. Study sites were chosen based on location, presence of vegetation, size and shape of the site, and field characteristics. These categories represent real life factors of small farms and topographic elements that challenge the abilities of RS imagery.

2.1 Location

The study area for this comparison consists of agricultural areas within Pittsylvania County; Virginia. Figure 5 gives reference to the location of Pittsylvania

County. The Commonwealth of Virginia grows a wide variety of crops and has a large number of small farms. The 2011 average farm size was 171 acres, which falls under the initial definition of a small scale farm. While the average farm size is 171 acres, the majority of farms within the state fall under 100 acres, with multiple fields per farm.

The 2007 Agricultural Census showed that the majority of acres harvested came from farms averaging less than 100 acres in size. Pittsylvania County is the largest county in Virginia and is comprised of 44% agricultural land (Rephann, Ellis, Rexrode, & Eggleston, 2013). In addition to having an abundant supply of available agricultural land, Virginia also participates in USDA's National Agricultural Imagery Program (NAIP). The NAIP program acquires 'leaf-on' aerial imagery during growing seasons across the United States. NAIP imagery is available to the public and government agencies for use in both agricultural and non-agricultural purposes. Virginia's participation in this program provided key RS data for this comparison as it is both publically available and high resolution.

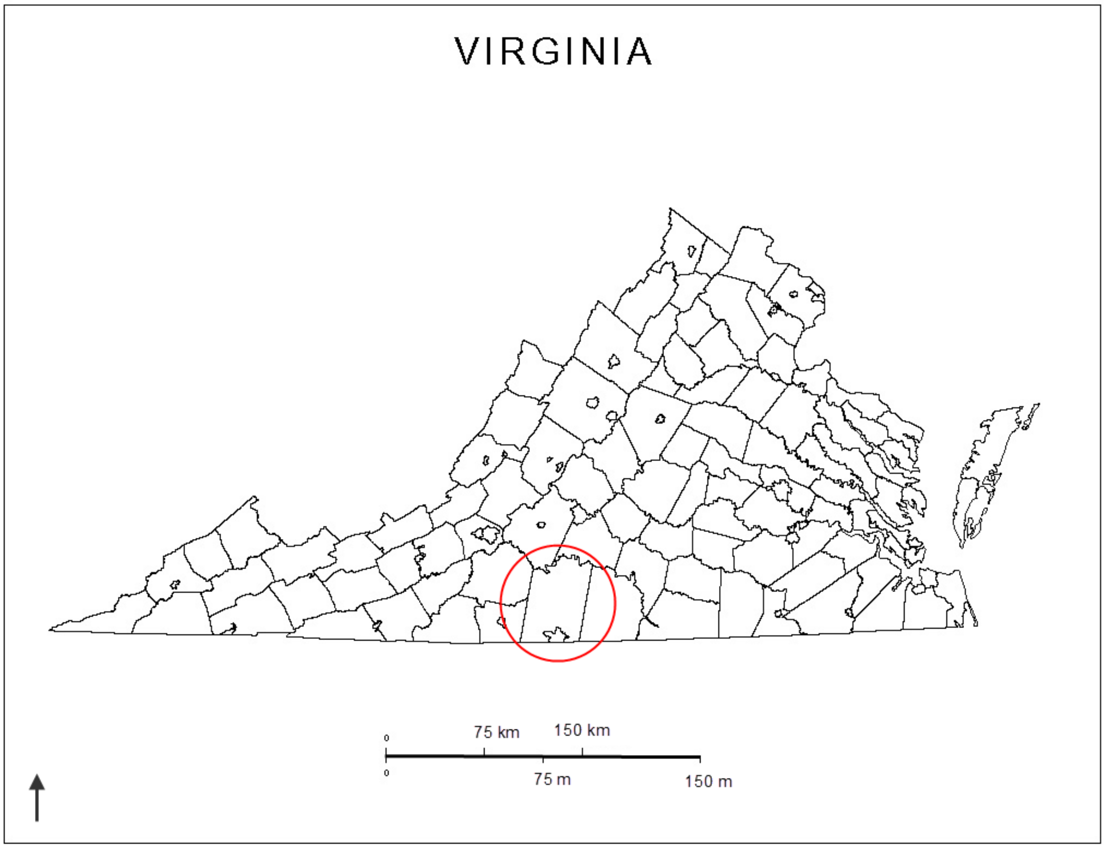

Figure 5. Study Location: Pittsylvania County is located in the South Central portion of the state of Virginia. It is the largest county in Virginia and is 44% agricultural land. The terrain includes hills, low land, and low mountains in the northern portion of the county. Rich soil content and a healthy growing season present optimal conditions for growing a variety of crops and livestock
Source: Yellow Maps, Blank County Maps of Virginia 2014

2.2 Sites Characterization Criteria

2.2..1 Presence of vegetation

Vegetation index analyses were used for the comparison, which required vegetation to be present within the imagery. Due to the wide range of vegetation grown in Pittsylvania County, there was a good chance of having vegetation within the collection areas for each set of imagery. In the case of Pittsylvania County, VA, the collection dates were rather early within the growing season, but despite this, there was usable vegetation within the hay and agricultural grasses category. These particular crops can have earlier harvesting dates, which allowed for the presence of Non-Alfalfa Hay vegetation. This type of vegetation served as a viable agricultural medium for VI analysis. To keep results uniform throughout the study, fields containing the same crops were sought. This was accomplished with the assistance of the USDA's National Agricultural Statistical Service (NASS). NASS collects and updates a national database, the Cropland Data Layer, with agricultural data, specifically crop types. The NASS utilizes the AWiFS sensor aboard the Resourcesat-1 satellite to gain 56m imagery. The data is analyzed in-house with commercial software (Erdas Imagine, ESRI ArcGIS, and Rulequest See5) to develop and process accurate ground cover types (Research and Development Division 2014). With the development of appropriate methodology, including the development of the Common Land Unit (CLU) program as a result, the information produced by this service was used to identify crop types for all fields during the selection process.

2.2.2 Size and shape of site

Small Scale farming is defined by the USDA as having an income less than $250,000 per year (Poole, 2004). A set range of 5 - 150 acres per field has been chosen for this analysis due to the average farm size for the middle income range ($10,000-$99,999/year) of 2011 is around 300 total acres. This accounts for 30% of the number of farms classified as small (the majority fall in the < $10,000/year, at 60%) (National Agricultural Statistics Service, 2012). Even though the majority of farms are well below the 300 sq. acre range, the same results can be used on any size farm by utilizing the information and processes as stated in this comparison.

The topology and terrain of small farms varies depending on a variety of factors, including availability of arable land, water features, irrigation practices, etc. Typical small scale farms utilize multiple fields, comprised of all shapes and sizes to maximize all available land that is owned by the farmer. Pittsylvania County's agricultural land showed no standard or consistent field size or shape throughout the county. To reflect this within the comparison, a range of field sizes and shapes was used. This variation in field size was necessary to test the limits of how the different resolutions represented fields varying in size and shape.

2.2.3 Site Additional Features Characteristics

In addition to selecting sites of different size and shapes, certain features characteristics were chosen to challenge the resolution of the imagery. These included the presence of non-vegetation features such as bodies of water, and erratic boundaries between vegetation features. The reasoning behind these characteristics is centered on the problem of mixed pixels. Mixed pixel is the result of a single pixel representing an "area occupied by more than one ground cover type" (Roosta, Farhudi, & Afifi, 2007). Mixed pixel situations occur in the following situations: 1) the pixels that are located at the edges of large features, like agricultural fields, present a mixed signature between 2 vegetation types or vegetation and non-vegetation ground cover materials; 2) objects that are relatively small, compared to the spatial resolution of the sensor, do contribute to the pixels signature value but cannot be isolated (Roosta et al., 2007). In the low resolution imagery, due to the larger area per pixel coverage, each pixel contains a larger amount of spectral variation.

In a single 30 x 30 meter plot of land (size of Landsat7 ETM+ pixels), there can be part of a water body, vegetation, a road, or bare ground. Each of those produces a different spectral value, which is then averaged out to give a single value for the pixel. With high resolution imagery, this issue becomes less apparent. Within a 1x1 meter pixel area (size of NAIP pixels), the potential differences in ground cover and features are limited. Areas along boundary features, such as roads and tree lines, have fewer mixed pixels which result in more defined boundary edges. An example of this can be found in one of the study areas, Study Site 14, shown in Figure 6. Site 14 has 3 lines of trees that extend out into the field. This pattern is easily distinguished when using high resolution imagery, but when viewed with low resolution imagery, the line of trees is somewhat delineated but not clearly and uniquely identifiable.

In order to challenge the data analysis a variety of features such as tree lines, dirt roads, tranches, ponds, and irregular boundaries were common in all selected sites. Moreover, the wide variety of different field sizes created a very diverse dataset for this study.

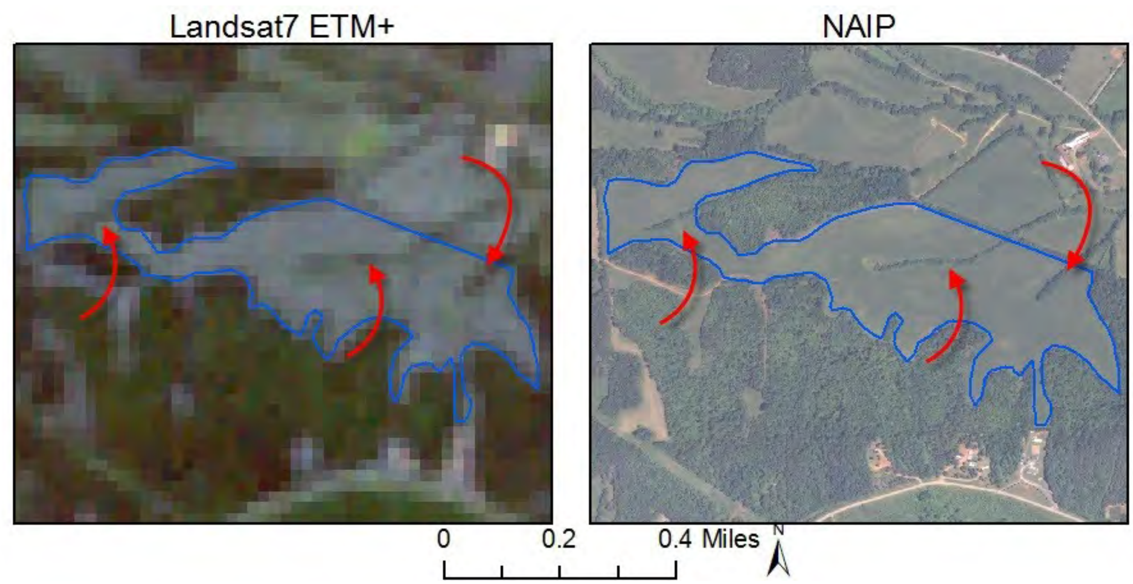

Figure 6. Site Characteristics: Study Site 14 shown utilizing both NAIP (right panel) and Landsat7 ETM+ (left panel) imagery. The red arrows point to three different tree lines that are within the field. Notice how defined the tree line is in the NAIP imagery (right panel). As for Landsat7 ETM+ imagery (left panel), the tree line is drastically exaggerated to the point of being almost unrecognizable. The area affected by mixed pixels is greater in the Landsat7 ETM+ imagery as compared to the NAIP. This larger area contains pixel averages that include unrelated tree vegetation, which skew vegetation reflectance values specific to the non-alfalfa hay crop that is being investigated in this study.

2.2 Sites Selections

After determining the criteria, the site selection process could begin. Both Landsat7 ETM+ and NAIP imagery were utilized during the site selection process. Each site is defined by a site number, group number, size in acres, and the different field characteristics found within it. A total of 14 study sites, ranging in field sizes from 7.5 to 152 acres, were chosen and by relative location separated into 5 groups, as shown in Figure 7. The 14 selected sites and attributes are summarized in Table 1. Footprint examples for Group 5 (sites 10 through 14) are shown in Figure 8 and all remaining site footprints are listed in Appendix A.

Table 2: Study Sites Characteristics

Site#	Group#	Size (Acres)	# of Pixels Landsat7 ETM+	# of Pixels NAIP	Crop Type	Site Characteristics
1	1	110.57	499	436,155	Non-Alfalfa Hay	Rounded boundaries, forested section within field boundary, hilly terrain
2	2	12.72	54	46,374	Non-Alfalfa Hay	Straight boundaries, no presence of foreign objects or vegetation
3	2	71.98	320	273,157	Non-Alfalfa Hay	Irregular boundaries, narrow field sections, outbuilding present and small wooded area
4	3	14.30	65	54,382	Non-Alfalfa Hay	Straight boundaries, no presence of foreign objects or vegetation
5	3	30.56	137	117,965	Non-Alfalfa Hay	Irregular boundaries, dirt road present
6	3	17.33	78	64,407	Non-Alfalfa Hay	Rounded boundaries, narrow field section
7	3	11.29	50	40,957	Non-Alfalfa Hay	Narrow field with barren patch of land within
8	4	33.49	151	128,512	Non-Alfalfa Hay	Irregular shape with a tree line and individual trees throughout
9	4	21.76	97	81,697	Non-Alfalfa Hay	Irregular shaped field with trees and barren sections contained within
10	5	152.35	686	605,657	Non-Alfalfa Hay	Large field with a dirt road, grove of trees and slight terrain variation throughout
11	5	23.42	104	88,032	Non-Alfalfa Hay	Straight boundaries with a narrow section surrounded by trees
12	5	7.5	31	26,173	Non-Alfalfa Hay	Rectangular shaped field with uniform vegetation and slight terrain variation
13	5	23.89	108	92,087	Non-Alfalfa Hay	Rectangular shaped field, a grove of trees, and a pond
14	5	86.61	391	331,107	Non-Alfalfa Hay	Sprawling field with narrow sections and tree lines entering the field

Figure 7. Study Sites on NAIP image. Their locations are contained within the usable NAIP and Landsat7 ETM+ imagery overlapping area (as discussed in section 3.1.2), and have been assigned to 5 Groups. Site details are contained within Table 1 and complete list of site footprints are contained in Appendix A.

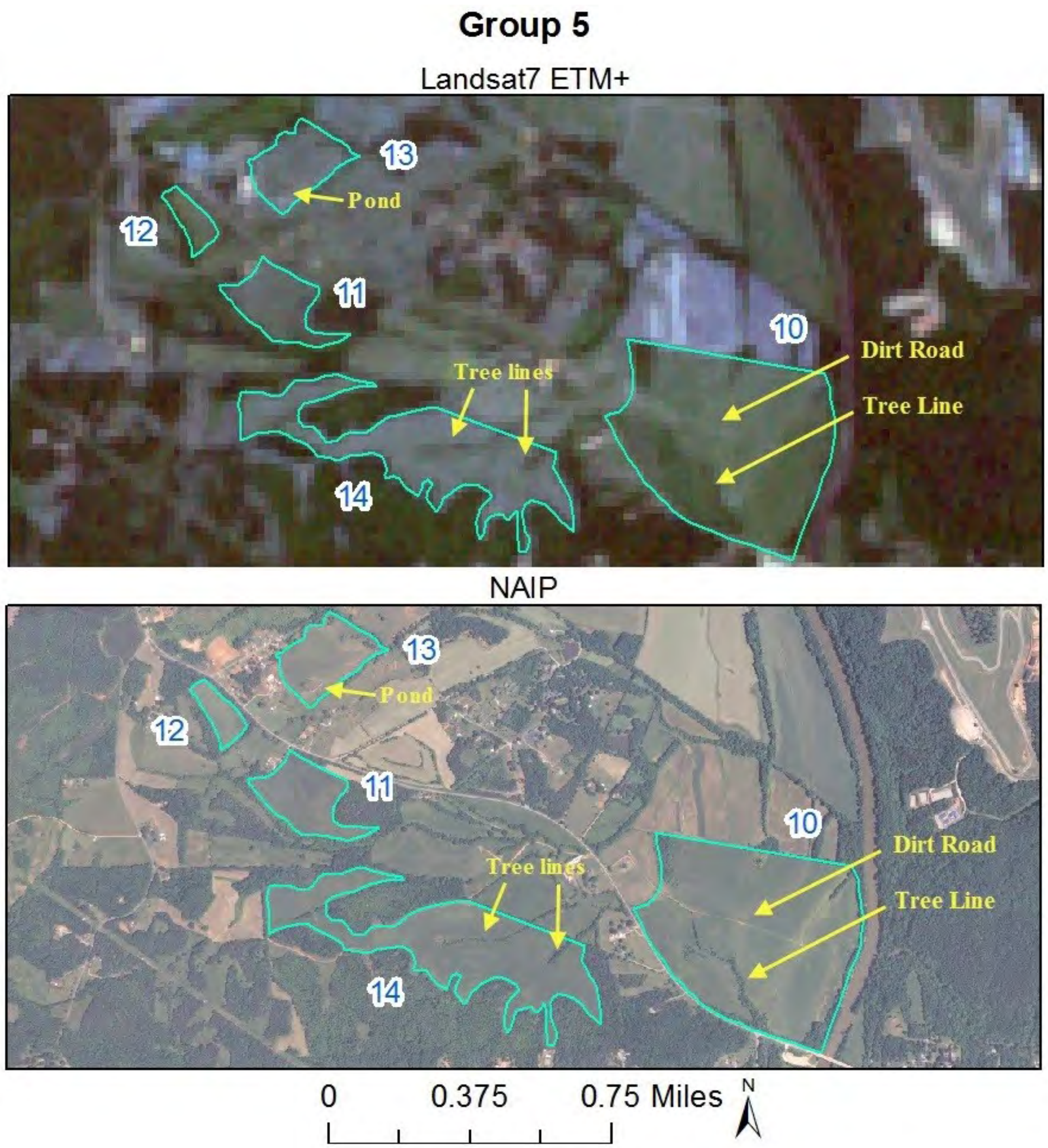

Figure 8. Site Footprints of Group 5. Landsat7 ETM+ (top panel) and NAIP (bottom panel). Group 5 consists of Sites 10 through 14. Several features exist that appear in the imagery, for instance Site 10 contains a dirt road and tree lines casting shadows, site 13 contains a pond, and site 14 contains tree lines casting shadows.

CHAPTER 3: DATA AND METHODOLOGY

This chapter describes in detail the data sources and their selection process, then focus on the selected methodology encompassing the analysis of four vegetation indices, vegetation indices percent error analysis, and values quantification and comparison.

3.1 Data Sources and Selection for Landsat7 ETM+ and NAIP Imagery

The search of available data was conducted with collection dates as close to one another as possible. This was done to reduce the variance between crops due to vegetation maturity. Vegetation at different stages in maturity reflect differently, which would not present identical site data between resolution datasets.

The Landsat7 ETM+ low resolution imagery were publicly available from the USGS's Landsat Archive, through the USGS web based Earth Explorer system (http://earthexplorer.usgs.gov/). The data was identified using the ground coordinates of the study area (Lat: 36.7440, Lon: -79.1704) among the available imagery from the data set L7 ETM+ SLC-off (2003-present).

The NAIP imagery were obtained from the USDA/NRCS imagery program and web portal (http://datagateway.nrcs.usda.gov/) in which a county system ID is used to retrieve county mosaics and DOQQs. The county ID used for the Pittsylvania County, located in the South Central portion of the state of Virginia, is 51143.

The similarity of the Green, Red, and Near Infrared spectral bands of the NAIP data and Landsat ETM+ data (Lillesand and Kiefer 1994; USDA 2008) provide the perfect data sets for this study.

3.1.2 Data selection

3.1.2.1 Landsat7 ETM+ Imagery

Landsat7 ETM+ multispectral data with less than 10% cloud cover factor was used for the comparison. In addition to cloud cover restraints, Landsat7 ETM+ data contains gaps within each scene due to a malfunction on the satellite platform that occurred in 2003. On May 31, 2003, the Scan Line Corrector (SLC), which compensates for the forward motion of Landsat 7, failed. The SLC-off effects are most pronounced along the edge of the scene and gradually diminish toward the center of the scene (Figure 9). The middle of the scene, approximately 22 kilometers wide on a Level 1 (L1G) product, contains very little duplication or data loss, therefore this region of each image is very similar in quality to previous ("SLC-on") Landsat 7 image data. Landsat 7 ETM+ inputs are not gap-filled in the surface reflectance production available through USGS Landsat Archive: L7 ETM+ SLC-off (2003-present). Because of this, the areas chosen using the Landsat7 ETM+ scene were within the unaffected areas as shown in Figure 9. The selected Landsat7 ETM+ imagery was collected on June 9, 2008, and was acquired as L1G Product or Surface Reflectance. In Table 2 are listed the bands characteristics of the acquired Landsat7 ETM+ scene encompassing bands B2 (Green), B3 (Red), and B4 (Near Infrared). Table 2 contains a summary of the Landat7 ETM+ dataset.

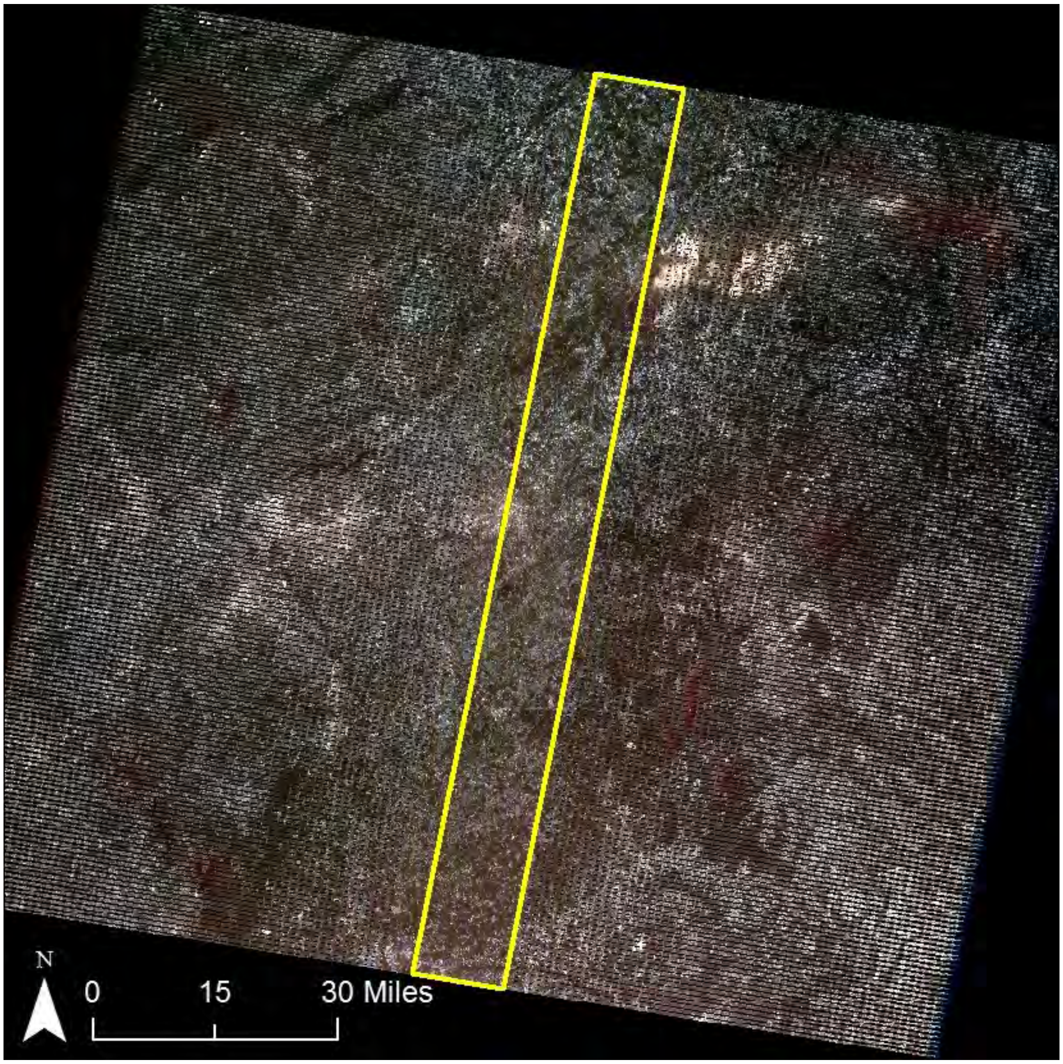

Figure 9. Landsat7 ETM+ scene. The yellow rectangle shown contains the area within the Landsat7 ETM+ scene is unaffected by the data gaps.

Table 3. Landsat7 ETM+ data

Landsat7 ETM+				
# of Bands Collected	B2 (.525-.605 µm) Green	B3 (.63-.690 µm) Red	B4 (.75-.90 µm) NIR	Surface Reflectance
Spatial Resolution	30 meters			
Date of Collection	9 June 2008			
Data Set	LE70160352008161EDC00			

Data Source: USGS Landsat Archive: L7 ETM+ SLC-off (2003-present) 2008

3.1.2.2 NAIP Imagery

The NAIP data for this study was collected in 2008, as it was the only available dataset with 4 bands for Pittsylvania County. NAIP procedures allow states to acquire 3 or 4 band imagery, and with the use of VI the 4 band imagery is required. The acquisition date on May 23, 2008, was the closest available dataset to match the Landsat7 ETM+ dataset. Figure 10 shows the same available data rectangle as seen in Figure 9, which represents overlapping data with Landsat7 ETM+. A summary of the NAIP Surface Reflectance dataset used in this study is listed in Table 3.

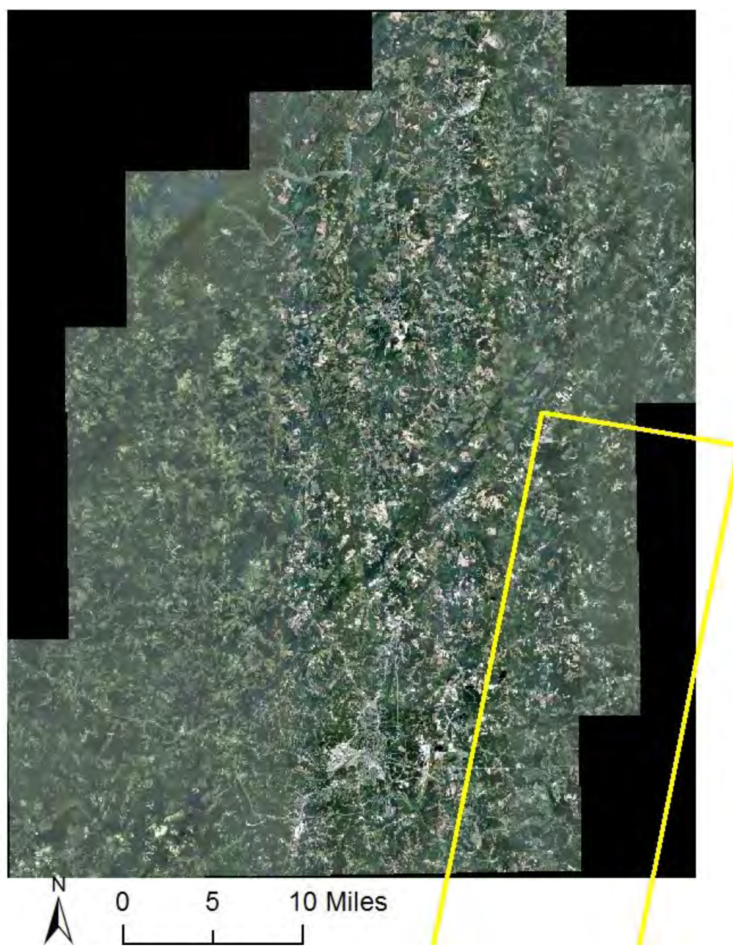

Figure 10. NAIP Scene. The yellow rectangle shown correlates with the available data section of the Landsat7 ETM+ scene. The NAIP scene contains only

Pittsylvania County Virginia, whereas the Landsat7 ETM+ scene contains a larger portion of counties within Virginia and North Carolina.

Table 4. NAIP data

NAIP				
# of Bands Collected	B2 (.480-.640 µm) Green	B3 (.580-.700 µm) Red	B4 (.680-.940 µm) NIR	Surface Reflectance
Spatial Resolution	1 meter			
Date of Collection	23 May 2008			
Data Set	51143_1m2008_6 Pittsylvania			

Data Source: USDA/NRCS NAIP 2008

3.2 Methodology

The methodology used in this study encompass a first phase for data preparation and vegetation indices extraction (Section 3.21, Vegetation Indices Analysis), a second phase of vegetation indices statistical analysis (Section 3.2.2, Percent Error Analysis), and a third phase for data products resolution comparison (Section 3.2.3, Quantifying Values).

The full methodology workflow, shown in Figure 11, was conducted using Model Builder (ESRI, 2014) Image bands were imported into ArcMap to begin the extraction process. Prior to the VI's calculations, statistical analysis, and value quantification processes, the spectral band from both Landsat7 ETM+ and NAIP imagery were extracted for each study site within the study area. This was accomplished by using the Extract by Mask tool in order to reduce the amount of disk space used and increase speed during processing time.

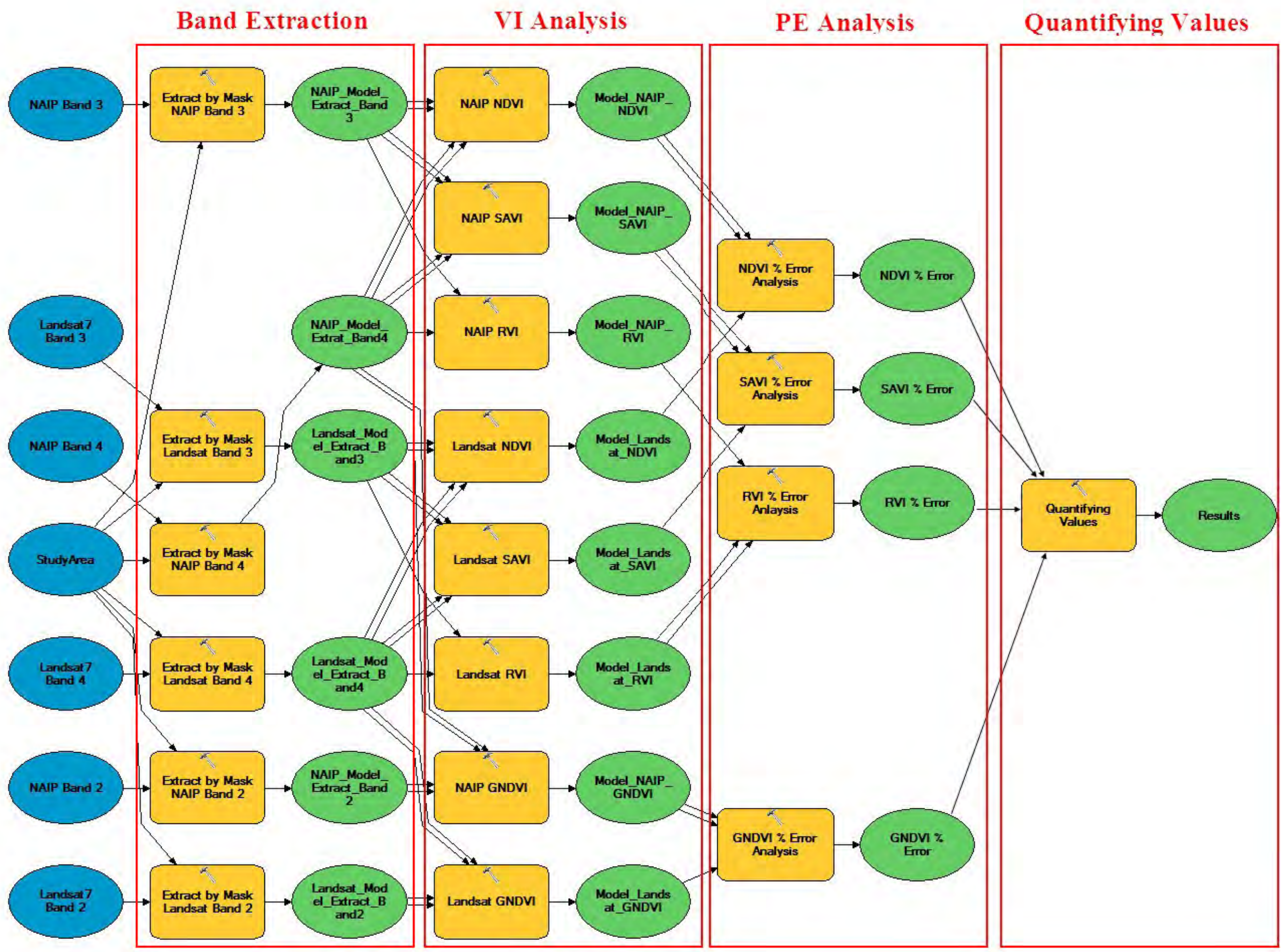

Figure 11. Methodology workflow. This ModelBuilder model illustrates the 4 main processing phases: 1) band extraction, 2) VI Analysis, 3) PE Analysis, and 4) Quantifying Values used to evaluate the effect of image resolution for use in PA applications.

3.2.1 Vegetation Indices Analysis

Four different VI's were utilized to give a variety of available indices used in the vegetation analysis:

1) Ratio Vegetation Index (RVI*)*

RVI = NIR / RED

2) Normalized Difference Vegetation Index (NDVI)

NDVI = (NIR – RED)/(NIR + RED)

3) Green Normalized Difference Vegetation Index (GNDVI)

GNDVI = (NIR - GREEN) / (NIR + GREEN)

4) Soil Adjusted Vegetation Index (SAVI)

SAVI = (NIR – RED)/(NIR + RED + L) x (1 + L)

These equations use spectral values associated with each individual pixel within a spectral band. NAIP's used spectral bands B2 (Green), B3 (Red), and B4 (Near Infrared). Analogously Landsat7 ETM+ used bands were B2 (Green), B3 (Red), and B4 (Near Infrared) spectral bands. Due to the spectral characteristics and interaction of red, near-infrared, and green bands with plants, these bands are used in most vegetation related indices. In addition to spectral band values, the SAVI equation uses a constant variable 'L' to adjust for bare soil. Based on the collection date, type of crop, and visual inspection of the imagery, a constant of 0.25 was used when calculating for SAVI. The 0.25 constant represents high vegetation and limited soil interference. From a visual inspection between both sets of imagery, each site contains a generous covering of vegetation with limited bare soil present.

Each site area was isolated from surrounding areas to reduce VI calculation times, and using the above mentioned equations on each pixel, VI values for both Landsat7 ETM+ and NAIP were calculated. These values were then used to complete the PE analysis.

3.2.2 Percent Error Analysis

To compare the differences between VI values at different resolutions the Percent Error (PE) analysis was used (University of California, Davis 2014). The PE analysis is not commonly used in agricultural purposes and has not been applied for PA applications observed in the literature, however, it is commonly used in chemistry and other sciences, where it involves measuring the difference between a known value (exact value) and an experimental (approximate value) value. The PE equation (5) used in this study measures the percent of error between a known value, exact value in this case assigned to NAIP VI value, and a measured value or approximate value that in this case was assigned to Landsat7 ETM+ VI value:

$$\frac{\textbf{Approximate Value} - \textbf{Exact Value}}{\textbf{Exact Value}} * 100\% \quad (5)$$

where : Exact value = NAIP VI value
Approximate value = Landsat7 ETM+ VI value.

The approximate value was designated as Landsat7 ETM+ values as it is being compared to NAIP and it is the average value of the largest pixel size. Exact Value is NAIP values as it is the value being compared to and is used as a more exact value due to the reduced pixel size. The equation was performed for each NAIP pixel, and results were collected and grouped into percentage categories. The resulting calculations give the amount of error present between the two resolutions. Because a single low resolution pixel represents a 30m x 30m land area within that pixel, there are 900 high resolution pixels for the same size area, therefore there will likely be a given percentage of error between the two. The percentage error calculation is two-fold as its output can give the percentage of value differences that are: 1) over-estimated, where value of the low resolution pixel is above what of the high resolution pixel value; 2) under-estimated, where value of the low resolution pixel value is lower than the high resolution pixel.

3.2.3 Quantifying Values

The PE analysis is performed on each site's VI values and the results are then categorized. Three categories were established based on the amount of error present. The categories are Grossly Over-estimated (+/- 100%), Debatable (between +/-100 & +/- 25%), and Acceptable (between +/- 25%). Each category's percent error range was based on the amount of error, compared to the amount of change between VI values.

The Acceptable category contains the percentage of pixels where the values fall closely together, with a +/- 25% error range. This range represents a minimal change in value. The Debatable category is separated into positive and negative percentages, which represent over and under estimation of values. This particular range is considered debatable, as the values have more than the accepted amount of error, but could potentially rest within an acceptable range of error if so decided by the user. The Grossly Overestimated category contains the percent of error +/- 100%, which is a significant difference between values.

The results of the PE analysis provided a basis for comparison, as it defined a measurable amount of error present. The greater the amount of error, the greater the difference between VI values, which translates to incorrect VI representations for the ground within that specific pixel. This applies directly to the use of RS data in PA, where monitoring applications, resource allocation, or yield estimation rely on accurate ground information. The greater the error, the more likely the resulting PA practices will not produce the intended results, such as incorrect moisture monitoring results leading to either over-watering or withholding irrigation. These actions would be detrimental to the crops and negate the intended use of RS and PA.

CHAPTER 4: RESULTS

The results of both the VI analysis and PE analysis gave two different viewpoints for imagery comparison. The VI analysis successfully calculated VI values for each field, allowing for the PE analysis to measure any differences between resolutions. The results are illustrated using the NDVI values due to their popularity in the agricultural literature, however, all VI's values are reported in Appendix B and C.

The results of the sites from Group 5 contain the largest number of fields, largest range of field size, and largest amount of site characteristics available, therefore are chosen as representative example of the general results. The remaining results obtained from Group 1, 2, 3 and 4 are listed in Appendices B and C.

The PE analysis results provided a statistical look at the differences between resolutions. As expected, there was a large amount of error present between the two resolutions. This error was present for each VI analysis with the exception of the RVI outputs. For this particular VI, the PE results were opposite of what was expected. PE values were calculated as within the Acceptable category for every field, which was drastically different than the other site PE results. Possible reasons for this to occur is that the RVI formula is not normalized and therefore the results would not conform to the rest of the VIs results.

4.1 Vegetation Indices Calculations

As mentioned in the site selection section, fields were chosen to include various characteristics and features to test the abilities of the RS imagery. Both the Landsat7

ETM+ and NAIP imagery showed these differences, but with different degrees of details. Results varied with each VI analysis due to the different spectral bands used in the VI formulas, therefore different reflectance response are at times emphasized and others subdued.

The NDVI values for the sites in Group 5 are shown in Figure 12. and 13. In figure 12 are shown the low resolution Landsat 7 ETM+ imagery (panel A) and NDVI (panel B), while figure 13 show the NAIP high resolution imagery (panels C) and NDVI (panel D). Figure 14 and 15 show the VI results on sites 10 through 14, for the Landsat7 ETM+ and NAIP imagery respectively. Looking at Group 5 for each resolution, the VI results do follow similar patterns and highlights the same general areas for vegetation and non-vegetation areas.

The greater differences are observable when comparing resolutions, not just between the VI results. For example Site 11, Figures 16 and 17, shows a substantial difference with regards to VI values between the low and high resolutions imagery. The difference suggests a great effect due to mixed pixels in the NDVI product form the Landsat 7 ETM+ imagery, which is unable to depict the high resolution features observable in the NADVI products derived from the NAIP imagery. Additionally, on a pixel level, PE analysis adds to the vast differences in VI values. The remaining VI results for the other sites and relative descriptions can be found in Appendix B.

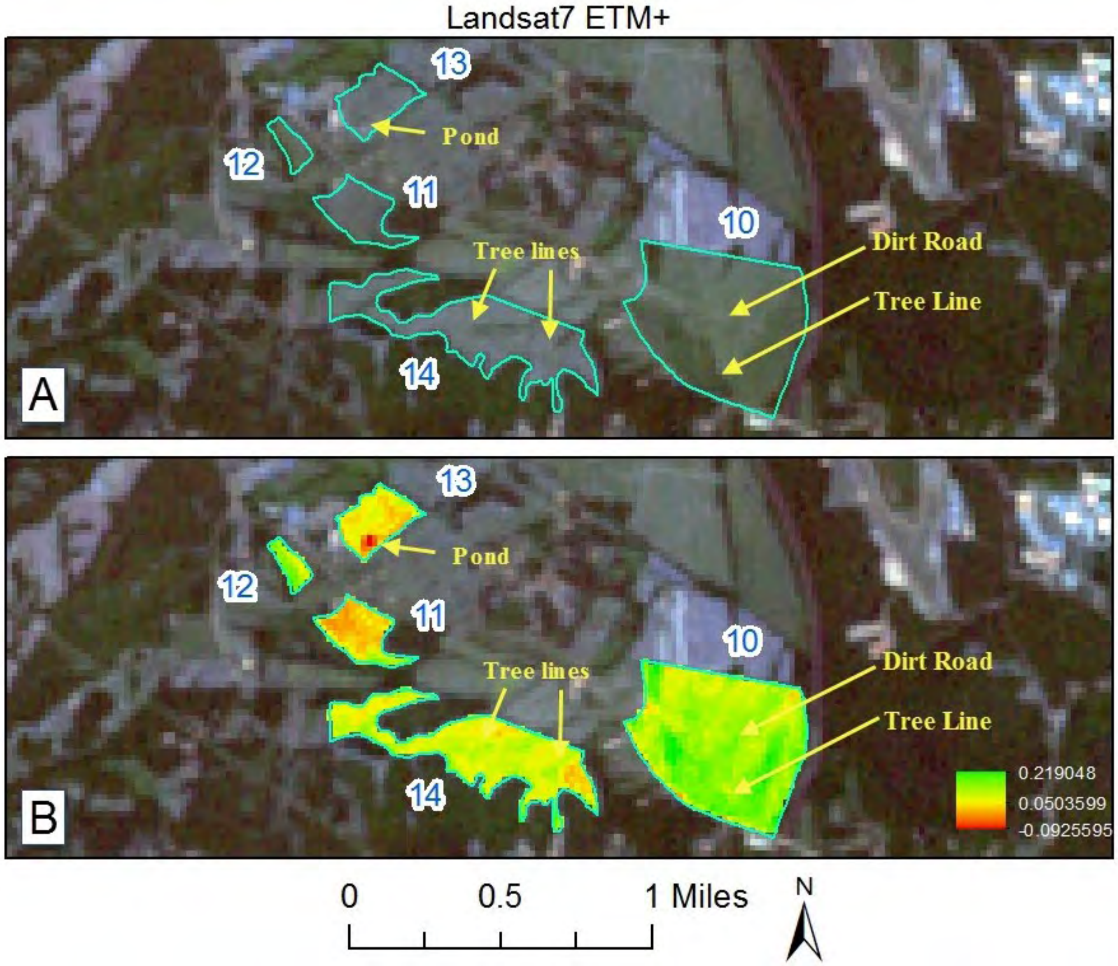

Figure 12. Group 5: low resolution Landsat7 ETM+ imagery (panel A) and NDVI (panel B). The Landsat7 ETM+ imagery (panel B) does outline similar features, however, they are not as well defined and are not outlined as well through the NDVI analysis.

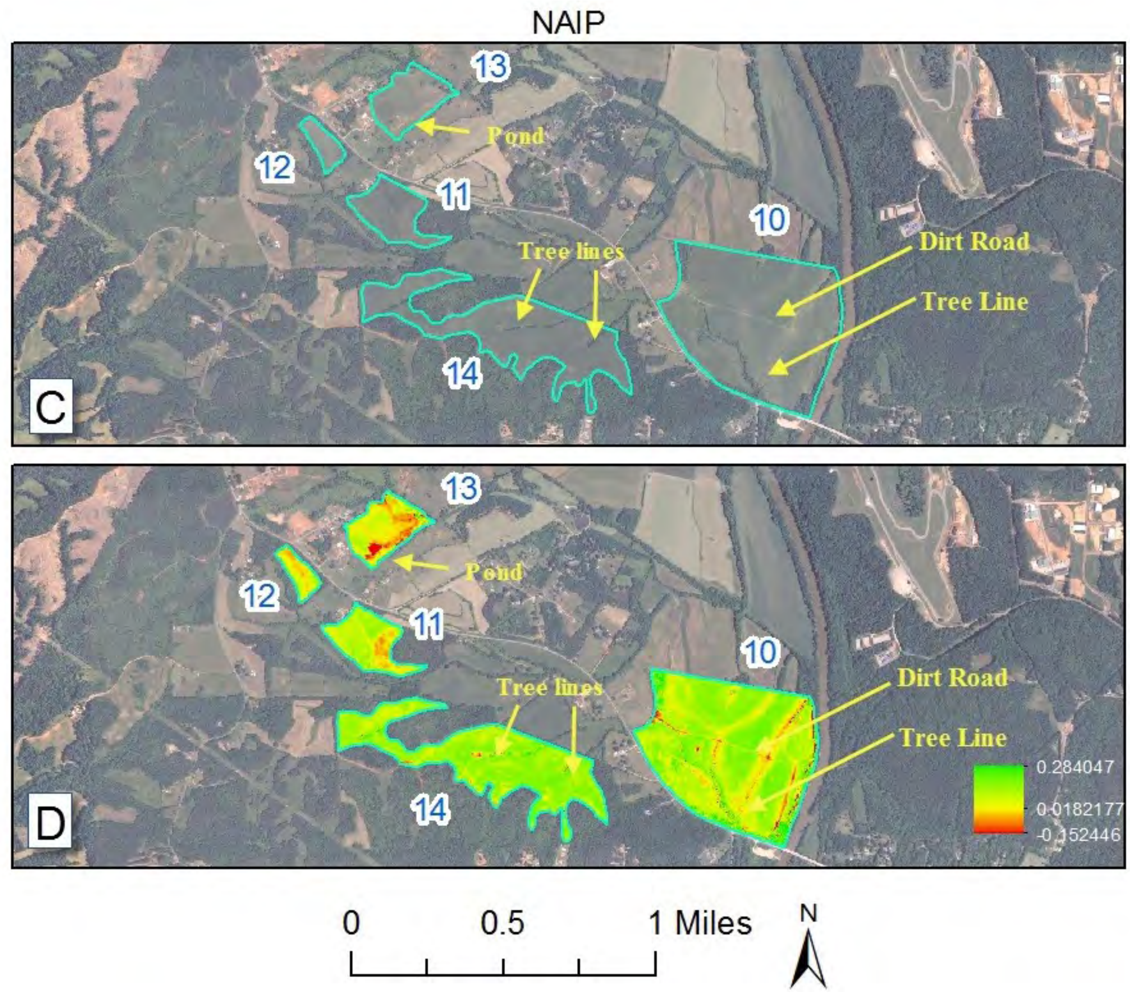

Figure 13. Group 5: high resolution NAIP (panel C) and NDVI (panel D). There are obvious differences between the VI's products due to the different resolutions. The NAIP NDVI analysis (panel D) shows more detail and outlines the such as a dirt road and tree lines casting shadows (site 10), site 13 contains a pond, and site 14 contains tree lines casting shadows.

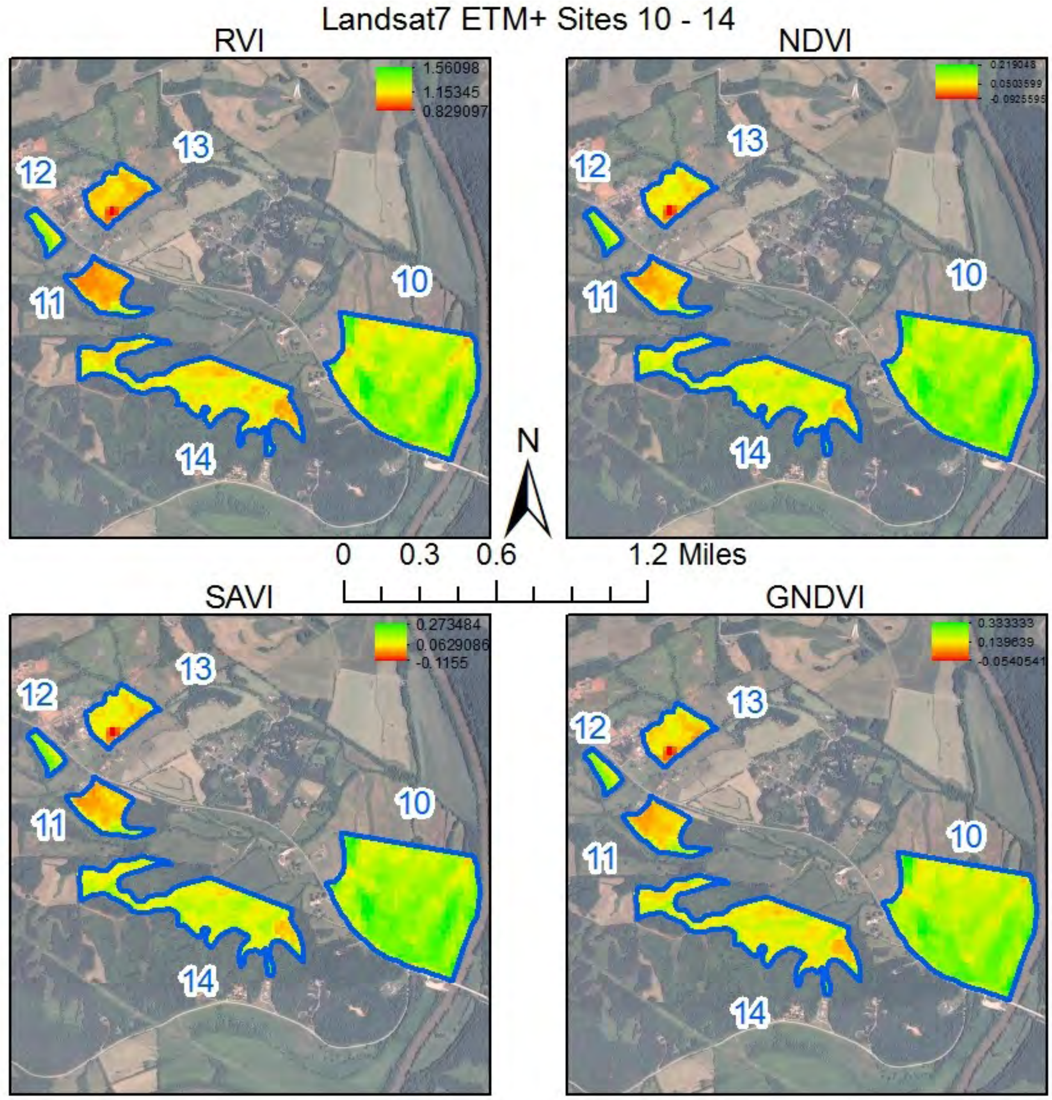

Figure 14. Group 5 Landsat7 ETM+ imagery VI analyses. VI values are overlying NAIP base imagery for clarity. Values for each VI vary for each field, but follow similar trends for vegetative areas and low vegetative areas. Site 13 contains a large red spot, which is a pond. Each VI identifies it, but the effects of mixed pixel averaging of surrounding ground values creates a disproportionate size and shape of the pond.

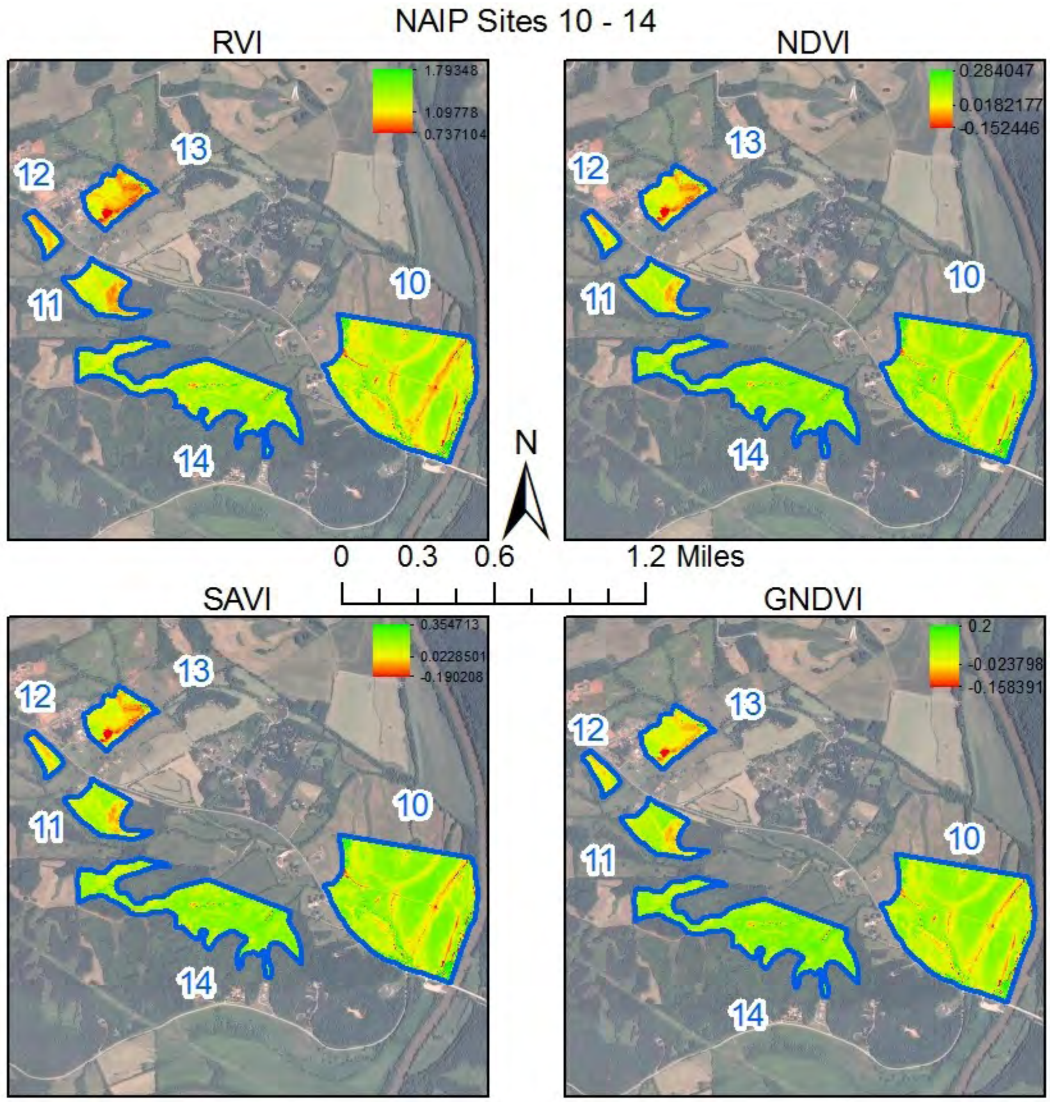

Figure 15. Group 5 NAIP imagery VI analyses. High resolution analysis reduces the impact of mixed pixels. Comparing Site 13, from Figure 14, same the pond is more defined and the effect of surrounding areas reduced. Additionally, distinct lines of low vegetation appear in Site 10, which are not clearly defined in the low resolution imagery (Figure 14).

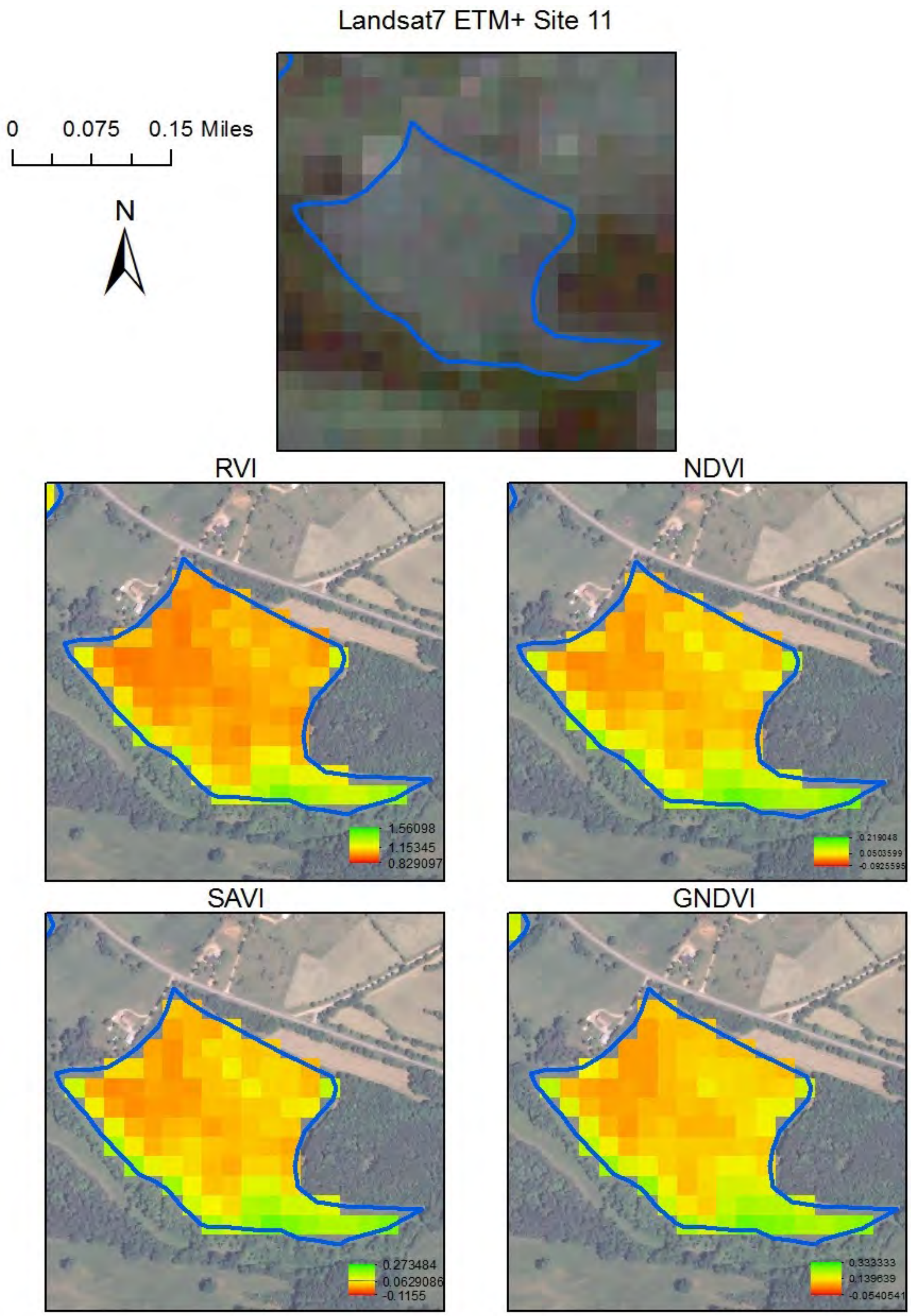

Figure 16. Site 11: VI products from Landsat7 ETM+. Similar results are observable among VI's values (overlying on NAIP base imagery for clarity). Pixels are noticeably larger and effect of mixed pixels occur, resulting in the inability to isolated higher resolution features visible in the NAIP results (Figure 17).

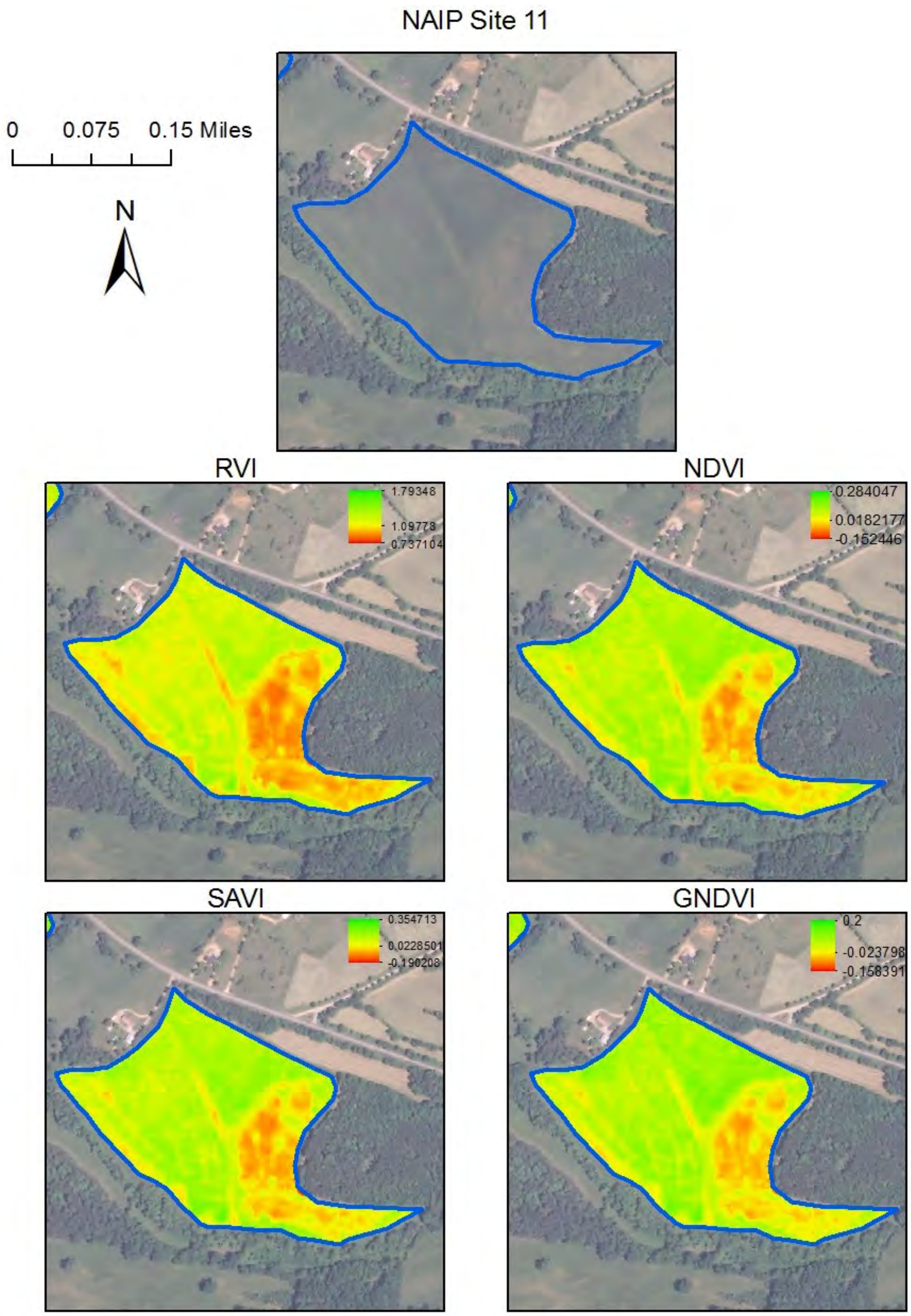

Figure 17. Site 11: VI products from NAIP. Similar results are observable. A large amount of difference is though present when comparing VI products from NAIP and Landsat7 ETM+ (Figure 16), in particular most of the low value vegetative areas are singled out within the eastern part of the field in the NAIP imagery.

4.2 Percent Error Results

The PE analysis results for the NDVI values, shown in Table 5, are broken into three different percentage categories: Grossly Overestimated, Debatable, and Acceptable. NDVI values for each site is represented in the table. NDVI values and the results from the remaining VI values are located in Appendix C. Referring back to Site 11, the large amount of visual difference equated to only 10% of the pixels (8,803 pixels) being within the Acceptable range, which represents a very low amount. The remaining 90% was found split between the Debatable and Grossly Overestimated categories.

Table 5. NDVI Percent Error Results

NDVI										
Site #	Grossly Overestimated				Debatable				Acceptable	
	Below -100%		Above 100%		Between -25% and -100%		Between 25% and 100%		Between -25% and 25%	
	PE	# of Pixels	PE	# of Pixels	PE	# of Pixels	PE	# of Pixels	PE	# of Pixels
1	14%	61062	12%	52339	45%	196270	10%	43616	19%	82869
2	25%	11594	10%	4637	49%	22723	5%	2319	11%	5101
3	51%	138713	20%	56384	20%	55019	3%	9653	6%	17459
4	62%	33717	6%	3263	18%	9789	9%	4894	5%	2719
5	84%	99091	2%	2359	10%	11797	1%	1180	3%	3539
6	75%	48305	1%	644	18%	11593	1%	644	5%	3220
7	3%	1229	41%	16792	8%	3277	36%	14745	12%	4915
8	45%	57830	1%	1285	52%	66826	1%	1285	1%	1285
9	24%	19607	1%	817	69%	56371	1%	817	5%	4085
10	7%	42396	24%	145358	8%	48453	29%	175641	32%	193810
11	30%	26410	13%	11444	42%	36973	5%	4402	10%	8803
12	24%	6282	62%	16227	1%	262	5%	1309	8%	2094
13	2%	1842	1%	921	5%	4604	12%	11050	80%	73670
14	2%	6622	3%	9933	51%	168865	7%	23177	37%	122510

In reference to the sites in Group 5, Table 6 contains the results for all the VI calculations. With the exceptions of RVI (which will be discussed later in Chapter 5) and

Site 13, all remaining VI results fall in the low percentages of Acceptable. This trend extends throughout the rest of the sites, with remaining amounts of Debatable versus Gross Overestimation varying.

Table 6: Group 5 PE results for all VI values

Site Info		Grossly Overestimated				Debatable				Acceptable	
		Below -100%		Above 100%		Between -25% and -100%		Between 25% and 100%		Between -25% and 25%	
Site #	# of Pixels	PE	# of Pixels	PE	# of Pixels	PE	# of Pixels	PE	# of Pixels	PE	# of Pixels
RVI											
10	605,657	0%	0	0%	0	<1%	595	9%	54509	91%	551148
11	88,032	0%	0	<1%	2	0%	0	2%	1761	97%	85391
12	26,173	0%	0	0%	0	0%	0	37%	9684	63%	16489
13	92,087	0%	0	2%	1842	<1%	169	6%	5525	91%	83799
14	331,107	0%	0	<1%	2	<1%	8	1%	3311	98%	324485
NDVI											
10	605,657	7%	42396	24%	145358	8%	48453	29%	175641	32%	193810
11	88,032	30%	26410	13%	11444	42%	36973	5%	4402	10%	8803
12	26,173	24%	6282	62%	16227	1%	262	5%	1309	8%	2094
13	92,087	2%	1842	1%	921	5%	4604	12%	11050	80%	73670
14	331,107	2%	6622	3%	9933	51%	168865	7%	23177	37%	122510
GNDVI											
10	605,657	23%	139301	74%	448186	0%	0	1%	6057	1%	6057
11	88,032	34%	29931	62%	54580	0%	0	2%	1761	0%	0
12	26,173	74%	19368	26%	6805	0%	0	0%	0	0%	0
13	92,087	64%	58936	32%	29468	1%	921	1%	921	1%	921
14	331,107	5%	16555	90%	297996	0%	0	4%	13244	<1%	11
SAVI											
10	605,657	6%	36339	25%	151414	8%	48453	29%	175641	32%	193810
11	88,032	34%	29931	13%	11444	43%	37854	5%	4402	5%	4402
12	26,173	24%	6282	63%	16489	0%	0	6%	1570	7%	1832
13	92,087	34%	31310	31%	28547	7%	6446	13%	11971	15%	13813
14	331,107	2%	6622	3%	9933	51%	168865	7%	23177	37%	122510

4.3 Assessment of Resolution Differences

The Percent Error analysis produced some very interesting results. The expected outcome was that there would be a high level of error between resolutions, which was due to the large pixel size and averaging of reflectance values within Landsat7 ETM+ pixels. A single Landsat7 ETM+ pixel value was compared to the 900 NAIP pixels contained within, and a single non-vegetative feature would produce many low or negative NAIP pixel values, which would differ drastically to the corresponding averaged Landsat7 ETM+ pixel value.

Because of the potential for difference between Landsat7 ETM+ and NAIP pixel values, there was a chance that the percentage would be greater than 100%. This happens when the approximate value (Landsat7 ETM+) is far greater than the known or expected value (NAIP). An example of this is found in Figure 18. The Landsat7 ETM+ pixel #213's NDVI value is 0.011 and the NAIP pixel # 188184 NDVI value is -0.077. Those values used in the PE formula result in a percent error of -114.669, which is greater than the +/- 100% mark.

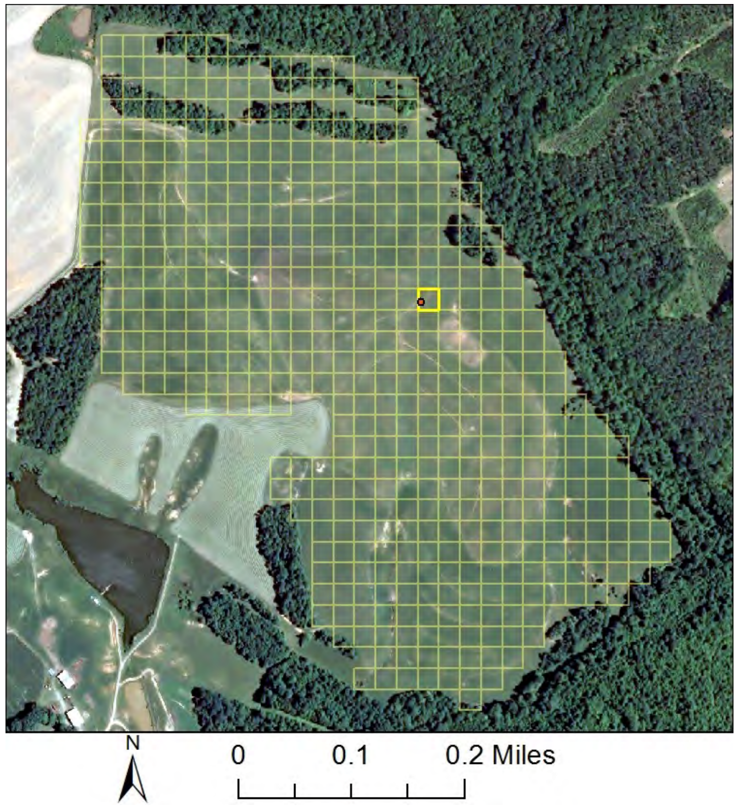

Figure 18. Site 1 PE example. The yellow square represents the Landsat7 ETM+ pixel and the red dot represents the location of the NAIP pixel. With their values used in the PE formula, the resulting PE is outside the +/- 100% mark, which falls within the Gross Overestimation category.

For this comparison, examples of the gross over or under estimation values can be attributed to VI values of shadows from vegetation found in high resolution data and not low resolution, or non-vegetation feature VI values in high resolution pixels that averaged out in low resolution pixels, and non-vegetation features within the low resolution pixel that are not being recognized due to pixel size vs. feature size. Site 10 contains site characteristics that fit the description above and causing PE of +/- 100%. Figure 19 shows a color representation of NDVI PE values, where the areas containing +/- 100% error follow the dirt road, tree lines with shadows, and changes in terrain.

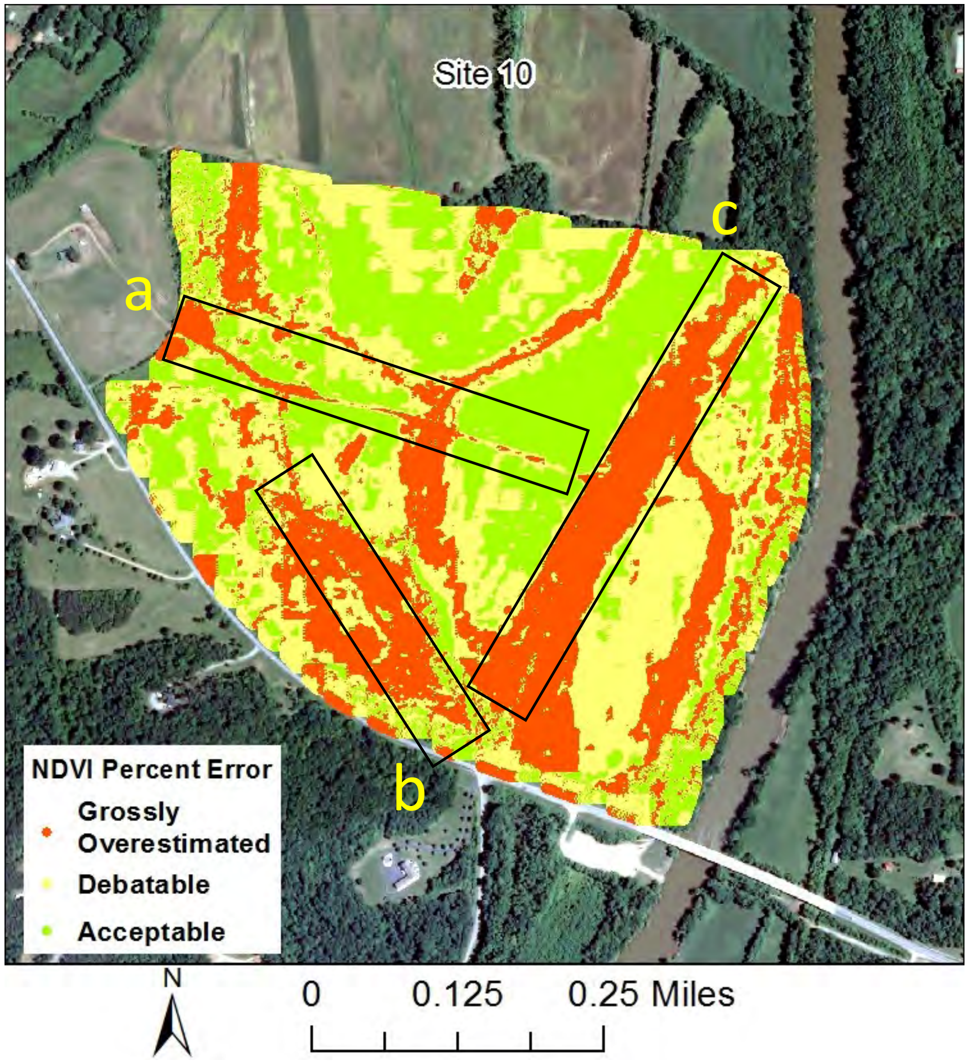

Figure 19. Site 10 PE. Dark red represents +/- 100% error pixels, which follow the dirt road (a) and surround the tree lines (b). One other area of interest is (c), where a change in terrain occurs and showing with a significant amount of error. This area (c) was not originally identified as significant site characteristic for testing resolution abilities.

In Table 6, the PE results for Group 5 show large amount of differences present among the various sites. To put the data into perspective, NDVI PE values for sites 10 and 13 will be used to explain the results. Table 7 contains NDVI PE results for sites 10 and 13, while remaining results can be found in Appendix C.

Table 7: Sites 10 & 13 NDVI PE Results

Site #	Grossly Overestimated	Debatable	Acceptable
10	31%	37%	32%
13	3%	7%	80%

In site 10 there is 31% of pixels falling within the Grossly Overestimated category, 37% of pixels falling within the Debatable category, and 32% of pixels falling within the Acceptable category. The overall results an even distribution across categories. Looking at it from a usability standpoint, straight from the data, only 32% of the data would result in correct ground values and conditions. Additional research and decisions on acceptable levels from the Debatable category could bolster this amount, but without that, there is too much error to safely rely on low resolution data to produce acceptable results.

In site 13 the NDVI results are different than that of the other sites. In contrast to the expected results, Site 13 produced high amounts of Acceptable error present. Site 13 resulted in only 3% of pixels falling within the Grossly Overestimated category, 17% in the Debatable category, and 80% in the Acceptable category. Even grouping Grossly Overestimated and Debatable together, the total amount of Acceptable error is significant enough to suggest that low resolution imagery, using NDVI calculations will provide correct ground values with an 80% accuracy. Although this is a significant amount, the remaining fields surrounding site 13 did not calculate this amount of Acceptable error, and it would not be efficient to utilize low resolution for a single field, where the surrounding fields need higher resolution imagery to be assessed.

As far as field size is concerned, there is a significant trend of larger fields containing more Acceptable percentages of Error than their smaller counterpart. Table 8 shows the average Acceptable PE for the larger 5 sites, medium 4 sites, and smaller 5 sites. Both RVI and SAVI show that larger sites correspond a higher number of pixels with Acceptable Error. RVI results have the larger averages in both the large and small sites, and respectively higher than the medium size fields. NDVI shows close percentages between the large and medium sites, with the lowest average in smaller sites. GNDVI has opposite results, with the larger fields averaging the lowest amount of Acceptable Error percentages.

Table 8: Average PE by Size

Average Acceptable PE			
	Large Size 5 Sites	Medium Size 4 Sites	Small Size 5 Sites
Avg. Landsat7 ETM+ Pixels	409	111	39
Avg. NAIP Pixels	354,918	90,622	49,917
RVI	88.20%	61.50%	74.60%
NDNI	19%	24.50%	8.50%
GNDVI	5%	11.50%	9.20%
SAVI	19%	10.25%	8%

CHAPTER 5: CONCLUSIONS AND FUTURE WORK

5.1 Conclusions

The results from the VI analysis of low resolution imagery did not provide results comparable to the high resolution imagery. VI analysis on the low resolution imagery resulted in a lower detail in features and characteristic delineation. Features within the low resolution imagery were identifiable but with less detail due to mixed pixels, therefore resulting in an exaggerated feature footprint, such as the tree lines and dirt roads as seen in Sites 10 and 14, which was highlighted in Figure 8, 12 and 13. As expected, the high resolution data provided a more detailed visual representation of the study sites, including all site features and characteristics.

Results from the Percent Error Analysis showed a great difference between VI values with the exception of RVI. These results showed that the size of the pixel affects the accuracy of data values. Landsat7 ETM+'s large pixel size averaged out the surrounding areas and fail to retain amount of usable data which is instead captured in the NAIP data. Even though there were amounts of acceptable error between the two resolutions, the majority of the error was found within the Grossly Overestimated and Debatable categories.

Examples used in section 4.3 examined the results of two sites, 10 and 13. The comparative results identified site 10 as the area with the higher number of pixels outside the Acceptable category. In contrast, site 13 produced results that went against the expected outcome, showing 80% in the Acceptable category. A similar results was found also for site 3 (Appendix C) also showing a higher amount of Acceptable error.

Site size was also a contributing factor in amount of Acceptable error. The larger the field, the greater the chance of having more pixels with Acceptable amounts of PE. The cause of this could be attributed to the same challenges overall; pixel size and mixed pixels, but also the limited amount of land and pixel field boundary overlapping. Smaller boundaries around fields and large pixels have the greater chance to include neighboring areas within each pixel averaging.

There was one exception to the VI results, where the entire set of RVI values resulted in almost 100% of pixels showing percentages of error within the Acceptable category. A potential reason as to why this occurred is that the output values for RVI were outside the normal range of outputs for normalized VI formulas. Fluctuations between RVI values between resolutions were nominal, and the largest difference between resolution VI results were found in the other VI formulas.

Overall, the results favored the expected outcome showing a greater difference between NAIP high resolution VI values compare to the Landsat7 ETM+ low resolution VI values. With the small nature of land applications used in small scale farming, the larger pixel size would retain less information to be of use compared to the high resolution imagery. If there was a higher percentage of acceptable error, +/- 25% was accepted here, then the results could be more in favor of the low resolution.

This study addressed issues related to the assessment of data resolution in PA applications, however, other factors could affect the use of different RS data such as cost, return on investment (ROI) on use of RS to manual site methods in distributing fertilizer or pesticide. In the next session, some considerations are provided for future work for development in the use of affordable RS imagery in PA applications.

5.2 Future Work

Precision Agriculture is not a brand new topic, but it is one that has seen an increase in research and activity in the past 20 years. With RS imagery, GIS integration, highly advanced computers, and a vast array of monitoring hardware steadily advancing the room for continued research is wide open. The basis of this comparison is to limit the financial strain on small scale farmers when adopting new technology, particularly RS imagery to use in PA applications. Cost is a main factor, and imagery resolution influences the cost. Any additional or future work associated with this comparison would include research in cost effective ways to implement RS or other advanced PA practices and policies.

An example of this research would be an in-depth look at the financial return on investment (ROI) applications of RS imagery. Begin a case study comparing the use of RS to manual site methods in distributing fertilizer or pesticide. The comparison would look at the time/cost data of the amount of labor used (man hours with relative pay), and a fertilizer/pesticide used, determining a time frame for a ROI of utilizing RS for a single specific use. This could then branch off to other uses as necessary.

Branching off from the ROI research, additional work including researching cost effective methods of implementing RS imagery. NAIP imagery is valuable, but imagery containing the NiR band is not available for every mapped location. Nontraditional sensor platforms would be a popular subject as drones or UAVs have become a household name in society today. Moving away from space-born and high altitude platforms could potentially reduce some costs associated with sensor tasking, flight scheduling, and weather related issues. Depending on the source, on-demand flights could be possible after weather related events, during specific growth timelines, or land surveying. Work already being completed by schools such a Utah State University's AggieAir UAV system (http://aggieair.usu.edu/) could be expanded with additional knowledge of resolution limitations for small scale farming applications.

Additionally, improving upon the data available would be beneficial, as some might be limited due to the intrinsic resolution of the data. This could be explored using Data Fusion, which refers to the combination of data from different sensors and resolutions to improve imagery interpretability (Ranchin, 2014). One of the advantages of data fusion is the capability to improve spatial resolution and thus increase the ability to identify features of interest. Despite the low performance of Landsat 7 ETM+ low resolution imagery in this study, data fusion could possibly be used as a combination of Landsat 7 ETM+ and LiDAR data (Cartus, 2012) to increase the interpretability and possibly discern the amounts of acceptable error, or simply use it to render the data into a useful mapping product for use in a different aspect of PA.

REFERENCES

ArcGIS Online, 2014. NAIP 2012 NDVI, California. http://www.arcgis.com/home/webmap/viewer.html?useExisting=1&layers=133cd34d24864f5099ca0dae7d6b628e (last accessed June9, 2014)

Birth, G.S., and G. McVey, 1968. Measuring the color of growing turf with a reflectance spectroradiometer, Agronomy Journal, 60:640-643.

Cartus, O., J. Kellndorfer, M. Rombach, and W. Walker. 2012. Mapping Canopy Height and Growing Stock Volume Using Airborne Lidar, ALOS PALSAR, and Landsat ETM+. *Remote Sensing* 4:3320.

Casady, W. W., and H. L. Palm. 2002. Precision Agriculture: Remote Sensing and Ground Truthing. *MU Guide: Environmental Quality* EQ 435:.

Department of Ocean Earth and Atmospheric Sciences, ODU. Spectral Vegetation Indices (SVIs). 2003 Available from http://www.ccpo.odu.edu/~lizsmith/SEES/veget/class/Chap_4/4_5.htm (last accessed 05/10 2013).

Diekmann, F., and M. T. Batte. 2010. 2010 Ohio Farming Practices Survey: Adoption and Use of Precision Farming Technology in Ohio. *Ohio State University Extension, Ohio Agricultural Research and Development Center*.

ESRI. 2014. ArcGIS Desktop.

Exelis. Vegetation Analysis: Using Vegetation Indices in ENVI. 2013 Available from http://www.exelisvis.com/Learn/WhitepapersDetail/TabId/802/ArtMID/2627/ArticleID/13742/Vegetation-Analysis-Using-Vegetation-Indices-in-ENVI.aspx (last accessed 12/10 2013).

Huete, A.R., 1988. A Soil-Adjusted Vegetation Index (SAVI), Remote Sensing of Environment, 25(3): 295-309.

Hunt, E. R., W. Hively, S. Fujikawa, M. Tranchitella, T. Ng, W. Raszula, D. Yoel, C. Daugherty, and G. McCarty. 2007. Remote Sensing of Leaf Area Index from Unmanned Airborne Vehicles (UAV's). Society for Range Management Meeting Proceedings.

Jensen, J. R. 1996. *Remote Sensing of the Environment: An Earth Resource Perspective.*Prentis Hall.

Kahabka, J., A. E. Staehr, J. Hanchar, and W. A. Knoblaunch. 2000. Precision Agriculture Technology: New York State's adoption, adaption, and future. *What's Cropping Up* 10 No.5:.

Liaghat, S. 2010. A Review: The Role of Remote Sensing in Precision Agriculture. - *American Journal of Agricultural and Biological Science*- 50+.

Lillesand, Thomas M., and Ralph W Kiefer. 1994. Remote sensing and image interpretation. New York, NY: John Wiley and Sons, Inc.

McLoud, P. R., and R. Gronwald. 2007. *Precision Agriculture: NRCS Support for Emerging Technologies.* East National Technology Support Center: NRCS, Report Number, Agronomy Technical Note No. 1

NASA Earth Observatory. Measuring Vegetation (NDVI &EVI). Available from http://earthobservatory.nasa.gov/Features/MeasuringVegetation/measuring_vegetation_2.php (last accessed 12/12 2013).

National Agricultural Statistics Service. 2012. *Farms, Land in Farms, and Livestock Operations 2011 Summary.* USDA, Report Number, 1930-7128.

Neblette, C. 1927. Aerial Photography for Study of Plant Disease. *Photo Era Magazine* 58:346.

Nowatzki, J., R. Andres, and K. Kyllo. 2004. *Agricultural Remote Sensing Basics.* North Dakota State University: NDSU Extension Service, Report Number, AE-1262.

Poole, T. E. 2004. *Operating a Profitable Small Farm.* University of Maryland:.

Qi, J., A. R. Huete, Y. H. Kerr, and S. Sorooshian. 1994. A Modified Soil Adjusted Vegetation Index. *Remote Sensing of Environment* 48:119.

Ranchin, T. Data fusion in Remote Sensing: Examples. In Ecole des Mines de Paris [database online]. Sophia Antipolis, France, Available from http://www.researchgate.net/publication/47805585_Data_fusion_in_remote_sensing_examples/file/e0b49515ae591d7a04.pdf(last accessed June 2014).

Rephann, T. J., J. Ellis, D. Rexrode, and C. Eggleston. 2013. *Growing Agribusiness: The Contribution And Development Potential Of Agriculture And Forest Industry In The Danville Metropolitan Area.* University of VIrginina: Weldon Cooper Center for Public Service, .

Research and Development Division. FAQ's. In National Agriculture Statistics Service [database online]. USDA, Available from http://www.nass.usda.gov/research/Cropland/sarsfaqs2.html#Section3_2.0 (last accessed June 2014).

Roosta, H., R. Farhudi, and M. E. Afifi. 2007. Comparison between Linear and Non-Linear Crop Acreage Estimation Methods. *International Journal of Energy and Environment* 1:115.

Schimmelpfennig, D., and R. Ebel. 2011. *On the Doorstep of the Information Age: Recent Adoption of Precision Agriculture.* USDA: Economic Research Service, Report Number, EIB-80.

Sturdevant, R. W. 2007. NAVSTAR, The Global Positioning System: A Sampling of Its Military, Civil, and Commercial Impact. In*Societal Impact of Spaceflight,* ed. S. J. Dick and R. D. Launius, 331. NASA.

Tenkorang, F., and J. Lowenberg-DoBoer. 2008. On-Farm Profitability of Remote Sensing in Agriculture. *The Journal of Terrestrial Observation*50.

Tucker, C.J. 1979. Red and photographic infrared linear combinations for monitoring vegetation. Remote Sensing of Environment 8: 127-150.

University of California, D. Physics Supplements. 2014. http://www.physics.ucdavis.edu/Classes/Physics9Lab/Phy9BLab/9ASupplements.pdf (last accessed 06/06 2014).

USDA National Commission on Small Farms. 1998. *A Time to Act.* United States Department of Agriculture, Report Number, MP-1545. http://www.csrees.usda.gov/nea/ag_systems/pdfs/time_to_act_1998.pdf (last accessed May 4, 2013).

USDA National Institute of Food and Agriculture. 2009. Precision, Geospatial & Sensors Technologies: Adoption of Precision Agriculture. http://www.nifa.usda.gov/nea/ag_systems/in_focus/precision_if_adoption.html (last accessed June 9, 2014).

US Department of Agriculture Aerial Photography Field Office. 2008. "Four band digital imagery information sheet." APFO Support Documents - NAIP Imagery. www.fsa.usda.gov/Internet/FSA_File/fourband_info_sheet_2008.doc (accessed June 9 2014).

Volkmer, H. L., D. A. Jolly, K. S. Kelley, C. W. Albertson, K. S. Armstrong-Cummings, J. R. Barber, E. L. Blount, C. D. Bolen, M. L. Bowlan, B. F. Burkett, N. Carrasquillo, E. W. J. Coward, R. M. I. Daniels, R. E. Gomez, D. V. J. Guerra, G. T. Gunthorp, J. Harness, C. Hassebrook, D. G. Henderson, E. Herness, G. B. Holland, and F. R. Magdoff. 1998. *A Time to Act; A Report of the USDA National*

Commission on Small Farms. Paper presented at: USDA Commission on Small Farms, .

Yellow Maps, Blank County Maps of Virginia. 2014. http://www.yellowmaps.com/maps/virginia_state_map.htm (last accessed June 9, 2014)

APPENDICES

Appendix A: Site Selection Footprints

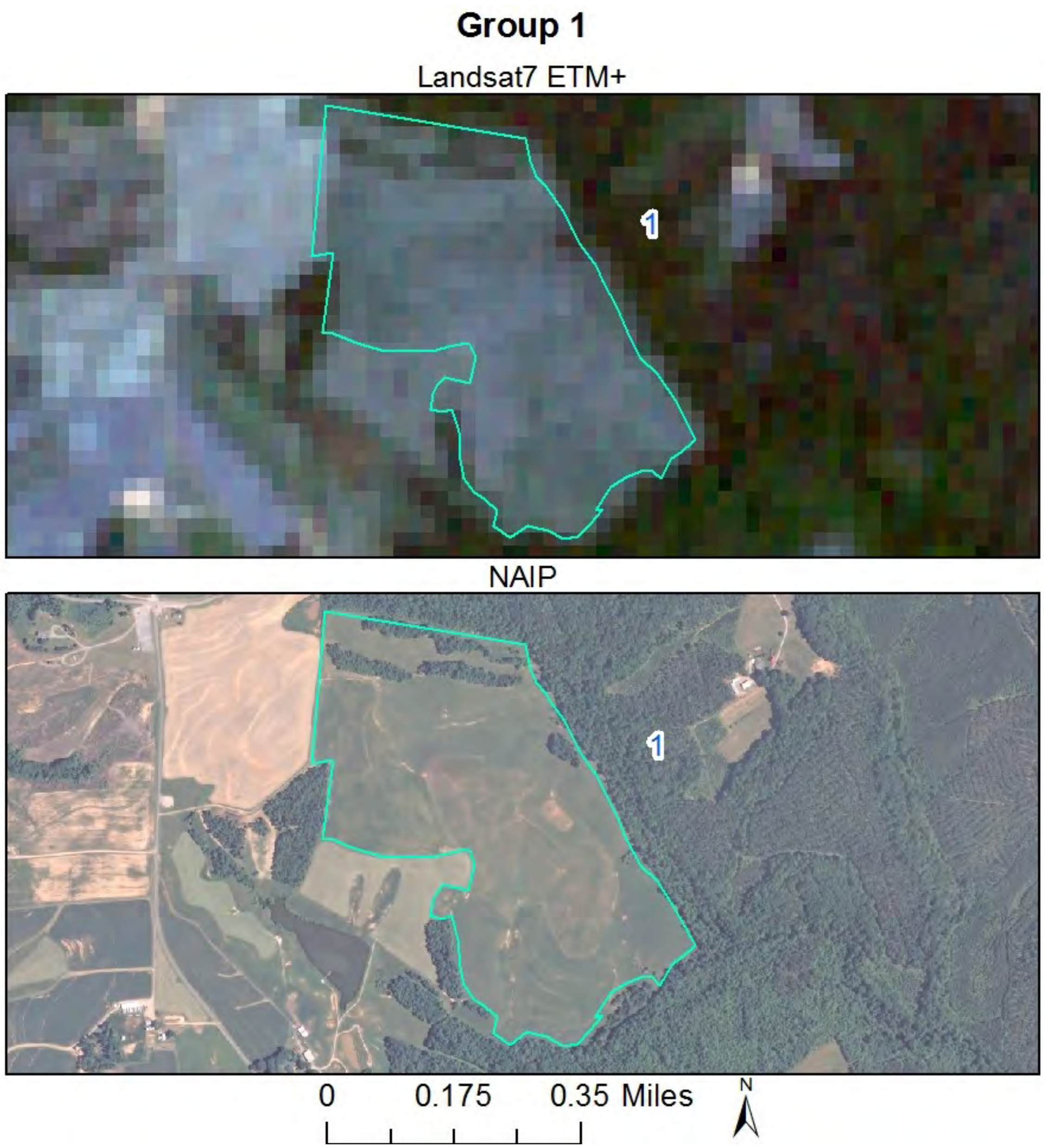

Figure 20: Group 1 Footprints. Level of detail is noticeably different between resolutions.

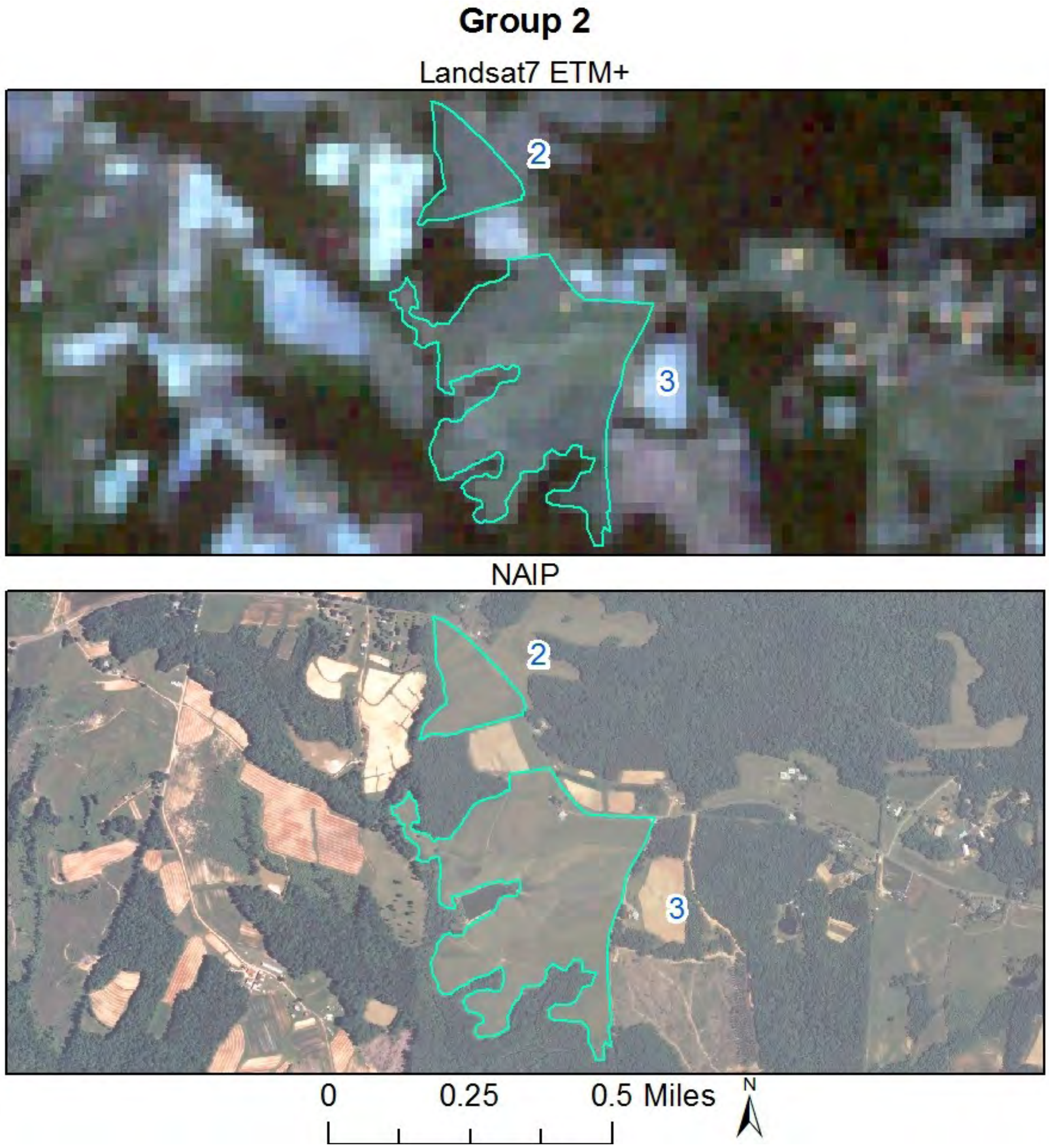

Figure 21: Group 2 Footprints. Site 3 has very erratic borders which as seen in the Landsat7 ETM+ do not follow visual field boarders.

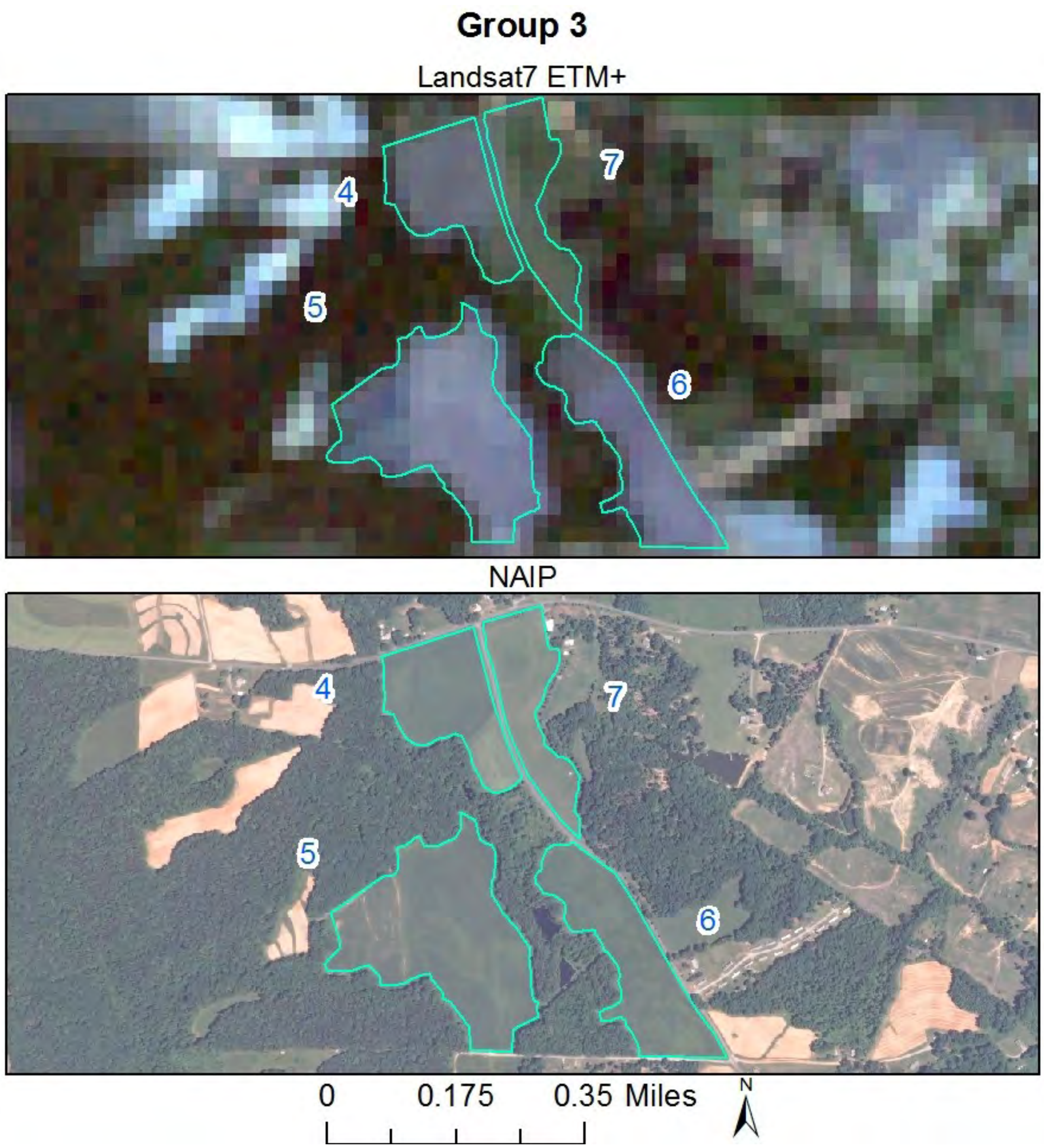

Figure 22: Site 3 Footprints. Site 7 footprint does not follow a noticeable field shape in the Landsat7 ETM+ imagery, which could possibly affect the VI and PE analyses.

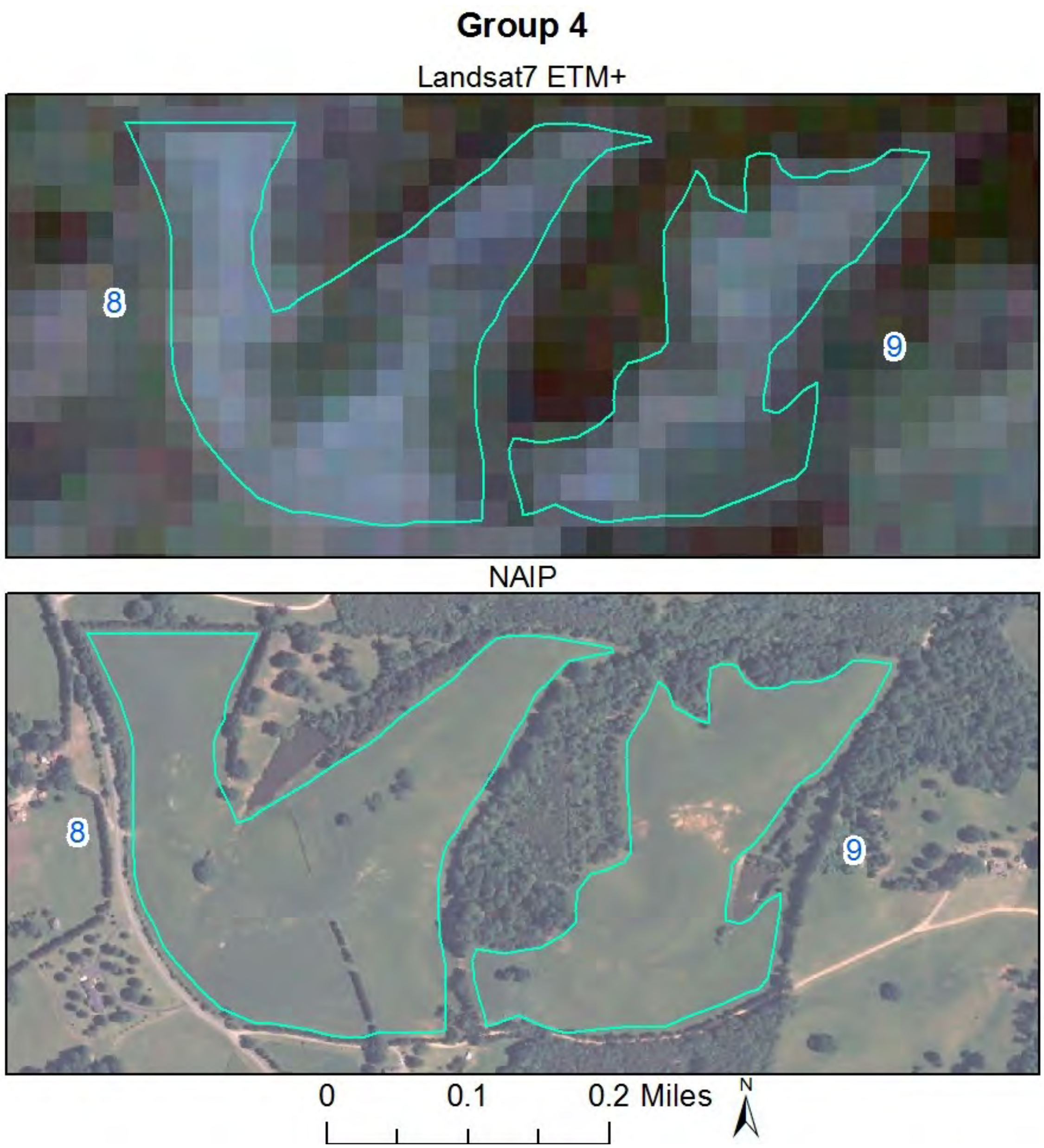

Figure 23: Group 4 Footprints. Great differences between resolutions. NAIP imagery shows large individual trees and tree lines within the site, which are completely lost within the Landsat7 ETM+ imagery. Features like these will affect the pixel that they are contained within.

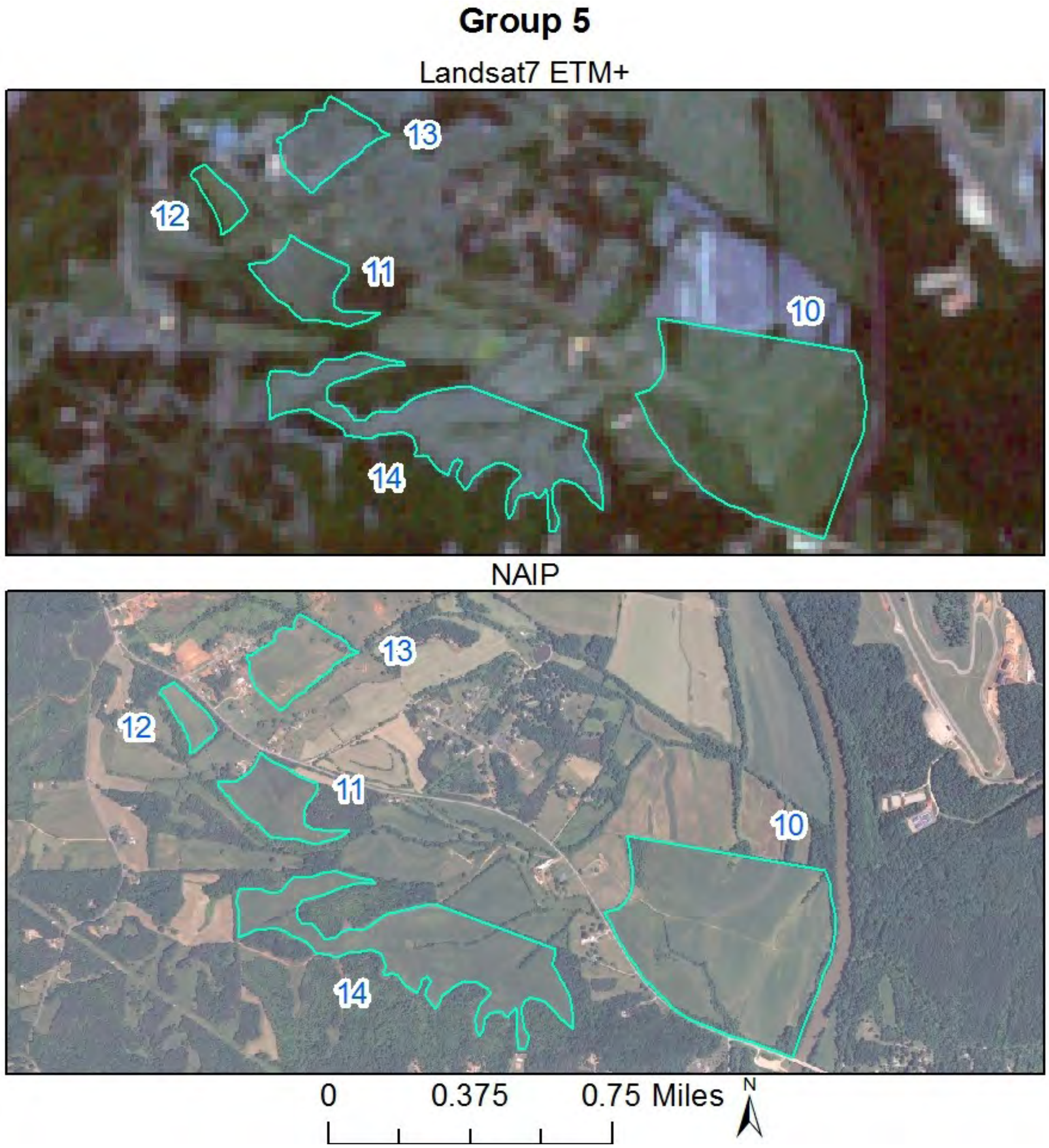

Figure 24: Group 5 Footprints. Just as with Group 4, NAIP imagery shows tree lines and other features within each site that are not identified within Landsat7 ETM+ imagery.

Appendix B: VI Analysis Results

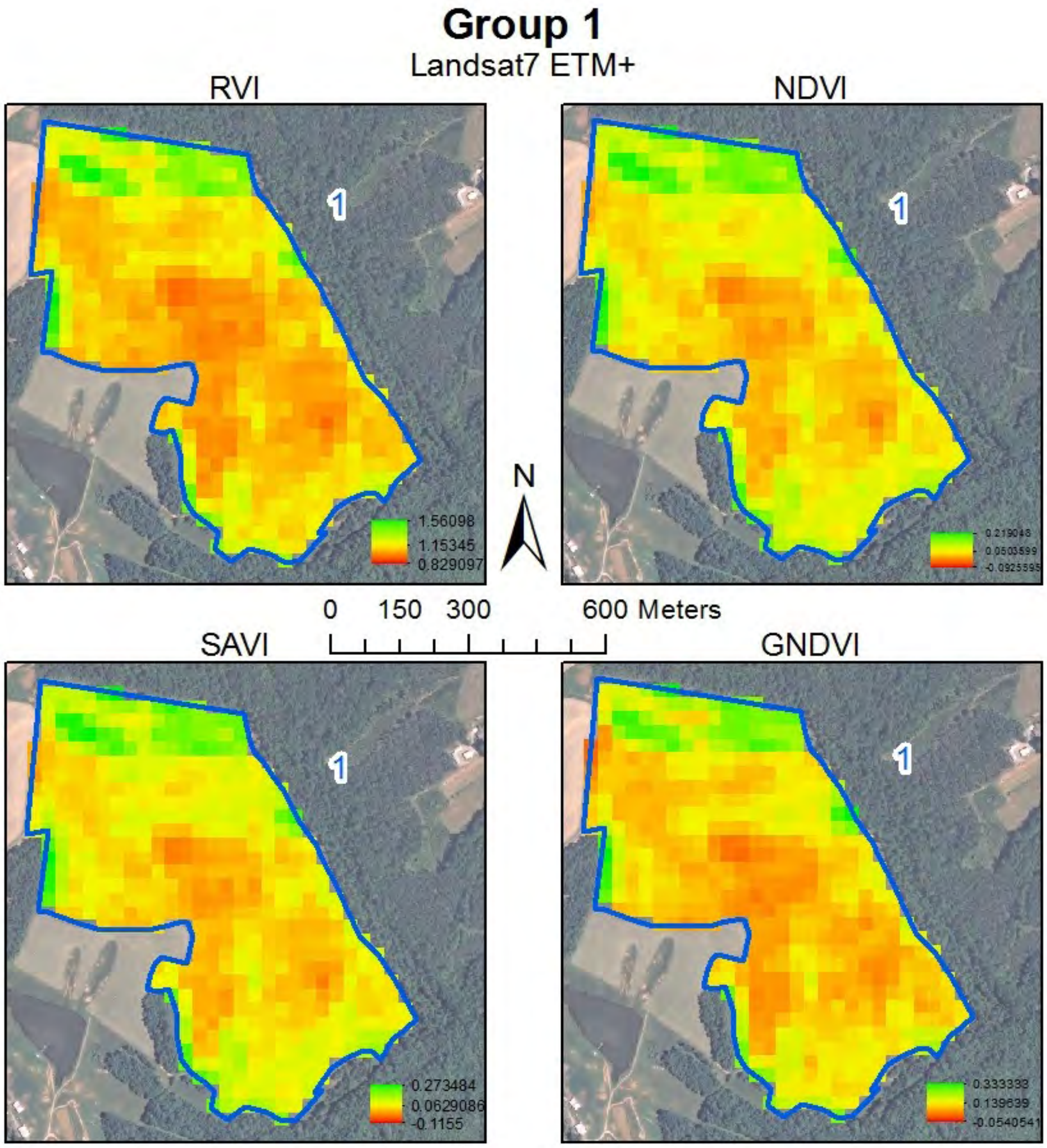

Figure 25: Group 1 Landsat7 ETM+ VI Results. VI results, overlying on NAIP base imagery for clarity, show a low vegetation trend throughout the entire field, with high vegetative values in the northern most part of the field.

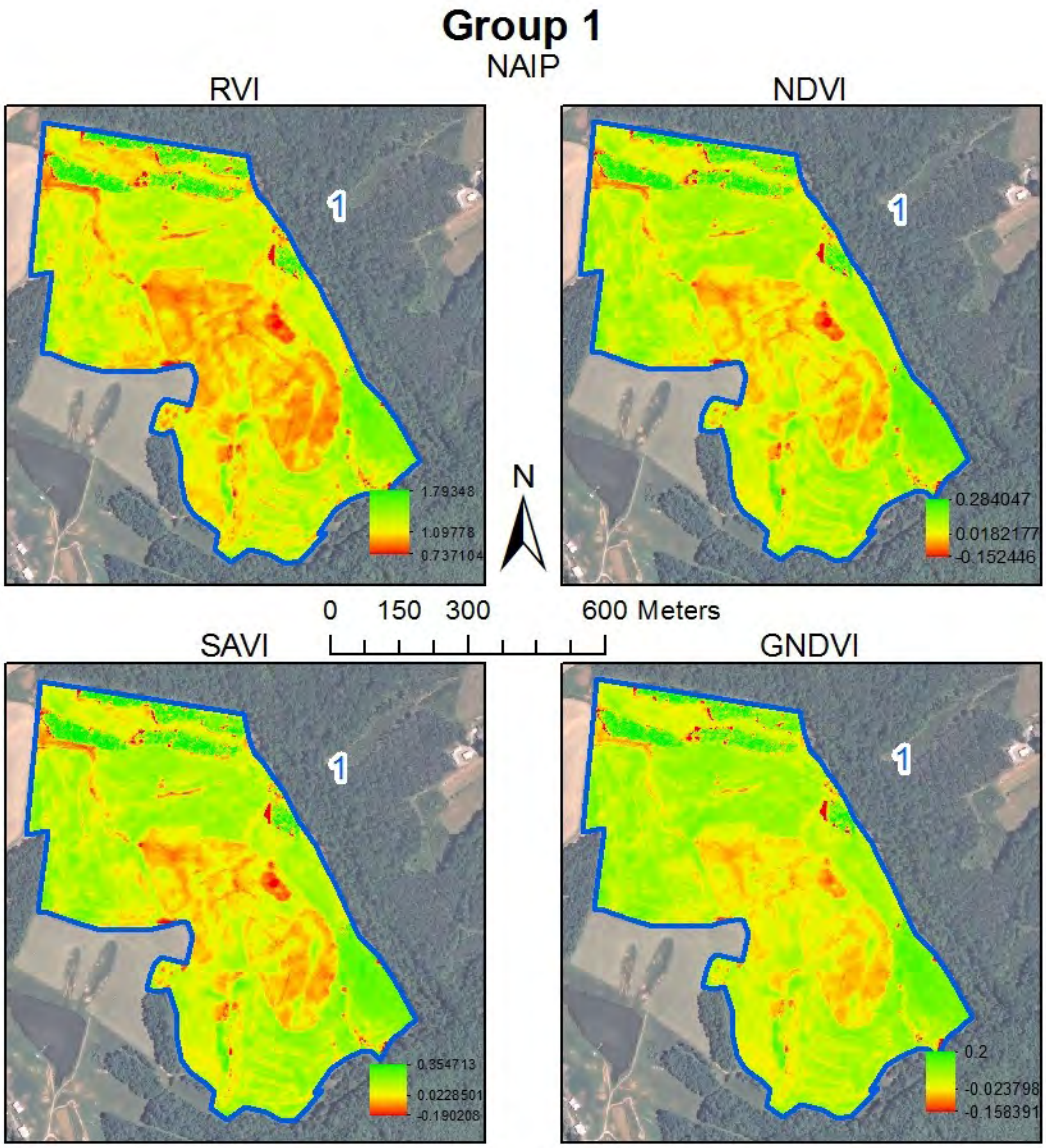

Figure 26: Group 1 NAIP VI Results. With the smaller pixels, more high vegetative areas are highlighted and a better contrast between areas is present. Rather than the entire field having low vegetative levels, an improved look at the results show more vegetation present as compared to Landsat7 ETM+ values.

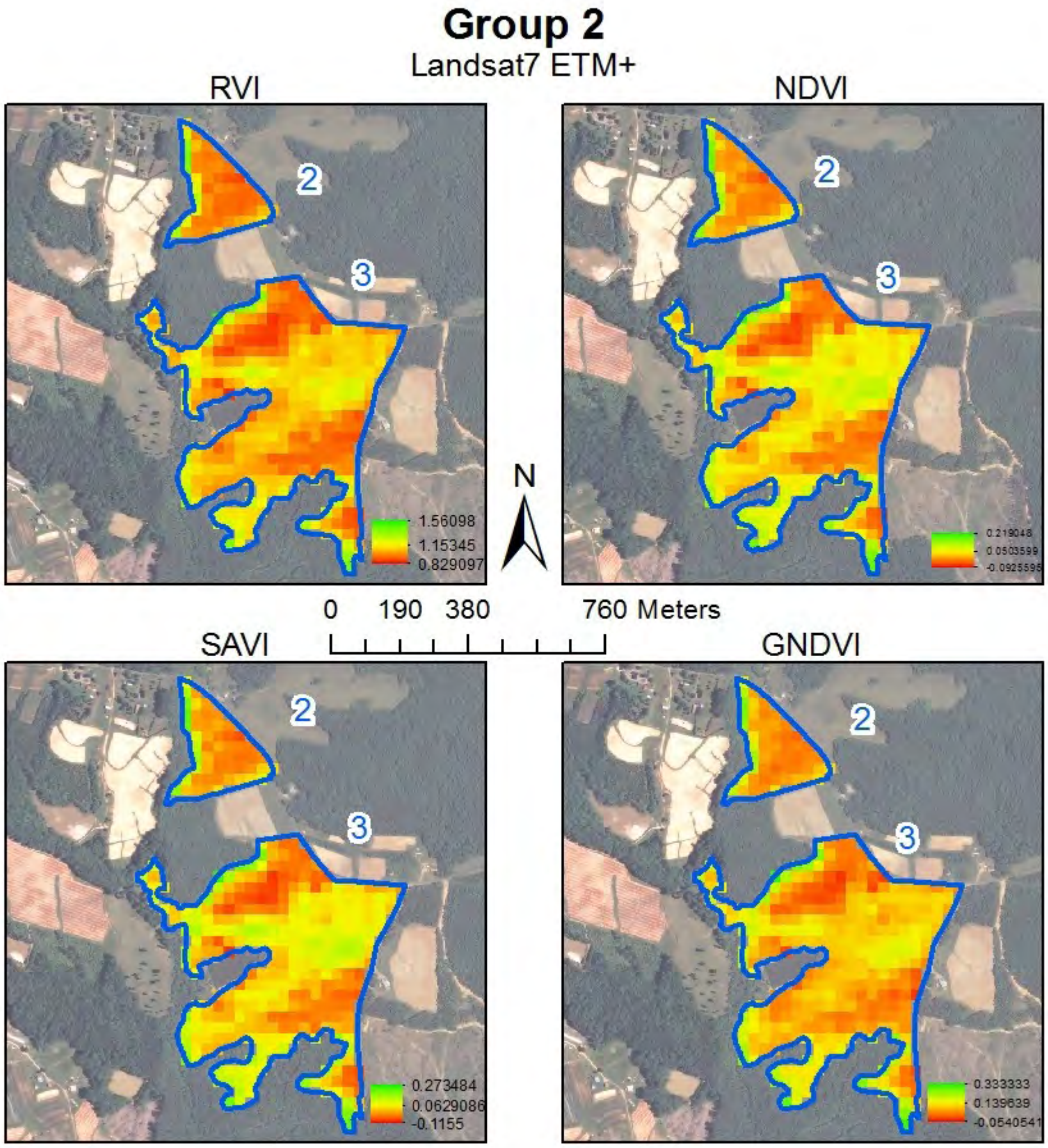

Figure 27: Group 2 Landsat7 ETM+ VI Results. VI results overlying on NAIP base imagery for clarity. Large amounts of low vegetative areas with the central portion of field 3 showing a fluctuation of high and low values.

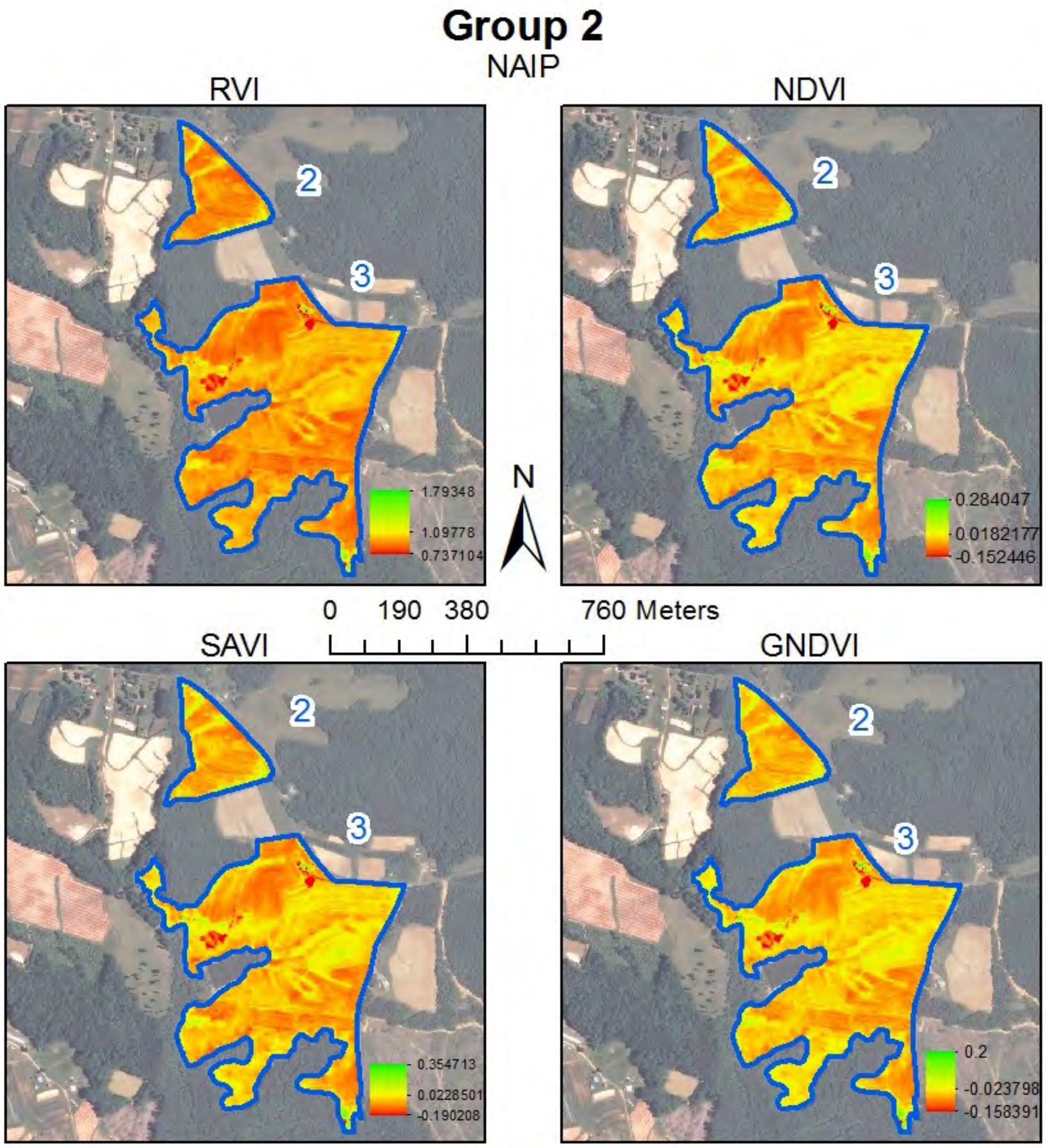

Figure 28: Group 2 NDVI VI Results. More detail is shown of the mid range (yellow) areas, where vegetation is present, but not at high levels.

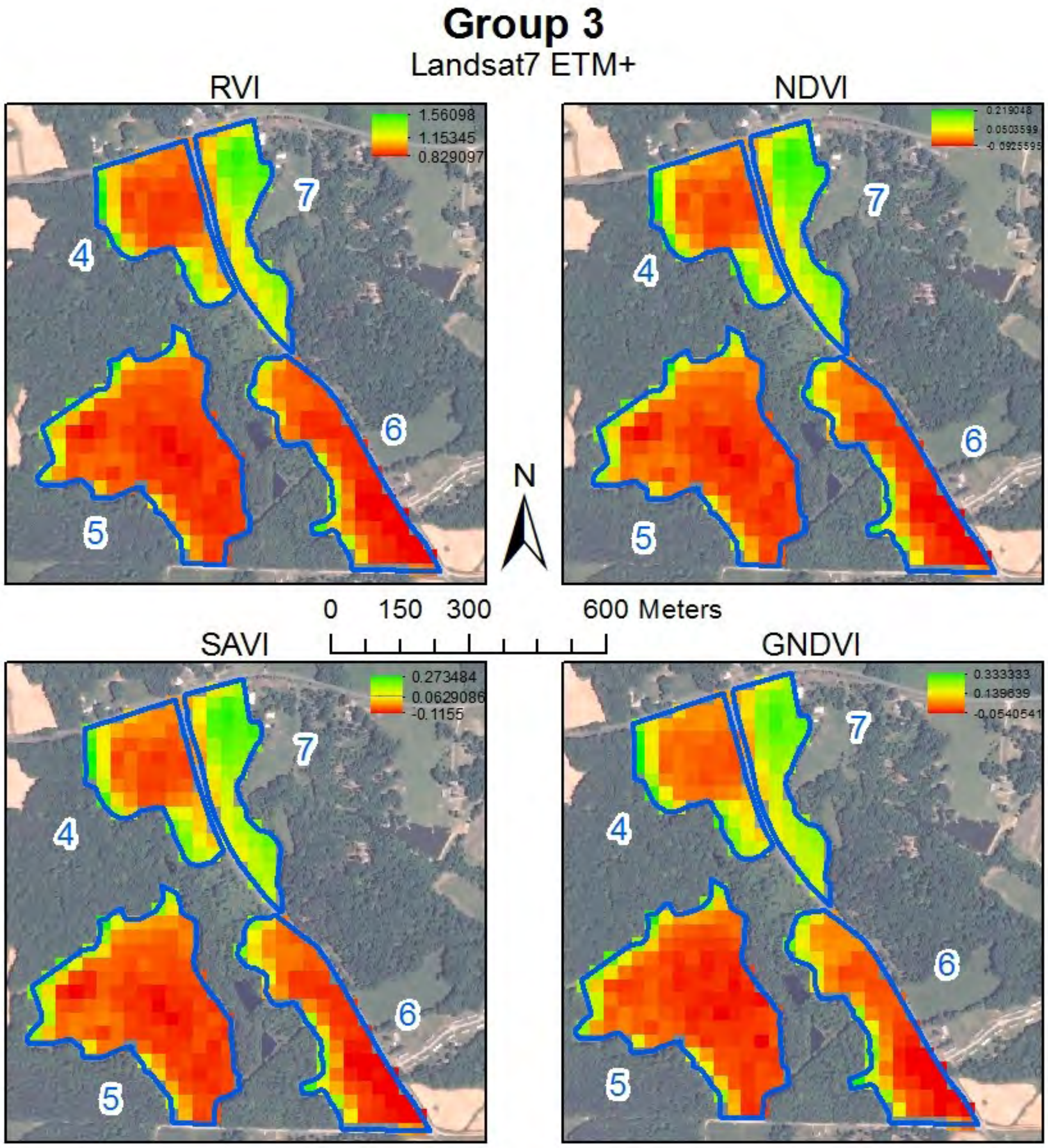

Figure 29: Group 3 Landsat7 ETM+ VI Results. VI results overlying on NAIP base imagery for clarity. Wide spreading of low values across each site except Site 7.

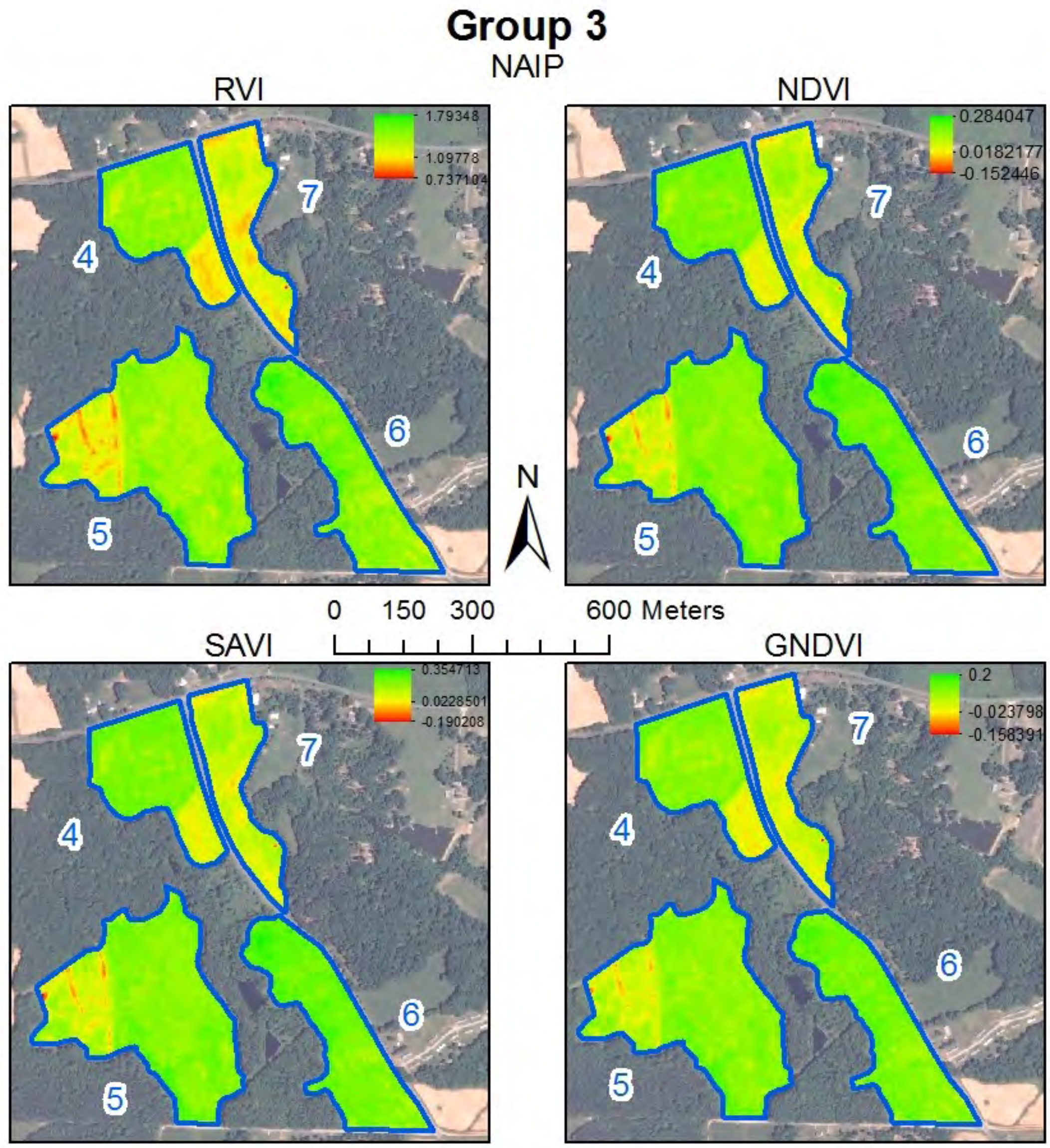

Figure 30: Group 3 NAIP VI Results. In comparison to the Landsat7 ETM+ results, here NAIP values show abundant vegetation with limited areas of lower vegetative levels.

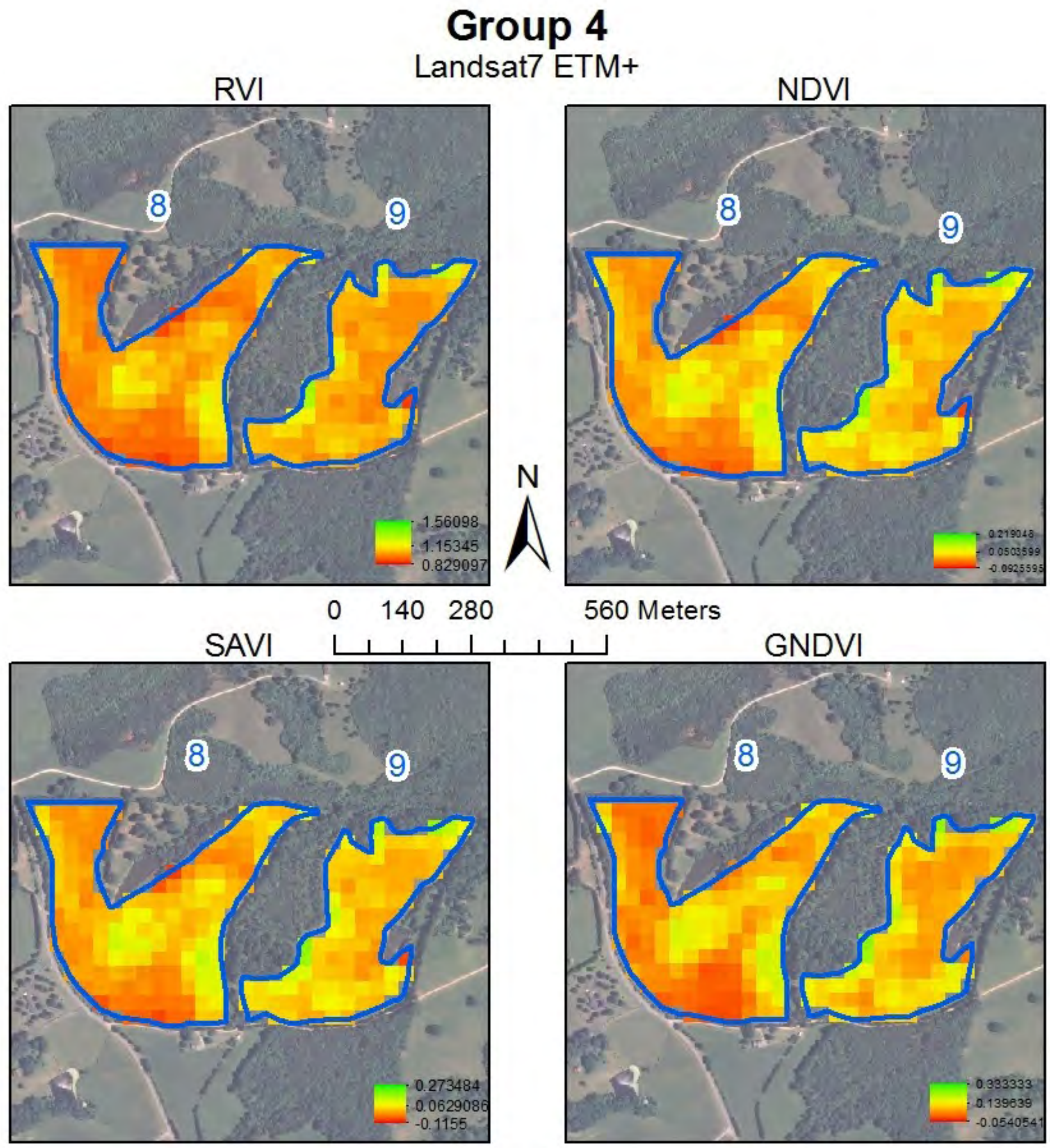

Figure 31: Group 4 Landsat7 ETM+ VI Results. VI results overlying on NAIP base imagery for clarity. Large amount of low vegetative levels in each site with few high values.

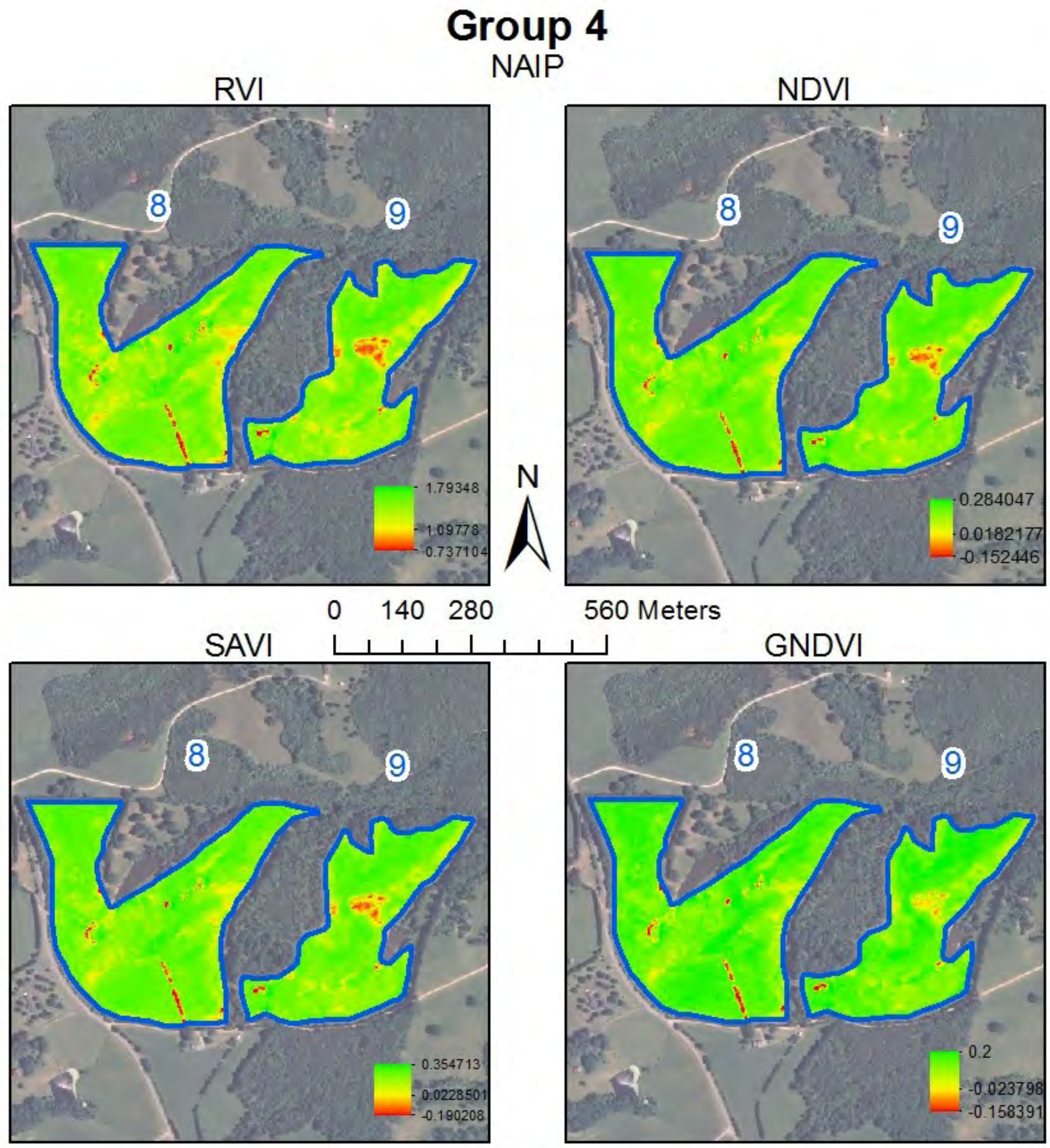

Figure 32: Group 4 NAIP VI Results. More detail about each site, including the site characteristics mentioned in the Site Characteristics table in Chapter 2. More high vegetative levels throughout, indicating more vegetation present than seen through the Landsat7 ETM+ data.

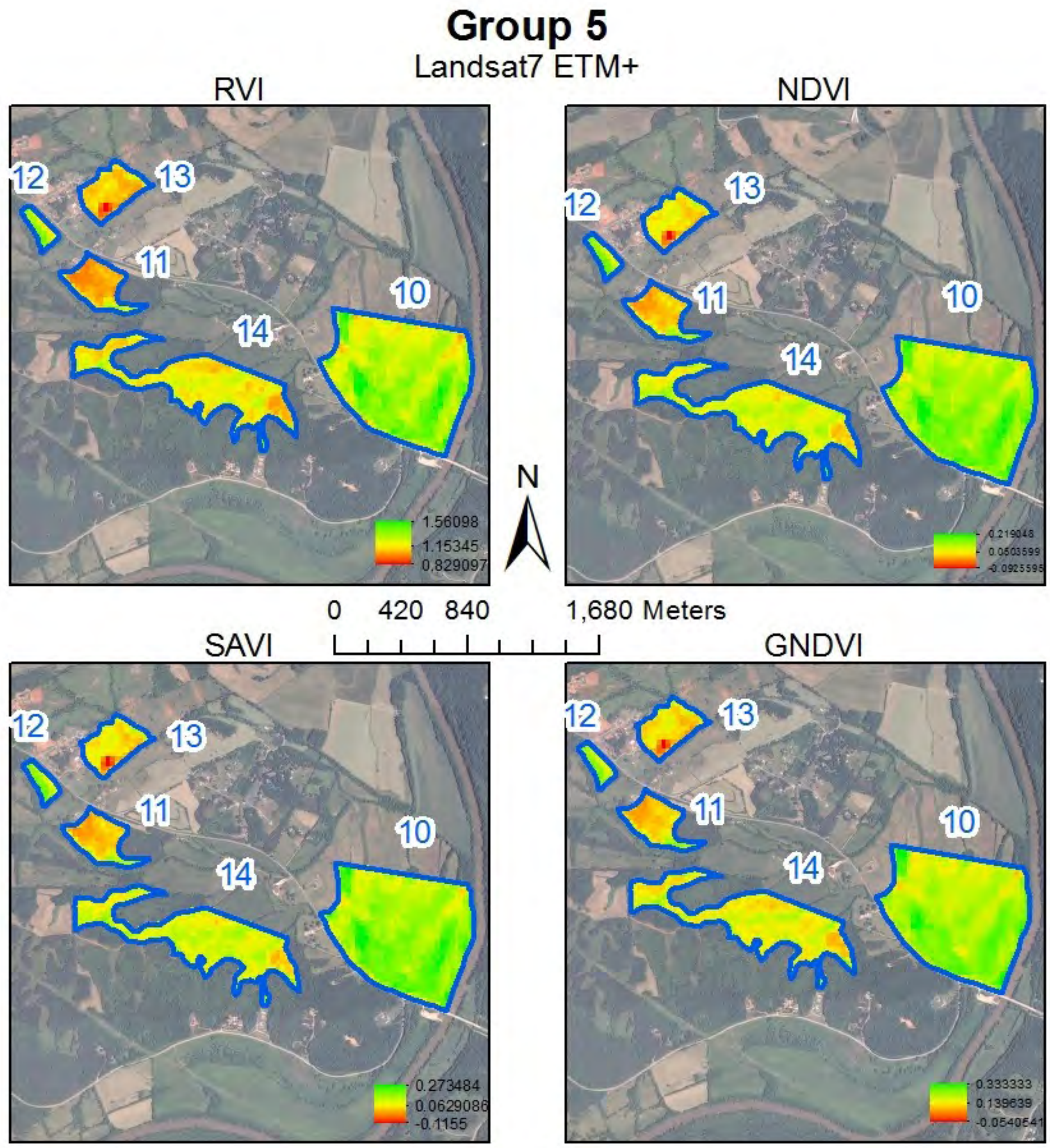

Figure 33: Group 5 Landat7 ETM+ VI Results. VI results overlying on NAIP base imagery for clarity. Higher vegetative levels present in these sites as compared to the other sites. Water feature is present in Site 13, but site characteristics of other sites are not present, such as the tree lines in Site 14 and dirt road in Site 10.

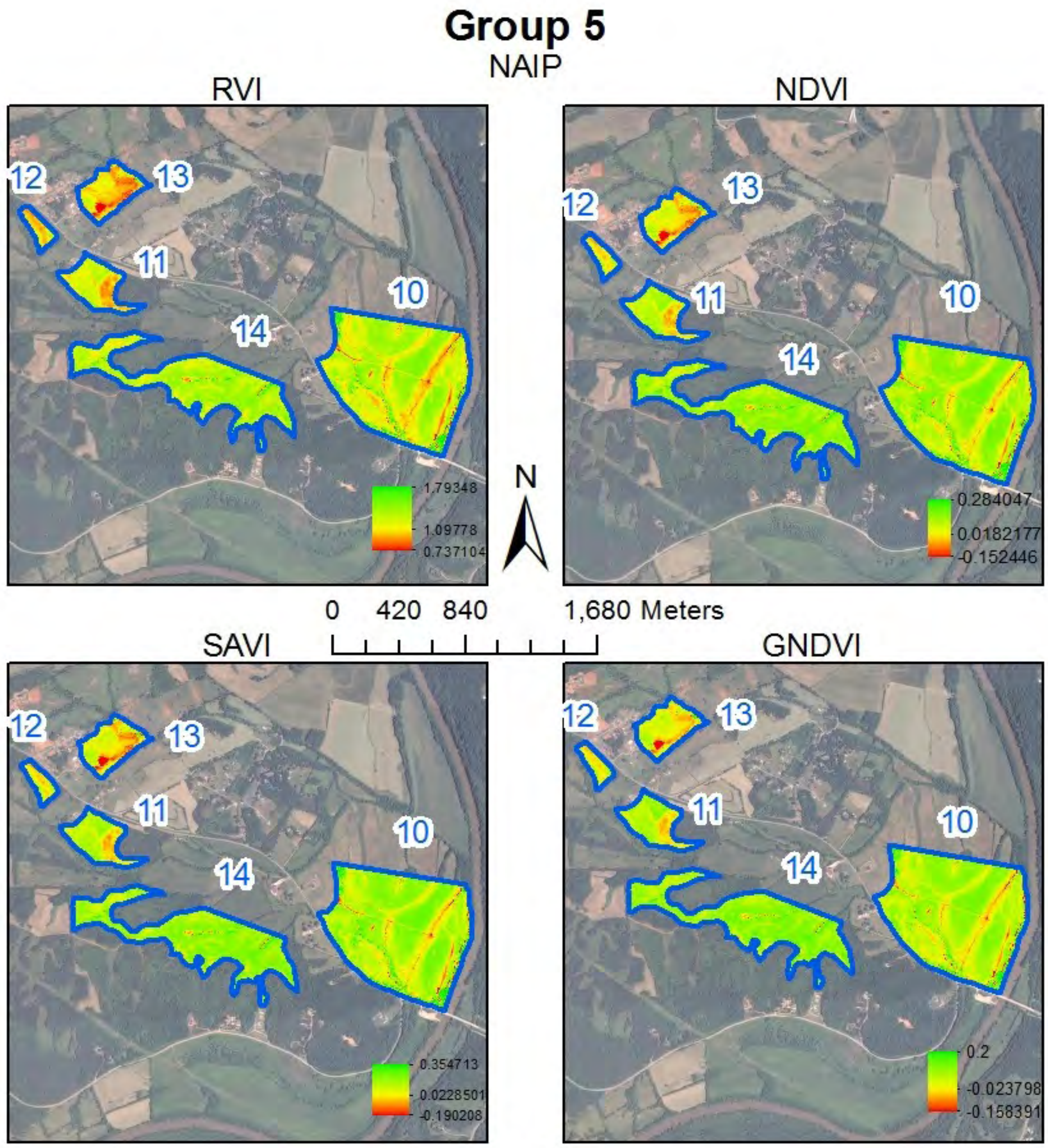

Figure 34: Group 5 NAIP VI Results. Lots of vegetation present in each site and site characteristics are more present than with Landsat7 ETM+ data.

Appendix C: Percent Error Analysis Results

Table 9: RVI PE Results

RVI											
Site Info		Grossly Overestimated				Debatable				Acceptable	
		Below -100%		Above 100%		Between -25% and -100%		Between 25% and 100%		Between -25% and 25%	
Site #	# of Pixels	PE	# of Pixels	PE	# of Pixels	PE	# of Pixels	PE	# of Pixels	PE	# of Pixels
1	436,155	0%	0	<1%	300	<1%	177	3%	13085	96%	418709
2	46,374	0%	0	0%	0	1%	464	11%	5101	88%	40809
3	273,157	0%	0	<1%	48	<1%	138	6%	16389	93%	254036
4	54,382	0%	0	0%	0	55%	29910	2%	1088	43%	23384
5	117,965	0%	0	0%	0	66%	77857	1%	1180	33%	38928
6	64,407	0%	0	0%	0	75%	48305	0%	0	25%	16102
7	40,957	0%	0	0%	0	0%	0	4%	1638	96%	39319
8	128,512	0%	0	0%	0	36%	46264	1%	1285	63%	80963
9	81,697	0%	0	<1%	3	16%	13072	<1%	646	83%	67809
10	605,657	0%	0	0%	0	<1%	595	9%	54509	91%	551148
11	88,032	0%	0	<1%	2	0%	0	2%	1761	97%	85391
12	26,173	0%	0	0%	0	0%	0	37%	9684	63%	16489
13	92,087	0%	0	2%	1842	<1%	169	6%	5525	91%	83799
14	331,107	0%	0	<1%	2	<1%	8	1%	3311	98%	324485

Table 10: NDVI PE Results

NDVI											
Site Info		Grossly Overestimated				Debatable				Acceptable	
		Below -100%		Above 100%		Between -25% and -100%		Between 25% and 100%		Between -25% and 25%	
Site #	# of Pixels	PE	# of Pixels	PE	# of Pixels	PE	# of Pixels	PE	# of Pixels	PE	# of Pixels
1	436,155	14%	61062	12%	52339	45%	196270	10%	43616	19%	82869
2	46,374	25%	11594	10%	4637	49%	22723	5%	2319	11%	5101
3	273,157	51%	138713	20%	56384	20%	55019	3%	9653	6%	17459
4	54,382	62%	33717	6%	3263	18%	9789	9%	4894	5%	2719
5	117,965	84%	99091	2%	2359	10%	11797	1%	1180	3%	3539
6	64,407	75%	48305	1%	644	18%	11593	1%	644	5%	3220
7	40,957	3%	1229	41%	16792	8%	3277	36%	14745	12%	4915
8	128,512	45%	57830	1%	1285	52%	66826	1%	1285	1%	1285
9	81,697	24%	19607	1%	817	69%	56371	1%	817	5%	4085
10	605,657	7%	42396	24%	145358	8%	48453	29%	175641	32%	193810
11	88,032	30%	26410	13%	11444	42%	36973	5%	4402	10%	8803
12	26,173	24%	6282	62%	16227	1%	262	5%	1309	8%	2094
13	92,087	2%	1842	1%	921	5%	4604	12%	11050	80%	73670
14	331,107	2%	6622	3%	9933	51%	168865	7%	23177	37%	122510

Table 11: GNDVI PE Results

GNDVI											
Site Info		Grossly Overestimated				Debatable				Acceptable	
		Below -100%		Above 100%		Between -25% and -100%		Between 25% and 100%		Between -25% and 25%	
Site #	# of Pixels	PE	# of Pixels	PE	# of Pixels	PE	# of Pixels	PE	# of Pixels	PE	# of Pixels
1	436,155	37%	161377	54%	235524	1%	4362	4%	17446	1%	4362
2	46,374	95%	44055	3%	1391	1%	464	1%	464	0%	0
3	273,157	96%	262231	2%	5463	<1%	85	<1%	160	<1%	96
4	54,382	16%	8701	22%	11964	26%	14139	9%	4894	27%	14683
5	117,965	30%	35390	16%	18874	33%	38928	7%	8258	14%	16515
6	64,407	22%	14170	15%	9661	66%	42509	10%	6441	19%	12237
7	40,957	39%	15973	55%	22526	6%	2457	0%	0	0%	0
8	128,512	2%	2570	16%	20562	34%	43694	21%	26988	27%	34698
9	81,697	3%	2451	28%	22875	9%	7353	28%	22875	31%	25326
10	605,657	23%	139301	74%	448186	0%	0	1%	6057	1%	6057
11	88,032	34%	29931	62%	54580	0%	0	2%	1761	0%	0
12	26,173	74%	19368	26%	6805	0%	0	0%	0	0%	0
13	92,087	64%	58936	32%	29468	1%	921	1%	921	1%	921
14	331,107	5%	16555	90%	297996	0%	0	4%	13244	<1%	11

Table 12: SAVI PE Results

SAVI											
Site Info		Grossly Overestimated				Debatable				Acceptable	
		Below -100%		Above 100%		Between -25% and -100%		Between 25% and 100%		Between -25% and 25%	
Site #	# of Pixels	PE	# of Pixels	PE	# of Pixels	PE	# of Pixels	PE	# of Pixels	PE	# of Pixels
1	436,155	16%	69785	11%	47977	45%	196270	10%	43616	18%	78508
2	46,374	24%	11130	10%	4637	50%	23187	5%	2319	11%	5101
3	273,157	51%	138713	20%	56384	20%	55049	3%	9653	6%	17430
4	54,382	61%	33173	10%	5438	16%	8701	8%	4351	5%	2719
5	117,965	84%	99091	3%	3539	8%	9437	2%	2359	3%	3539
6	64,407	76%	48949	4%	2576	14%	9017	1%	644	5%	3220
7	40,957	3%	1229	41%	16792	8%	3277	36%	14745	12%	4915
8	128,512	45%	57830	<1%	539	52%	66826	<1%	588	2%	2570
9	81,697	11%	8987	1%	817	69%	56371	1%	817	18%	14705
10	605,657	6%	36339	25%	151414	8%	48453	29%	175641	32%	193810
11	88,032	34%	29931	13%	11444	43%	37854	5%	4402	5%	4402
12	26,173	24%	6282	63%	16489	0%	0	6%	1570	7%	1832
13	92,087	34%	31310	31%	28547	7%	6446	13%	11971	15%	13813
14	331,107	2%	6622	3%	9933	51%	168865	7%	23177	37%	122510

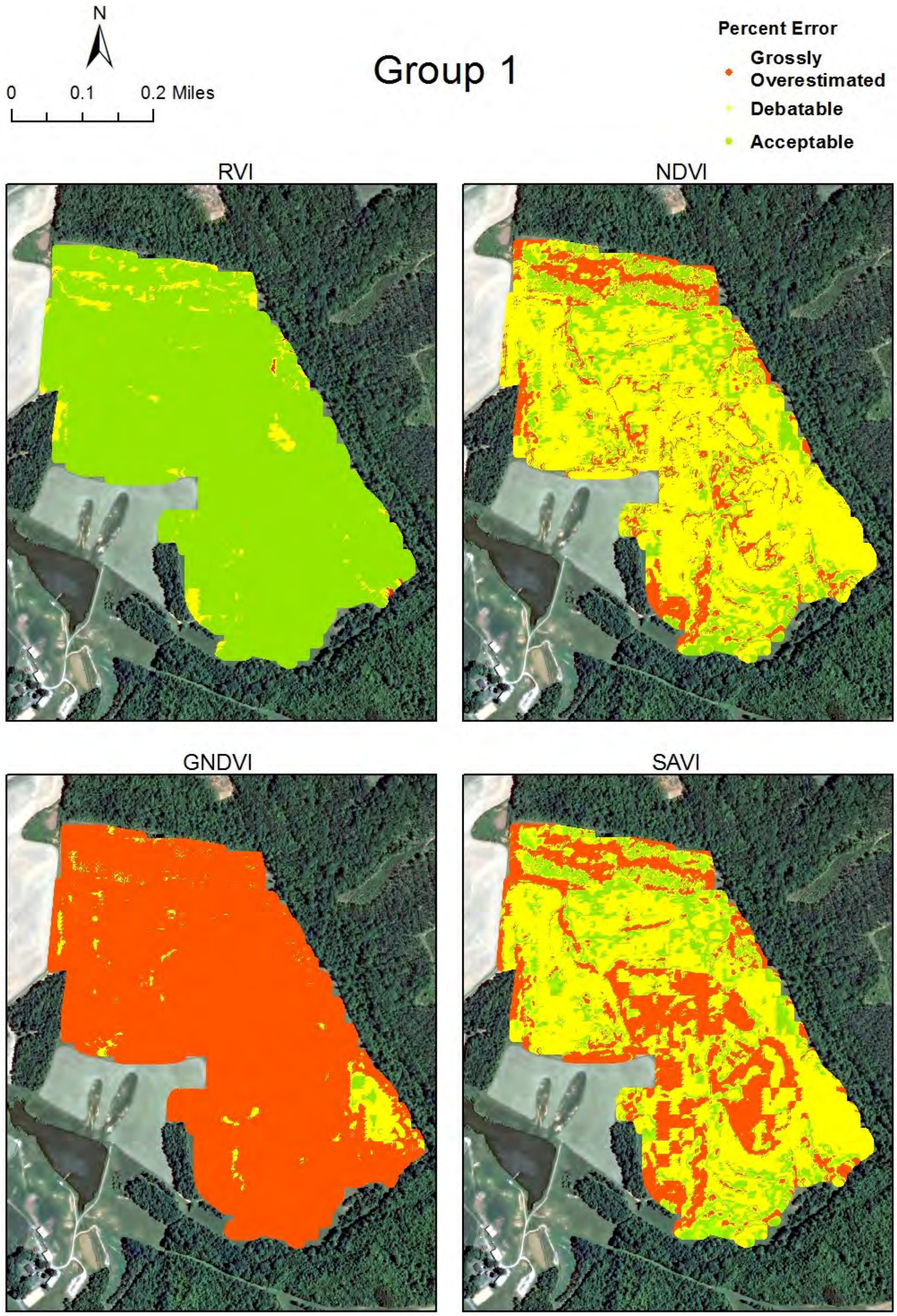

Figure 35. PE Results Group 1. NDVI and SAVI show more detailed results throughout the field than GNDVI and RVI.

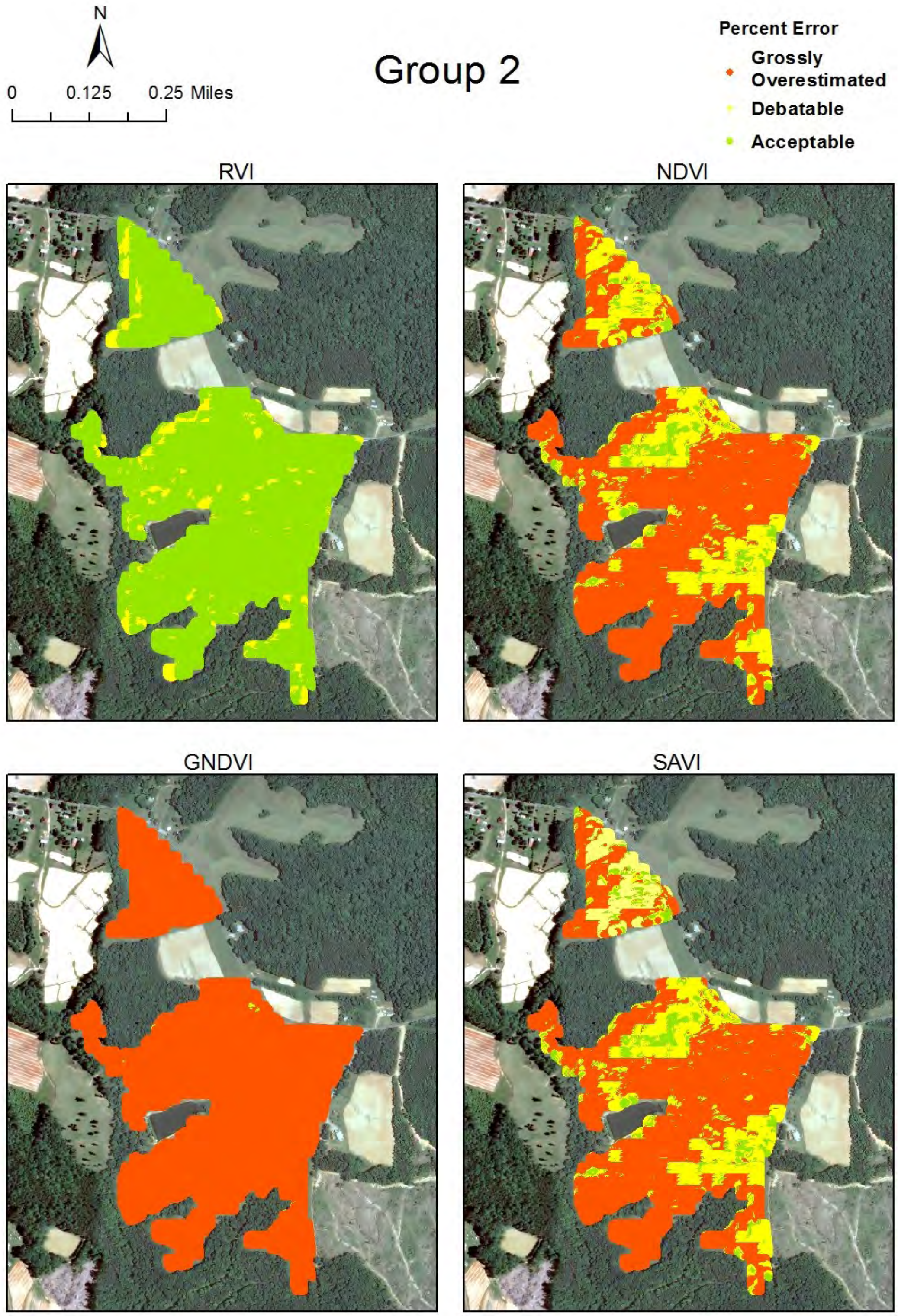

Figure 36. PE Results Group 2. Site 3 NDVI results show the largest amount of Grossly Overestimated and Debatable pixels throughout its center. This is also reflected in SAVI due to the similarity in the VI formulas.

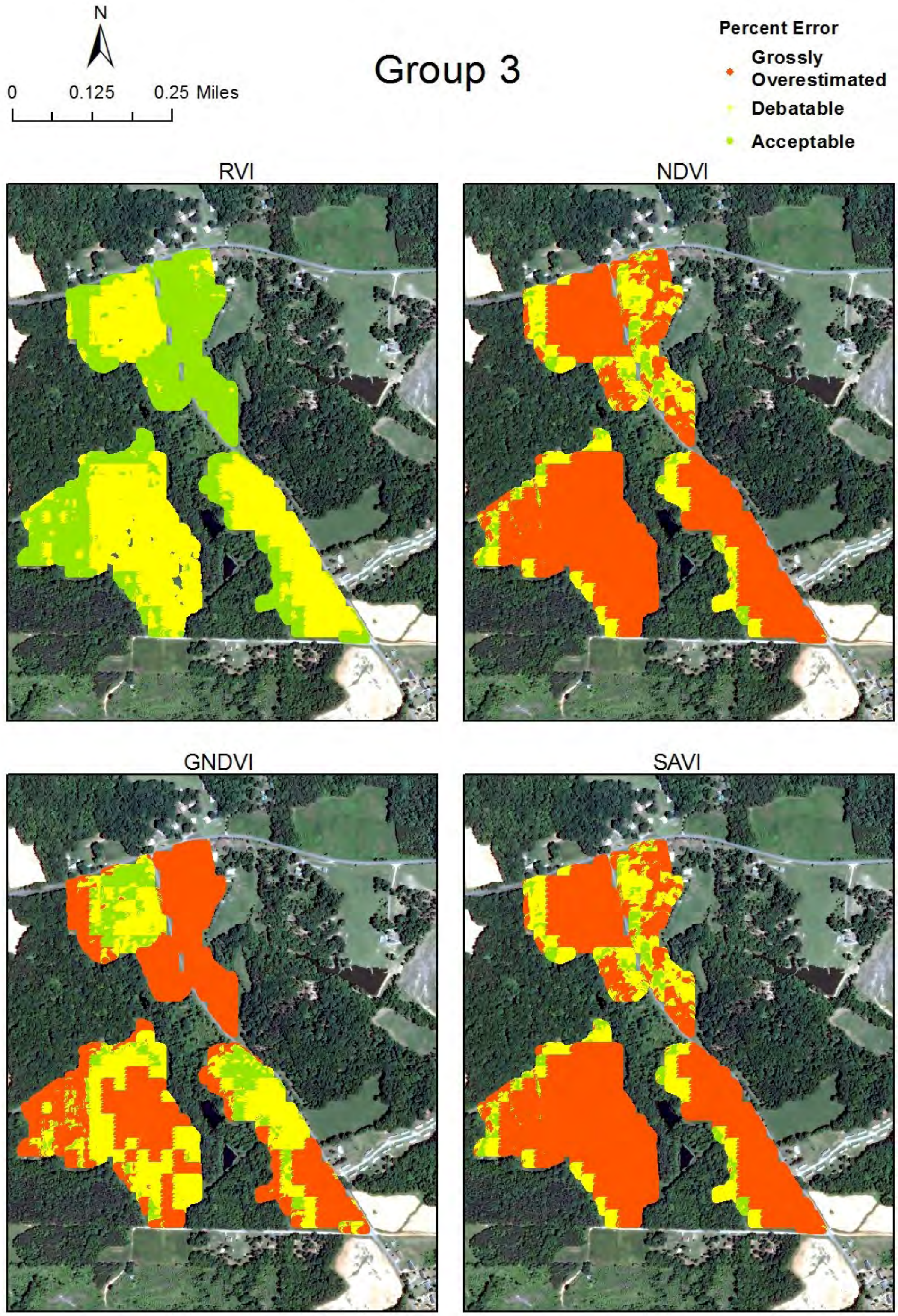

Figure 37. PE Results Group 3. SAVI and NDVI show similar results, with GNDVI showing some possible differences, which could depend on the use of the green band over the red.

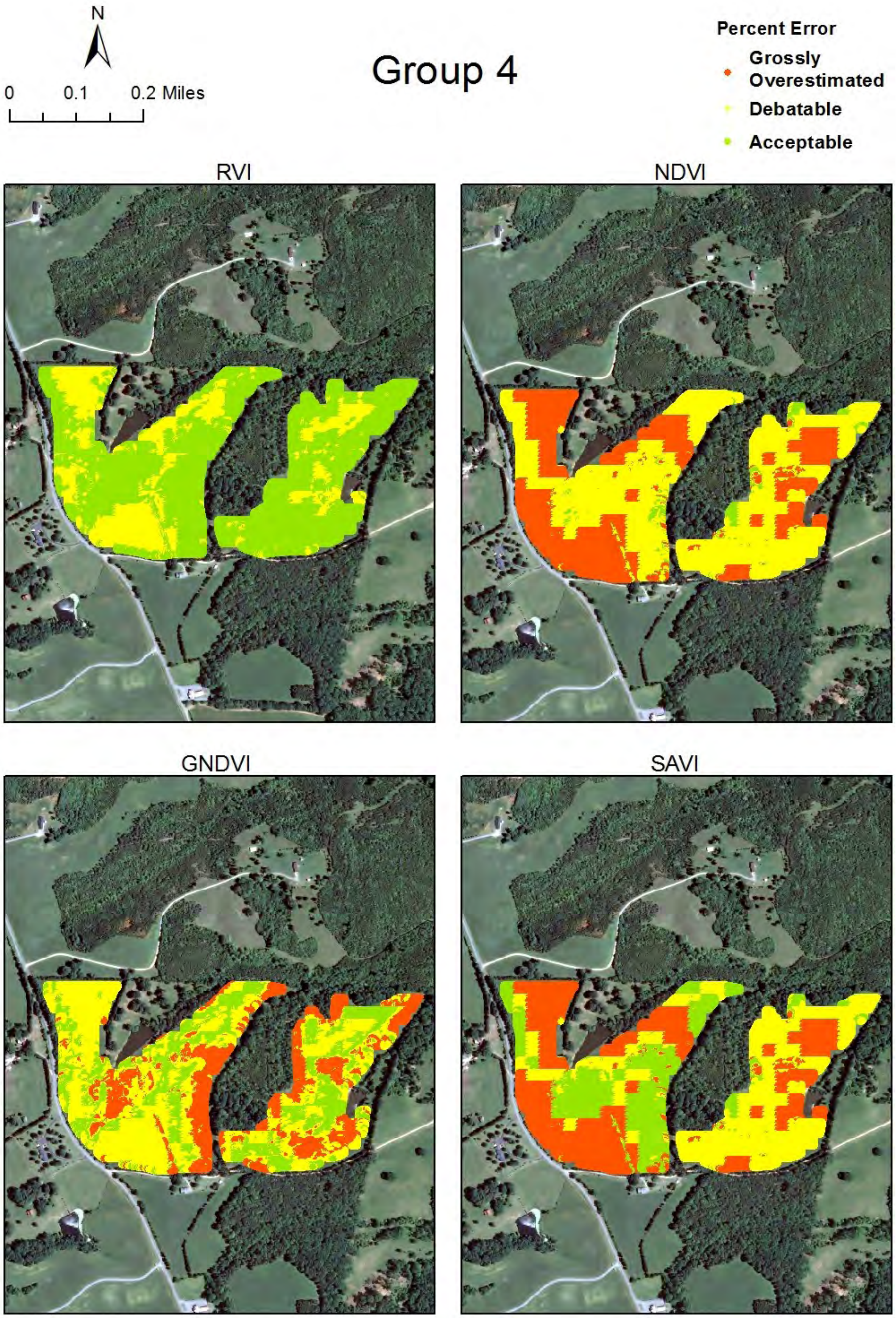

Figure 38. PE Results Group 4. Each VI shows a different set of results for each site. The pixel appearance in the NDVI and SAVI is due to sharp differences in the VI's derived values from Landsat 7 ETM+ and NAIP data.

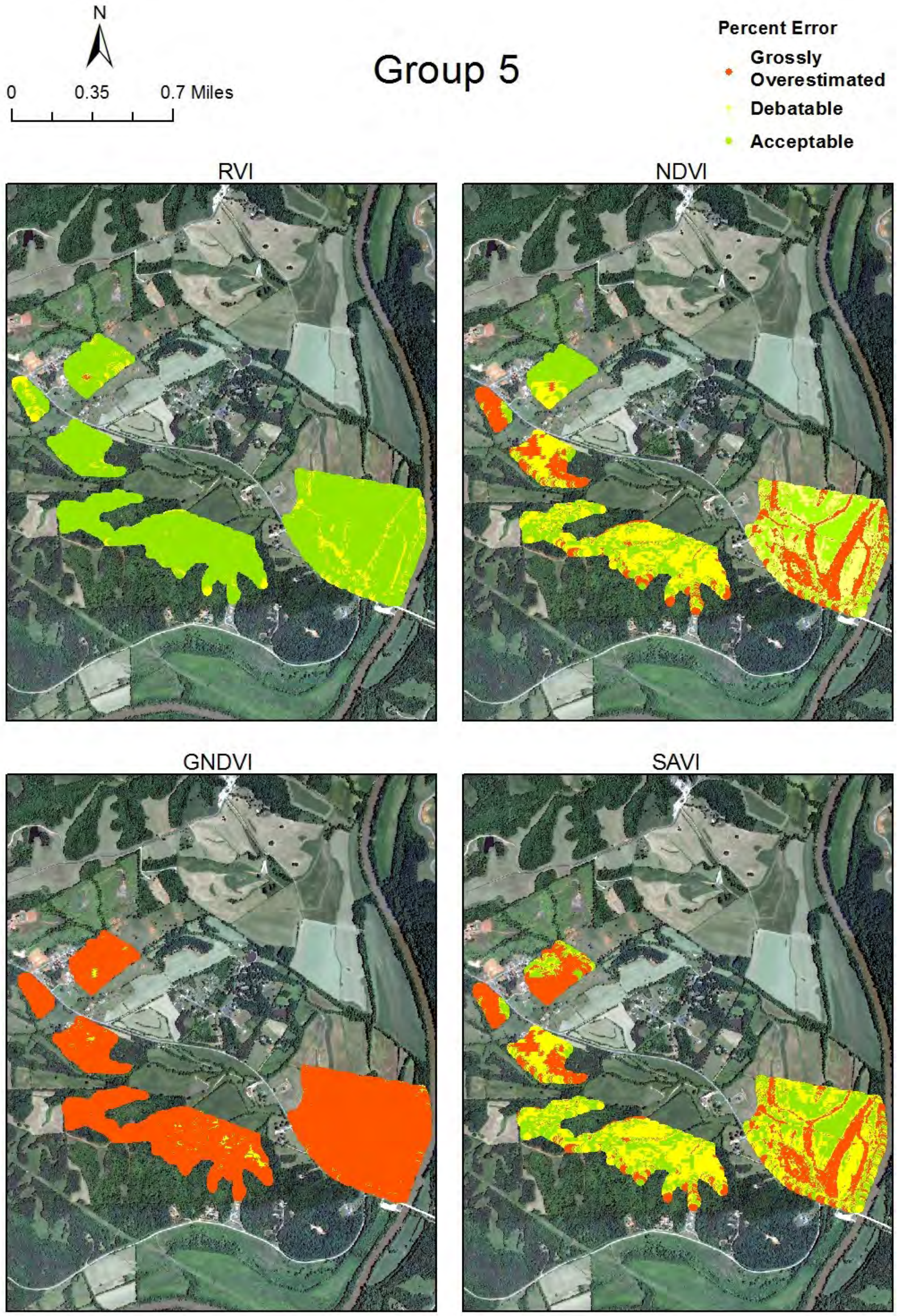

Figure 39. PE Results Group 5. Areas around main features within the sites contain pixels that fall in the Grossly Overestimated category in both NDVI and SAVI.