Identifying subsurface tile drainage systems utilizing remote sensing techniques

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A Thesis

entitled

Identifying Subsurface Tile Drainage Systems Utilizing Remote Sensing Techniques

by

James Thompson

Submitted to the Graduate Faculty as partial fulfillment of the

requirements for the Master of Arts Degree in Geography

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December 2010
The purpose of this research is to develop a method that will identify subsurface tile drainage systems in agricultural areas. Subsurface tile drainage systems allow ground water to drain out of a field in order to control the water level but they also allow nutrients such as nitrogen and phosphorous to be drained into surrounding waterways, affecting the water quality in negative ways. These subsurface drainage systems are common in the Midwest because they were used as the primary land drainage strategy when developing the land for agricultural uses. Many of the tile drain locations are not known because of the age of the systems, change in land ownership, or the lack of documentation during installation. Due to research that indicates their potential impact on surface water and new developments in sustainable agriculture practices, it is important to locate and document the existence of subsurface tile drainage systems.

This research project focused on Wood County which is a predominantly agricultural area located in Northwest Ohio and covers a large portion of the Maumee River Watershed. Aerial photographs of Wood County with one meter spatial resolution collected through the United States Department of Agriculture’s National Agricultural Imagery Program were used for this research. Moisture retained in soil that is not drained
shows up as dark in the imagery while drier soil, such as that above the subsurface tile drainage lines, has a lighter reflectance. Remote sensing software was used to extract the edges between light and dark soils that indicate the presence of subsurface tile drainage systems.

The results of the detection process showed the most discernable tile patterns in the 2005 imagery, with similar results in the 2006 imagery. The tile lines were detected evenly across all eleven areas of interest in Wood County which was expected. The process was only able to validate 13.5 percent of detected tile drains, leaving room for additional research to increase the accuracy. Crop cover, tillage practice, and soil classification were analyzed in relation to the presence of subsurface tile drainage systems to create a holistic perception of when and where tile drains can be detected. Soybean fields yielded the highest amount of tile drain lines with corn fields in a close second. Tile detection in relation to tillage practices was overwhelmingly biased towards fields that were not tilled. Tile line detection on soil classifications was consistent throughout the three years of imagery, matching the soil type predictions based on drainage characteristics.

**Key Words:** Remote sensing, subsurface tile drains, aerial photographs, NAIP, GIS, subsurface tile drain detection
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Chapter 1

Introduction

Subsurface tile drainage systems have been a common practice in agriculture in the United States for over 100 years. The Maumee River Watershed has a large amount of area drained by subsurface drainage systems due to its extensive agriculture and relation within the former Black Swamp. Tile drains are able to lower the seasonally high water table to control cultivation times and crop growth more effectively.

Subsurface tile drainage systems are utilized to keep land arable that would be otherwise unusable but, due to their impact on the environment, can raise concerns for water quality. For these reasons, it is important to know the location of these tile drainage systems. This research is part of a larger research project that is currently investigating crop and tillage practices in the Maumee River Watershed so that their impact on water quality of the Maumee River can be determined.

In the past, subsurface tile drainage systems consisted of a network of perforated clay tubes, and now plastic tubes that are commonly installed two to four feet below the surface (EPA 2009). The perforated holes allowed excess water to leave the soil and exit through the network of pipes into the targeted waterway. Often, ground water is not the
only thing leaving the soil through these subsurface tile drainage systems. Nitrogen application has become a common practice in agricultural field management. Annually, large loads of residual nitrogen are exported to surrounding waterways because of timing of application and improper management of subsurface tile drainage systems (Goswami et al 2009). Many of these incidents can be controlled with proper subsurface drainage management if the location of tile drains was known.

Conversely, not all applications to agricultural fields result in overloading and damaging of surrounding waterways. Phosphorus and surface soil particle runoff, though not an issue with subsurface drainage, often takes place where there is no subsurface drainage. In fields where there is no subsurface drainage, soil moisture is not relieved effectively and therefore large increases of moisture on the surface cause significant runoff from the surface layer. Pesticide and herbicide runoff are two other water quality maintenance challenges that can be confronted with the knowledge of subsurface tile drainage system locations and the implementation of proper management techniques (Gilliam et al 1999).
FIGURE 1-1: An outflow pipe into a waterway near an agricultural field. Many environmental issues can arise because of this water drainage. (Photo attributed to the United States Environmental Protection Agency CADDIS)

Perhaps the most obvious effect subsurface tile drainage systems can have on agricultural fields is an increased control over yield from crops. Knowledge of tile drain placement and proper management can allow the farmer to drain excess moisture from the root zone for enhanced aeration, leading to earlier planting and a more efficient usage of machinery. The crop will have a better environment for emergence and growth, rewarding the owner with a more efficient yield for the year (Sands 2001).
FIGURE 1-2: The difference between plant growth above and below the surface with and without artificial subsurface drainage methods. (Photo attributed to Gary Sands and Lowell Busman)

In order to harness the benefits and minimize the negatives, the locations of the subsurface tile drainage systems need to be known and well documented. In some cases, the tile drains are far apart and the farmers may benefit from augmenting current systems by putting in more closely spaced tiles. Since subsurface drainage systems can have such a large impact on agriculture and the surrounding environment, it is important to know the location of these drainage systems to analyze and properly manage the health of a watershed.

Current methods of identifying subsurface tile drainage systems are limited to physically probing the soil until tiles are detected. This method is time consuming, labor intensive, and generally impractical for larger areas (Ale et al 2007). Utilizing remote sensing and GIS technologies can then play a large role in the detection of these drainage
systems because of the overall speed and ability to handle large areas of data efficiently (Verma et al 1996, Ale et al 2007, Naz and Bowling 2008).

These studies began by looking at the dry soil above the drainage lines that was discernable in different band combinations in color infrared aerial photographs. Using GIS technology, the tile lines that became visible under the different band combinations were traced manually (Verma et al 1996). The research grew into finding an automated method of drainage detection that would require minimal input from the user. Using a decision tree classifier to select land that would most likely have tile drainage present, researchers were able to narrow their focus to specific areas and use automated remote sensing methods to detect drainage patterns (Ale et al 2007). Validation of these detected methods was addressed by detecting drainage systems in controlled areas with in situ drainage maps available (Naz and Bowling 2008).

Utilizing remote sensing techniques allows the user to process imagery covering large areas while using GIS aids in converting the data to a more user friendly, vector format (Ale et al 2007, Naz and Bowling 2008). The process allows the user to create a rough draft tile map that needs to be processed further to create complete drainage systems. However, there are limitations in imagery availability, occurrence relative to rainfall, and crop residue that may affect the accuracy and ease of replication for this project.

This project utilized one meter spatial resolution aerial images of Wood County to detect the presence of subsurface tile drainage systems using changes in soil moisture reflectance. These detected pixels were then digitized using ArcMap 9.3 to vector format in a comprehensive tile drainage map. The accuracy of the tile drainage map was
validated using tile drainage installation blueprints from the Soil and Water Conservation District in Wood County, Ohio. Finally, the locations of detected tile lines were cross referenced with cropping patterns, tillage practices, and soil classifications to detect trends in visible subsurface tile drainage system locations.

1.1 Problem Statement

Subsurface tile drainage systems are an important part of agriculture in the Midwest allowing farmers to reduce uncontrolled runoff by controlling water levels in agricultural fields. These drainage systems are often not documented and remote sensing along with GIS technologies can help develop an efficient way to locate these tile drainage systems.

1.2 Objectives

- Locate subsurface tile drainage systems using remote sensing and GIS technology
- Produce a vector map of subsurface tile drainage systems to be used with other applications
- Validate the process using in situ drainage installation maps
- Compare soil classes and land cover trends where tiles can be effectively detected
Chapter 2

Subsurface Tile Drainage Systems

Subsurface tile drains are described as perforated conduits that are installed below the surface of the ground, with the perforations facing downward to move drainage water (Brady and Weil 2008). The conduits can be present in the form of clay tiles, pipe, or tubing (www.mighigan.gov 1992).

FIGURE 2-1: A machine commonly used for tile drain installation. The machine digs a trench, places the tile, and covers it in one pass, much faster than previous methods. (Photo attributed to Hans Kandel)
The term *tile* is used today to describe drainage that utilizes perforated polyethylene tubing because drainage installed until the 1970’s used cylindrical sections of concrete or clay called *tiles* (Busman and Sands 2002).

FIGURE 2-2: A pile of clay tile sections after being removed from a field. The term “tile” used to describe the drainage practice originated because of their original composition. (Photo attributed to IUPUI Center for Earth and Environmental Science)

Figure 2-3: A large roll of perforated subsurface tile drainage pipe. This roll is waiting in the field for installation. Often the size and manufacturer can be distinguished by the color of the pipe. (Photo attributed to David Green)
Other terms used to describe these drainage systems include drainage tile, interceptor drain, relief drain, tile, and underground drain (www.michigan.gov 1992). Tile drainage systems can take many forms after pre-installation considerations have been addressed including type of drain, capacity, velocity, size, outlet location, and design layout (Busman and Sands 2002).

Artificial drainage in the Midwest began after large stretches of land owned by the federal government were released by the Swamp Land Acts of 1849 and 1850 (Fausey et al. 1995). Some may argue that draining the Midwest, in particular the swamp areas such as the Black Swamp which includes Northwestern Wood County, was the key to settling Western states (Kaatz 1955). With the Reclamation Act of 1902, the Bureau of Agricultural Engineering was established to construct drainage ditches and organize drainage districts (Fausey et al. 1995). It was important to organize farmers and their land into drainage districts because individually, farmers would dig ditches away from their land which would result in the water running directly into a neighbor’s field (Kaatz 1955). These large scale drainage efforts in the Midwestern United States have created an area that is recognized as one of the most agriculturally productive in the entire world (Fausey et al. 1995).

The combined drainage of Illinois, Indiana, Iowa, Ohio, Minnesota, Michigan, Missouri, and Wisconsin (the Midwest states) was estimated at 31 million acres in a 1985 United States Department of Agriculture economic survey. Today this subsurface tile drainage would be worth over $30 billion (Allred et al. 2004). On top of these installed drainage systems, it is important to remember that subsurface drainage systems are
installed every year and would cover even more area currently than was estimated in 1985.

2.1 Environmental Impacts

The ability of subsurface tile drainage systems to efficiently remove excess water from agricultural fields can cause them to be environmentally deterministic. For example, liquid manure application is a common practice in agricultural field maintenance which can replenish some of the nutrients that plants need to grow. Subsurface drainage systems can cause overloading of liquid manure into the waterways if too much is applied or the drainage systems are not recognized. Between 2000 and 2003, the Ohio State Extension Service reported that there were 98 incidents in Ohio where liquid manure application directly caused large scale fish kills in the surrounding waterways by overloading the water with agrichemicals (Hoorman and Shipitalo 2006). In reviewing the causes of these 98 incidents, it can be argued that 69 of these incidents are in direct relation to subsurface tile drainage mismanagement with respect to liquid manure application. From this example alone, one can see the immense environmental impacts that subsurface tile drainage systems can have.

The most discussed environmental impact of subsurface tile drainage systems is nitrogen loading in surface water due to nitrogen transport through tile drainage systems. Nitrate concentrations in drinking water in Midwestern states usually exceed the maximum contaminant level that has been established by the United States Environmental Protection Agency (Goswami et al. 2009). Conventional agricultural practices rely heavily on nitrogen, commonly in the form of fertilizers, to prepare
agricultural fields for the crop growing season. Any surplus nitrogen, not used by the plants is then free to be washed away by rainfall or removed by drainage water through subsurface drainage systems. Nitrogen fertilizer use increased in the Midwestern United States beginning in the 1960’s (Gentry et al. 1998). In 2008, it was estimated that corn covered 57% of crop land in the United States. In the Midwest, corn has nitrogen fertilizers applied in the spring and fall which puts a large nitrogen load in the fields with the ability to become water-borne through runoff or subsurface drainage (Goswami et al. 2009). These effects of drainage systems on nitrogen loading can be controlled if proper drainage management is put in place. Knowing where tile drainage systems are located can lead to a more conservative approach to fertilizer application in those areas.

Appropriate timing of nitrogen application can help alleviate the unneeded stress on waterways along with the utilization of cover crops which can aid in controlling nitrogen in the soil before and after the growing seasons (Malone et al. 2007).

Another nutrient concern associated with agricultural water drainage is phosphorous. Some scientists consider phosphorous to be a leading nutrient in causing algae growth and loss of oxygen in freshwater ecosystems. Phosphorous runoff is typically credited to surface runoff although soluble phosphorous can be removed through subsurface drainage which further contributes to the problem (Gilliam et al. 1999). Although the research done by Gilliam et al. (1999) is concerned with Southern states and Histosols, phosphorous is also used in the Midwest where it can be drained into waterways and wreak havoc on the ecosystem if not regulated by controlled subsurface drainage practices.
Corn, soybeans and wheat typically make up the crop rotation that is practiced in the Midwestern United States. These three crops are conventionally treated with pesticides and herbicides to clear the fields of organisms that may compete with or harm the cash crop being planted. A survey conducted by the National Agricultural Statistics Survey in 1992 concluded that herbicides were used on 94% of corn, 96% of soybeans, and 28% of wheat and insecticides were used on 30% of corn, 2% or soybeans, and 6% of wheat in the United States (Gilliam et al. 1999). Surface runoff is the leading culprit of herbicide and pesticide loss from agricultural fields but, subsurface drainage carries a small percentage as well. In general, the better the subsurface tile drainage systems function, the less surface runoff occurs because the water level is controlled and the soil is allowed to function to mediate runoff. Therefore, it can be concluded that improving subsurface drainage will lower surface runoff and control sediments, phosphorous, pesticide, and herbicide runoff. At the same time nitrogen leaching that is higher in subsurface drainage would increase as the efficiency of the subsurface drainage system increases (Gilliam et al. 1999).

There has been pressure put on the United States Department of Agriculture-National Resource Conservation Service to stop assisting in land draining projects (Gilliam et al. 1999). However, this is not a good practice because drainage systems, if installed properly and well regulated, actually give the owner more options in managing their agricultural land and the effect it may have on the environment. With proper drainage management, nutrient and sediment losses are usually lower from fields that have established drainage systems as opposed to areas where there is no drainage (Gilliam et al. 1999).
Research is being done that would give farmers in different regions a blueprint on how to effectively utilize their subsurface tile drainage systems by raising or lowering the outflow pipe that would control the amount of water that can be drained from the field. An example of this type of research was done at Purdue University. In this project, they examined the effect of raising and lowering tile drainage outflow pipes with relation to precipitation, soil characteristics, and growing season standing. In the conclusion of their research, they determined the best dates for raising and lowering the outlet with respect to planting date (Ale et al. 2006). The target of these research projects was to put a management structure in place that links farmers from all regions together in helping to alleviate the stress that agricultural drainage can put on the environment. Groups such as the Agricultural Drainage Management Systems (ADMS) Task Force have been organized to promote drainage management plans in the Midwestern United States and promote research on the topic (Allred 2005).

2.2 Previous Research: use of remote sensing in tile drain detection

Since there is such a great need for subsurface tile drainage management, it comes as no surprise that research aiming to detect these drainage systems using primarily aerial imagery dates back to the early 1990’s. In 1996, Ashok Verma, Richard Cooke, and Leon Wendte brought research to the American Water Resources Association’s symposium on GIS and water resources. The researchers from the University of Illinois at Urbana-Champaign had focused their research on using the reflective properties of dry soil versus moist soil to develop a more time and cost effective way of locating

Their research began with the collection of color infrared aerial photographs that were taken during flights flown between March and April of 1984, a few days after a heavy rain storm had occurred. The researchers targeted the spring for useful imagery because of the relation to the spring thaw and the beginning of tile flow for the season. The researchers made note that the best images are acquired on a cloud free day, two to three days after a rainfall event of two inches or more. This allows the images to be clear of cloud interference and the soil to be moist enough to show a difference in reflectance. It is difficult to find a perfect time to collect images because of the overcast skies that follow significant rainfall events. Other data used by these researchers included a soil map, elevation map, administrative boundaries, and surface drainage map for Vermillion County (Verma et al 1996). The main purpose of these data layers was to make the delineation of tile lines more accurate as they were being digitized.

In order to delineate the tile drainage lines, different bands were used individually and in combinations. These band combinations created an image where the differences between the dry and moist soils were more obvious than they had been in the original color infrared photographs. After the optimum band combination was determined, the researchers delineated the tile lines by digitizing what they determined to represent a difference in the dry and moist soil areas. The secondary data layers that were used helped to determine if a questionable line was a subsurface tile drainage signature or not (Verma et al 1996).
The next research conducted to detect subsurface tile drainage system using an automated method was done in 2007 by researchers at Purdue University. Their area of interest was the Hoagland Watershed located in Northwest Indiana, which covered parts of three counties and five sub-watersheds. The researchers used a black and white aerial photograph with one meter spatial resolution acquired in April of 1998. The reason this imagery was chosen was due to the relation to rainfall events totaling over two inches the week before the data were collected (Ale et al 2007). In addition to these aerial photographs, the researchers added a land cover layer from the National Agricultural Statistics Survey, soil drainage classification and surface slope layers that were obtained from the Soil Survey Geographic database in the United States Department of Agriculture (Ale et al 2007).

The subsurface tile drainage line identification method for this research is more automated than the research done by Verma et al (1996). The researchers used horizontal and vertical edge detection methods to highlight linear areas of contrast. After these pixels were highlighted, they were classified into “tile” and “no-tile” areas using a density slice classification method. The pixels determined to be “tile” were then subjected to Clump, Sieve, and Majority Analysis functions to remove any noise, representing erroneous pixels. The remaining pixels were automatically converted from raster format to vector format and connected to form subsurface tile drainage patterns. The results of the tile line detection process yielded results that could be used in estimating drainage spacing and drainage density. The researchers do comment that it is unfortunate that no tile map was available at the time of the research to validate the accuracy of the technique they implemented (Ale et al 2007).
The follow up to the research done by Ale et al (2007) also came out of Purdue University. This research by Naz and Bowling (2008) was focused on the Agronomy Center for Research and Education (ACRE) in West Lafayette, Indiana. This controlled research area is managed by Purdue University so; a surplus of data is available for this specific area. The researchers used aerial photographs taken in 1976, 1998, and 2002 at ACRE because of their relation rainfall events. 2003 and 2005 imagery were also available but there were problems detecting soil moisture because of the lack of rain and the height of the vegetation in the field. Additional data layers used in the research were the same as Ale et al (2007), including land cover, soil drainage classification, and surface slope layers (Naz and Bowling 2008).

The method used to identify the subsurface tile drainage lines was the same method that was used by Ale et al (2007). After the raster to vector conversion was complete, the researchers used the in situ tile maps for ACRE to compare the accuracy of their detected lines to the known location of subsurface tile drainage. The overall accuracy of the automated detection of tile drainage lines was 86% for area 1 and 84% for area 2. The problems related to using the tile maps to determine accuracy include the nature of edge detection which may cause a shift in the detected location of the tile line from the middle of the dry soil to the outside of the dry soil where the dry soil contrasts with the moist soil. Another issue that affects accuracy is the differences in crop residues and soils that may affect the reflectance of the soil. The researchers also cite tillage practices as having a potential effect on tile line detection but since limited data are available, the actual affect was difficult to quantify (Naz and Bowling 2008).
Chapter 3

Methodology

3.1 Study Site

Wood County, Ohio covers 610 square miles in northwestern Ohio. The northern part of the county, near Toledo, Ohio, is mostly industrial but the majority of the county is agricultural (2009 Annual Information Statement). In fact, the entire county is very rural with approximately 80% of the land cover being agricultural related. There are 1,040 farms located in Wood County, with an average farm size of 289 acres. The farms are incredibly important to Wood County economically, with approximately $120,000 of products being sold annually per farm (2008 Wood County Profile).
The presence of agriculture in Wood County, Ohio is apparent and so are the environmental impacts of these farms because of Wood County’s location. The northern border of Wood County lies along the Maumee River. Northwestern Wood County, which is very heavily influenced by agriculture, lies in the Maumee River Watershed which flows into and has a very large impact on Lake Erie. The agricultural practices in northwestern Wood County then have a significant impact on the health of the watershed and Lake Erie. Southern Wood County on the other hand drains into the Blanchard River which is a major contributor to the Maumee River. Wood County’s location in relation to these two major northwestern Ohio Rivers emphasizes the immense
impact field runoff, pesticide usage, and other agricultural practices would have on these watersheds and in turn, the quality of water in Lake Erie.

3.2 Region of Interest

In 1853 the Perrysburg Journal predicted that “…the wet and overflowed lands of Wood County will be drained and eventually become the garden spot of Ohio. It will take time…the tide of emigration will no longer pass by them to go further and fare worse.” Drainage began in the region as a by product of the construction and maintenance of the Maumee-Western Reserve Road which was the main road in the region at that time. As the popularity of artificial drainage grew, the “ditch laws” were passed in 1859 to control where water could be drained to. The need for more efficient drainage systems than the wooden planks that were in use at the time lead to the development of clay tile factories in northwestern Ohio because of the abundance of clay soils in the area. By 1900, tile drain companies were creating 10,000’s of feet of clay tiles each season (Kaatz 1955).

Subsurface tile drainage systems have evolved and remain a very important part of Wood County, Ohio. Concern with water quality has lead to an increased awareness in what is being leached into surface waters with special attention being paid to artificial agricultural drainage. Large scale watershed conservation plans have become more popular in trying to protect regional environments with a more holistic approach. In northwestern Ohio, the Maumee Remedial Action Plan has begun looking at pollution sources from urban areas, industry, sewage treatment, etc. The plan has also put focus on analyzing sediment loads in the Maumee River and determined that the agricultural
runoff may be the issue that requires the most watershed-wide effort (Nelson and Weschler 1998). There are a large number of similar groups that are looking at environmental impacts of soil erosion in the northwestern Ohio and Lake Erie regions of the United States including the Great Lakes Basin Program for Soil Erosion and Sediment Control, the Lake Erie Lakewide Management Program, the Ohio Lake Erie Office, the Ohio Department of Natural Resources, the Ohio Environmental Protection Agency, and the Ohio Geographically Referenced Information Program (Nelson and Weschler 1998). Identifying the location of subsurface tile drainage systems could be a key in determining the best way to develop a comprehensive agricultural and environmental management plan.

3.3 Wood County Soil Profile

Many factors that affect the efficiency, design, and successful implementation of subsurface tile drainage systems relate directly to the type of soil where the system will be installed. The soil can determine which drainage pattern will be used, whether additional pumping stations are needed, and even what type of artificial drainage will be used (Brady and Weil 2008). The soils found in Wood County, Ohio have been significantly affected by glacial activity, with the Wisconsin glaciers being the last to recede, approximately 10,000 to 15,000 years ago. In turn, six different levels of Glacial Lake Maumee had an effect on the formation of soils in Wood County. Soils that were affected by Glacial Lake Maumee include the Alvada, Belmore, Cygnet, Digby, Haney, Millgrove, Oshtemo, and Shawtown soils which were formed from the beach ridges of the glacial lake. Granby, Ottokee, Spinks, Tedrow, and Wauseon were formed by the
reworking of beach material by readvancing water. These soils tend to be sandier and are located in Northwestern Wood County. The winnowing process of the glacial lake waves moving finer sediment out of the area, leaving the coarser material behind helped to form the Aurand, Haskins, and Mermill soils. In areas where sand was deposited on top of glacial till Rimer and Seward soils were formed. Hoytville and Nappanee soils were formed where water planed the till with the back and forth motion of shallow waves. In the areas where the water was last present, the Fulton, Latty, and Toledo soils, represent a lacustrine deposit left by the receding waters of Glacial Lake Maumee (Wood County Soil Survey 2000).

In analyzing the detailed soil descriptions in Wood County, it becomes obvious what soils are most likely to have subsurface tile drainage systems installed. Slope, drainage classification, and permeability are three characteristics that can be analyzed to determine whether or not a soil needs subsurface tile drainage. Soils in the most need of artificial drainage typically have a surface slope of 0 to 2 percent (Ale et al 2007 and Naz and Bowling 2008). Drainage classification is usually an indicator of the severity of the need for artificial drainage methods. Seasonal wetness and ponding is a concern for about 355,232 acres in Wood County (approximately 90% of the county) so, any drainage class can have its drainage capabilities enhanced with the addition of artificial drainage including moderately well drained soils that sometimes have subsurface tile drainage systems installed to improve control over cultivation and maximize crop yields. Very poorly drained soils are so naturally wet that they have to be artificially drained in order to be profitable at all, while poorly drained soils can be profitable but crops are often damaged during excessively moist years. Another characteristic indicative of a
greater need for artificial drainage is the permeability of the soil. The slower or lower
rate of permeability that characterizes a soil indicates a more severe need for subsurface
drainage. If the permeability is really slow, the tile drainage lines in the system can be
spaced closer together (Wood County Soil Survey 2000).

These soil characteristics can be related directly to the sand, silt, and clay
composition of the individual soil classes. Some of the more obvious properties of sand,
silt, and clay that affect their need for subsurface tile drainage system installation are
water holding capacity, natural drainage rates, susceptibility to water erosion, and the
ability to be tilled after rainfall.

<table>
<thead>
<tr>
<th>Property</th>
<th>Sand</th>
<th>Silt</th>
<th>Clay</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water Holding Capacity</td>
<td>Low</td>
<td>Medium-High</td>
<td>High</td>
</tr>
<tr>
<td>Natural Drainage Rate</td>
<td>High</td>
<td>Slow-Medium</td>
<td>Very Slow</td>
</tr>
<tr>
<td>Susceptibility to Water Erosion</td>
<td>Low</td>
<td>High</td>
<td>Low (aggregate) High (not agg.)</td>
</tr>
<tr>
<td>Ability to Till After Rain</td>
<td>Good</td>
<td>Medium</td>
<td>Poor</td>
</tr>
</tbody>
</table>

Looking at the Ternary Soil Texture Diagram, it can be said then that the soils
with higher concentrations of silt and especially clay would be more likely to need
subsurface tile drainage installation in order to make the land profitable. The types of
soils would include clays, clay loam, loam, silty clay, and silty clay loam. Although soils
with the characteristics that have just been outlined can now be located for through the soil survey of Wood County, that work has already been done and can be found under the “Use and Management Considerations” section for each detailed soil unit in the soil survey. In this section, use for cropland, pastureland, woodland, building site development, septic fields, road and street development for each soil series is summarized. The cropland use section refers to winter crop use, pesticide and fertilizer application, and other crop management practices including the use of artificial drainage systems. Some soils that do not fit the slope, drainage classification, permeability, and composition characteristics outlined here, still have a recommendation for the use of subsurface tile drainage systems to remove excess water. Aurand fine sandy loam for example has a slope of 0 to 2 percent, somewhat poorly drained classification, and moderate permeability which all point to a soil that could benefit, if only slightly, from artificial drainage. Upon further analysis, it can be seen that this soil has a seasonally high water table because of its location near rivers and lakes making it more prone to the height of the regional water table. The depth to the seasonal high water table for this soil is .5 to 1 foot which also indicates that without the presence of subsurface tile drainage there would be a high risk of crop damage (Soil Survey of Wood County 2000).

Although there are some exceptions like Aurand fine sandy loam, most of the soil with the recommendation of artificial drainage usage fits the characteristics described above. The soil characteristics are important when detecting subsurface tile drainage systems because of their effects on design, placement, and spacing of tile systems.

Soil characteristics also affect soil moisture and in turn soil reflectance. Weidong et al (2002) showed that all soils they tested showed similar trends of decreasing
reflectance as moisture levels were increased. Muller and Decamps (2000) found that the best, most consistent regressions for soil reflectance and moisture levels were shown obtained for sand and clay soils, not silts or silty clays. Perhaps most importantly, the researchers found that soil reflectance at relatively low moisture levels, similar to those levels experienced in typical agricultural situations, showed a consistent regression trend with reflectance decreasing as soil moisture levels increased (Weidong 2002).

Using remote sensing software has proven efficient and cost effective in identifying subsurface tile drainage systems for research projects because of the differences in reflectance of dry and moist soils (Verma et al. 1996, Ale et al. 2007, Naz and Bowling 2008). In order to reach the most accurate and comprehensive interpretations to this research project, Leica Geosystem’s ERDAS Imagine 9.3 and Environmental Systems Research Institute’s ArcGIS 9.3 will used for remote sensing and GIS applications.

3.4 Data

For this project, imagery was acquired from the National Agricultural Imagery Program (NAIP). NAIP is a project that acquires “leaf on” imagery during the agricultural growing season on a county level. The processing dates for the images used in this study were September 10, 2005 for the 2005 image, November 7, 2006 for the 2006 image, and October 10, 2009 for the 2009 image (NAIP 2005, 2006, and 2009 metadata). Although these are the processing and upload dates, it is difficult to infer the exact date the photographs were collected is unknown. The imagery was collected by independent contractors from aircrafts producing one meter spatial resolution images.
NAIP has been in effect since 2001 and is controlled by the United States Department of Agriculture Farm Service Agency Aerial Photography Field Office in Salt Lake City, Utah (NAIP Information Sheet 2009). The imagery from 2005 and 2006 was collected using digital mapping cameras and GPS units and then rectified to base points that were previously established for the program to georectify collected data (2005 NAIP metadata, 2006 NAIP metadata). The 2009 imagery was collected using ADS 40, ADS 40-SH51, and ADS40-SH52 sensors on an aircraft flying at an average height of 21,000 feet above the mean terrain (2009 NAIP metadata). All of the data were checked for issues including smoke, cloud cover, contrails, light conditions, sun glint, and sensor issues before being published. The imagery has 24 bit pixels and was projected using North American Datum 1983, Universal Transverse Mercator Zone 17 North (2005 metadata, 2006 metadata, 2009 metadata).

In order to analyze the soil classification relationship to subsurface tile drainage detection, USDA National Resource Conservation Service Soil Survey Geographic Database (SSURGO) data were acquired. These data are in a vector polygon format and represent the most detailed geographic soil data. The data for the entire country are made available by the USDA NRCS through the Geospatial Data Gateway. For this data set, which represents all of Wood County, Ohio, the data were contracted to Fuller, Mossbarger, Scott, and May Engineers to be prepared on a county level. The data were reprojected from Geographic Coordinate System North American 1983 to North American Datum 1983, Universal Transverse Mercator Zone 17 North (Wood County SSURGO 2005).
Comparing the crop cover and tillage practice relationship to subsurface tile drainage systems detection required data from the USDA was used to reference these practices at control points throughout Wood County, Ohio. The data were available through the University of Toledo Geography and Planning Department’s Maumee GIS project (http://maumee.utoledo.edu). Data were given to the project that included in situ observations of 602 transect points throughout Wood County that were collected annually to depict crop cover, crop residue, and tillage practices in certain fields to be used as a sample of the entire county (USDA Transect Data 2010). Each of the records in the transect data were converted from degrees to UTM coordinates so they could be easily projected onto the NAIP and SSURGO data.

Subsurface tile drainage system plans for selected fields were collected from the Wood County Soil and Water Conservation district archives. This agency aids in the implementation of plans involving subsurface tile drainage installation in order to keep updated data on potential water contamination sources. The difference between moist and dry soils for functioning subsurface tile drainage systems can be detected using the difference in reflection. In situ subsurface tile drainage maps obtained from the Wood County Soil and Water Conservation District Office were georeferenced, digitized for use in validation. The maps obtained cover individual fields randomly assorted throughout northwest Wood County, Ohio. These maps are blueprints for subsurface tile drainage installation, not surveyed locations of previously installed drainage systems. The reference points of drainage system blueprints are sometimes represented by objects that cannot be referenced in an aerial image such as concrete slabs or fence posts. These maps could not be accurately georeferenced so they were discarded and maps with
reference points that were visible on an aerial image, such as driveways and road
intersections, were kept to be used in the accuracy assessment. The *in situ* maps were
scanned into the computer and added to a map file in ArcMap to be georeferenced using
the 2005 NAIP images for Wood County (See Appendix). The 2005 NAIP imagery was
projected with North American Datum 1983, Universal Transverse Mercator Zone 17
North so the *in situ* maps share that same projection. This makes the *in situ* maps match
the detected tile lines which also share that same projection for an easier assessment of
accuracy. Using the benchmarks that are visible on the aerial image such as roads and
intersections, the maps were georeferenced then checked for accuracy by measuring the
distances between lines and referencing that information to the planned distances
recorded on the blueprint. After the *in situ* maps were georeferenced, the tile lines on the
map were traced and digitized using a heads-up method similar to the one used for
digitizing the detected tile lines. In total, blueprints of subsurface tile drainage systems
for eight fields were obtained and digitized to be used as an accuracy assessment.
FIGURE 3-2: Subset areas of analysis in Wood County, Ohio
FIGURE 3-3 Validation field locations in Wood County, Ohio

3.5 Remote Sensing

High spatial resolution imagery is a technique used to detect subsurface tile drainage systems. The first step is to convert the pixels of the imagery into a format that can be easily compared using the remote sensing software. One way of doing this is to compute functions of band combinations (Verma 1996). Other researchers have used color aerial and color infrared aerial imagery and perform an edge detection to compare the pixels in relation to each other (Ale et al. 2007, Naz and Bowling 2008).
Remote sensing imagery can be used to detect the different between moist and dry soils through their reflectance. Researchers agree that as soil moisture increases, soil reflectance in all bands and potential band combinations decreases up to a point of near saturation (Muller and Decamps 2000, Weidong et al. 2001, Lobell and Asner 2002). Researchers have also indicated that there are soil moisture reflectance variations between soil types which support the need to utilize SSURGO data in this research. Muller and Decamps (2000) found that the most reflectance variations were detected in soils primarily comprised of sand and clay while silts and silty clays yielded the poorest results. Understanding the differences in reflectance between moist and dry soils is what will allow functioning subsurface tile drainage systems to be detected in this project.

The one meter NAIP images cover entire counties which can be very difficult for the remote sensing program to analyze at one time because of the large amount of data so, eleven subset areas of approximately one to two square miles were selected to perform the detection process (Figure 3.1). Similar to Ale et al. (2007), the area studied was limited in order to eliminate errors in the imagery processing (Ale et al. 2007). Unlike their research, large plots of land were not eliminated because they did not fit the ideal drainage area prototype. Instead of using criteria that would determine where subsurface tile drainage systems are likely to be found, smaller areas of interest were utilized to eliminate potential errors and detect all tile drainage systems.

The first step of this subsurface tile drainage detection process was to perform an unsupervised classification on the one meter spatial resolution NAIP imagery subsets. Unsupervised classification is a computer automated process that recognizes groups of
pixels with similar spectral characteristics (Pouncey et al. 1999). The recognition of spectral characteristics is important to this research because of the differences in dry and moist soils. As soil moisture increases, the amount of electromagnetic energy that is reflected is decreased as well because most of it is absorbed by the water surrounding individual soil particles (Jensen 2007). Due to the differences in soil series in northwest Ohio, it is more beneficial to allow the computer to select classes based on reflectance characteristics rather than attempt to classify a dry and moist soil region for each soil type found in the imagery. Wood County has 123 different soil series (Wood County SSURGO data). The unsupervised classification method is very useful for generating basic sets of classes in relation to the rest of the image (Pouncey et al. 1999). For this research, the program used twenty unsupervised classes for each imagery subset. Twenty classes gave the program enough leeway to classify trees, roads, water, and the differences between moist and dry soils for each soil series.

After the subset images had been classified, an edge detection method was used to identify abrupt changes in the classifications performed in the previous step. Edge detectors in remote sensing smooth areas of low spatial frequency and creates a sharp contrast between groups of homogeneous pixels thus highlighting the edges in the image (Pouncey et al. 1999). Directional detection algorithms can enhance edges in imagery by adjusting the pixel brightness based on the values of adjacent pixels (Ale et al. 2007, Naz and Bowling 2008). Since there are no perfect edges in raster data, these edge detection algorithms adjust the pixels and generalize the enhanced edges (Pouncey 1999). The most common types of directional algorithms are horizontal and vertical which detect horizontal and vertical patterns in the imagery by applying a kernel grid to the imagery.
For this project, horizontal and vertical direction algorithms were ineffective, ignoring any edge that was not horizontal or vertical and leaving the image blurry. Instead, left and right diagonal edge detection algorithms were utilized. When applied to a three pixel by three pixel (3x3) filter, the resulting images showed horizontal, vertical, and diagonal edges.

After the edge detection was performed, the image was still difficult to decipher and many erroneous edges existed. Methods to reduce the noise after edge detection include Clump, Sieve, and Majority analysis (Ale et al. 2007, Naz and Bowling 2008). The Clump method “clumps” together pixels of the same spectral characteristics. The Sieve method is used after the Clump method to remove groups of pixels smaller than a predetermined threshold. Majority analysis uses a kernel filter of 3x3, 5x5, or 7x7 to adjust pixel values based on the value that is most common among the surrounding pixels (Naz and Bowling 2008). These methods are effective at eliminating small groups of pixels that are probably errors but, they can also eliminate small sections of subsurface tile drainage lines that should not be disregarded. In this research, a low pass filter was used to smooth the pixel values and eliminate some of the potentially erroneous lines in comparison to the surrounding pixel values. Low pass kernel filters average the values of pixels compared to the surrounding pixels, making the image more homogeneous and smooth appearing (Pouncey et al. 1999). This filter serves the same purpose as the clump, sieve, and majority operations but, the low pass filter does not eliminate any of the pixels, so no data are lost.
The imagery was then added to ArcMap software for further analysis. It is important to note that the data could be analyzed in the current form because the subsurface tile drainage system lines are visible in raster format. This project aims to transform these tile lines from raster to vector because of the general familiarity and ease of use of vector data. It would be much more efficient to convert this raster data to vector data one time instead of interpreting the values of each raster cell every time the data is analyzed. To perform this conversion, tools exist in the ESRI Arc Extensions that will automatically identify vector points, lines, and polygons from raster data. Ale et al (2007) and Naz and Bowling (2008) used a function found in ArcGIS called ArcScan. This function creates linear features from connected cells in raster data. This function also allows the user to establish a tolerance of total pixels between linear features that will be connected even if no data exists there (Naz and Bowling 2008). This method worked very efficiently for the research done by Ale et al (2007) and Naz and Bowling (2008) but, it was found to be inappropriate for this study. The use of ArcScan more often than not produced tile line maps that were deemed to be inaccurate by comparing the aerial imagery. Besides the general inaccuracy, it was determined that automatically closing the gaps between detected linear features would result in eliminating data indicative of tile drain sections that may not be functioning. As an alternative to this method, a heads-up digitizing approach similar to that used by Verma et al (1996) yielded the best results. Heads-up digitizing is a method where features are drawn directly on the computer screen by tracing an aerial photograph, a scanned map, or any other representation of spatial data (Ormsby et al 2004). Verma et al (1996) used the IDRISI software for on-screen digitization of the subsurface tile drainage systems that could be
seen visually after manipulation of band combinations in the aerial images. IDRISI is a software package developed by Clark Labs at Clark University that is very comparable to ESRI ArcGIS software. IDRISI includes a comprehensive GIS analysis package, image processing tools, and in-depth environmental modeling functions (IDRISI 2009).

For this research, heads-up digitizing in ArcMap was used to decipher subsurface tile drainage system lines in the processed imagery and transfer that data into a shapefile that would represent a tile drainage map. When the imagery was added to ArcMap, the symbology had to be changed for a more accurate view of what each raster cell actually represented. The symbology was changed to graduated colors, in three classes based on the Jenks natural breaks method which divides the data into naturally occurring groups based on the clumping of the data. The reason three classes were chosen was because it allowed some leniency on what class the cell would be categorized. Using only two classes caused the “either-or” method to miss some tile lines that would have been detected as tile lines. Using three classes would allow the user digitizing the tile lines to decide on whether some of the middle grouping of cells would be classified as tiles or not. After the appropriate symbology was determined, digitization was performed of each subset image. The digitization of the lines connected only cells that were adjacent to one another, eliminating the potential errors caused by the ArcScan method of closing cell gaps in the image. By digitizing the lines in this way, potentially non functioning tiles and soil classification differences would not be ignored.

After the subsurface tile drainage system lines were digitized, common land use units were digitized. Using a heads-up method where the user added the newly digitized
tile drainage lines to the original NAIP images in ArcMap. Agricultural fields with detected tile lines as well as transect data points from the United States Department of Agriculture present were digitized for ease of reference and comparison. Each polygon then has a reference of the amount of tile lines present, the crop cover, tillage practice, and spatial connection to soil series.

Another method of analysis that relates to the digitization of common land use polygons that was used in this research is the identity tool that is found in ArcToolbox. The Identity tool utilizes a polygon layer to cut another layer (point, line, or polygon) into segments based on the boundaries of the polygon. This function classified the tile lines based on the soil classification of the area. Each tile line is cut into segments based on the soil series it is located on.

The validation of these detected tile lines utilized the \emph{in situ} blueprints obtained from the Wood County Soil and Water Conservation District Office. The individual line segments from both the \emph{in situ} maps and the detected lines were categorized to produce an error matrix for the 2005, 2006, and 2009 imagery, as well as an overall accuracy for the three years combined. The segments were quantified regardless of their length or direction.

The analysis of the location of detected tile drain lines began with overlaying the transect data points obtained from the USDA onto the NAIP imagery and the detected tile drain lines. The transect points lying on each field on a studied subset area were analyzed and the crop cover and tillage practice were recorded. After recording the crop information consisting of corn, wheat, soybeans, or grass/hay, the field was classified into
three categories based on visual analysis by the researcher, i.e. “no tiles detected,” “some tiles detected,” and “tiles detected.” “No tiles detected” represents fields that had no lines detected in the boundaries of the field. “Some tiles detected” represents areas that had some lines detected but no patterns or tile systems were discernable. “Tiles detected” includes all fields that had tile lines detected and formed some type of tile system design or long enough segments of lines that could not be mistaken for errors or inconsistencies in the imagery (Figures 3.4 to 3.6).

FIGURE 3-4: Example of a field with no tile lines detected (“no tiles detected”)
FIGURE 3-5: Example of a field with some tile lines detected (“some tiles detected”)

FIGURE 3-6: Example of a field with tile lines detected (“tiles detected”)
The process of analyzing the tillage practices was similar to the process of analyzing crop cover whereby the fields in each tillage classification were recorded as being one of the three tile detection classifications. For the three years of interest, four classifications of tillage practices were analyzed, no till, mulch till, ridge till, and conventional till (Figures 3.7 to 3.10).

FIGURE 3-7: Example of a no till field. (Photo attributed to Mahdi Al-Kaisi)

FIGURE 3-8: Example of a mulch till field. (Photo attributed to Gerald H. Miller, Peter Schultz, Linda Schultz, and Brian Tiffany)
FIGURE 3-9: Example of a ridge till field. (Photo attributed to Gerald H. Miller, Peter Schultz, Linda Schultz, and Brian Tiffany)

FIGURE 3-10: Example of a conventional till field. (Photo attributed to David Bosch, Tom Potter, Clint Truman, Craig Bednarz, and Glen Harris)
The segmented detected tile lines were analyzed based on the soil that each line segment was located on. The tile line segments were recorded based on what detailed soil unit they are located on, then those soil units were quantified and only the units with a significant number of segments were studied for characteristic trends, etc. Any soil classification with over 100 segments for that specific year was accepted to move forward with the analysis. The number of tile segments for each soil classification with over 100 total segments for that year was recorded in a series of three tables representing the 2005, 2006, and 2009 imagery.

The crop, tillage, and soil classification analyses were quantified and entered into tables. The fields described as “Fields with Tiles Detected” and “Fields with Some Tiles Detected” were referenced by the crop (Corn, Soybeans, Wheat, or Hay) planted in the field and added to the table. The “Total Fields” column indicates the total number of fields for each crop classification. The table shows the number of fields with tile lines detected compared to the total number of fields with that particular crop.

The tillage classification analysis was quantified in a similar way to the crop data. The fields described as “Fields with Tiles Detected” and “Fields with Some Tiles Detected” were referenced by the tillage (No Till, Mulch, Ridge, Conventional) pattern in the field and added to the table. Again, the “Total Fields” column indicates the total number of fields for each tillage classification. The table shows the number of fields with tile lines detected compared to the total number of fields with that particular tillage practice.
Chapter 4

Results

4.1 Accuracy Assessment

Each field with an *in situ* subsurface tile drainage map from the Wood County Soil and Water Conservation District office was evaluated for presence of detected lines and the accuracy of those detections. There were eight fields with tile drainage maps for validation. 2005 was the best year for validating the detected location of subsurface tile drainage systems with four of the eight fields having tile drain lines detected within their boundaries.

Field 1 did not have any tile lines detected within its boundaries for 2005, 2006, or 2009 (Figure 4.15). In both 2006 and 2009, tile lines were detected in the field directly east of Field 1 but no lines were detected within the boundaries of Field 1. Field 1 was planted with wheat after mulch till in 2005, soybeans after mulch till in 2006, and soybeans after no-till in 2009.
FIGURE 4-1: Validation Field 1; 2005, 2006, and 2009 detected lines mapped against *in situ* blueprints of tile drain systems.
Field 2 was the most consistent of all eight fields because tile lines were detected within its boundaries in 2005 and 2006. In both years, the tile lines that were detected were found in the western half of the field. In 2005, there were seven lines detected with an average length of 152 meters. The inaccuracy of each line was measured by comparing the location of the tile line to the location of the in situ map line at the closest and furthest points then averaging those measurements to obtain an average inaccuracy distance for each individual line segment. The overall inaccuracy for the detected lines in 2005 was 3.5 meters. The 2006 image yielded similar results, showing seven detected lines with an average length of 205 meters and an average inaccuracy of 3.5 meters.
Interestingly, the main collector line in the field is visually apparent however it is not detected in any of the years. In 2009 however, Field 2 had no tile lines detected. Field 2 was planted with corn after no-till in 2005, soybeans after no-till in 2006, wheat after no-till in 2009.

FIGURE 4-3: Validation Field 2; 2005, 2006, and 2009 detected lines mapped against *in situ* blueprints of tile drain systems.
FIGURE 4-4: Validation Field 2; 2005, 2006, and 2009 aerial images that the detected tile lines in figure 4.3 were derived from.
Field 3 had no tile lines detected within its boundaries for any of the three years. This tile map is represented as half intersecting tiles with a larger main that feeds into a smaller fishbone section of tile drainage but, none of the areas have any lines detected. The main line is especially apparent in 2009, but still not detected. Field 3 was planted with corn after no-till in 2005, soybeans after no-till in 2006 and wheat after no-till in 2009.

FIGURE 4-5: Validation Field 3; 2005, 2006, and 2009 detected lines mapped against *in situ* blueprints of tile drain systems.
FIGURE 4-6: Validation Field 3; 2005, 2006, and 2009 aerial images that the detected tile lines in figure 4.5 were derived from.
Field 4 had lines detected within its boundaries in 2005. However, none of these lines are of a similar orientation as the tile map shows. There were twelve lines detected with an average length of 327 meters. In 2006 and 2009, no tile lines were detected in the field but lines were detected in the field area directly east of Field 4. Field 4 was planted with corn after mulch till in 2005, wheat after no-till in 2006, and wheat after no-till in 2009.

FIGURE 4-7: Validation Field 4; 2005, 2006, and 2009 detected lines mapped against in situ blueprints of tile drain systems.
FIGURE 4-8: Validation Field 4; 2005, 2006, and 2009 aerial images that the detected tile lines in figure 4.7 were derived from.
Field 5 had no tile lines detected in 2005 or 2009 but, in 2006 two lines showed up that could be part of the tile system but they were not close enough or in a definite pattern, so they were not classified as such. Field 5 was planted with soybeans after mulch till in 2005, wheat after no-till in 2006, and soybeans after no-till in 2009.

FIGURE 4-9: Validation Field 5; 2005, 2006, and 2009 detected lines mapped against \textit{in situ} blueprints of tile drain systems.
FIGURE 4-10: Validation Field 5; 2005, 2006, and 2009 aerial images that the detected tile lines in figure 4.9 were derived from.
Field 6 had thirteen tile lines detected in the same pattern as the *in situ* map. Five of the lines fell in an area where the map was missing data so only eight of the lines could be measured for accuracy. The eight lines had an average length of 169.3 meters with an average inaccuracy of 4.8 meters. Most of the inaccuracy came from gaps that occurred because the map seemed to be shifted South on the Eastern side. In 2006, there were no tile lines detected in this field but, there were lines detected in the field directly east. In 2009, there were lines detected but they did not have the same orientation as the tile map. These lines were long and connected and could represent something significant, similar to the situation in Field 4. Field 6 was planted with soybean after mulch till in 2005, wheat after no-till in 2006, and wheat after no-till in 2009.

**FIGURE 4-11: Validation Field 6; 2005, 2006, and 2009 detected lines mapped against *in situ* blueprints of tile drain systems.**
FIGURE 4-12: Validation Field 6; 2005, 2006, and 2009 aerial images that the detected tile lines in figure 4.11 were derived from.
Field 7 has an interesting pattern with a fishbone pattern in the western half of the field and a parallel, intersecting pattern in the eastern half. In 2005 there were eight lines detected on the regular shaped half with an average length of 82.25 meters and an average inaccuracy of 4.25 meters. In 2006 and 2009, there were no tile lines detected. When looking at the aerial images for field 7, it appears as though the visually detected tile lines do not match the blueprints for the area. This could be due to non-functioning tile lines that were re-tiled recently. Field 7 was planted with soybeans after no-till in 2005, corn after mulch till in 2006, and wheat after no-till in 2009.

FIGURE 4-13: Validation Field 7; 2005, 2006, and 2009 detected lines mapped against in situ blueprints of tile drain systems.
FIGURE 4-14: Validation Field 7; 2005, 2006, and 2009 aerial images that the detected tile lines in figure 4.13 were derived from.
Field 8 had no tile lines detected in 2005 but there were tiles detected in fields directly north, south, and west. In 2006 some lines were detected but they were not the same orientation as the tile map lines. In 2009, lots of lines were detected in a different orientation than the tile map which may hint to a similar situation as Field 4 and Field 6. Field 8 is similar to field 7 in that the tiles that can be seen through visual interpretation of the image do not match the blueprints for the field. In 2005 and 2006, the west to east pattern of the tiles is very obvious but the blueprints show the tiles in a north to south orientation with a main line running west to east. Field 8 was planted with wheat after no-till in 2005, soybeans after no-till in 2006 and corn after mulch till in 2009.

FIGURE 4-15: Validation Field 8; 2005, 2006, and 2009 detected lines mapped against in situ blueprints of tile drain systems.
The overall accuracy of the detected tile line segments that were validated using *in situ* was 13.5 percent. The accuracy represents the number of line segments that were detected and matched the *in situ* maps with proper placement and orientation. Tile lines that were detected that ran North to South were considered inaccurate if the *in situ* lines ran East to West and vice versa. The accuracy of the detected tile lines totaled for 2005, 2006, and 2009, and divided by validation field number can be found in Table 4.1. The accuracy for the individual years can be found in Tables 4.1, 4.2, and 4.3, respectively.
TABLE 4.1 Tile line detection accuracy for 2005 NAIP imagery

<table>
<thead>
<tr>
<th></th>
<th>Detected Tiles</th>
<th>No Detected Tiles</th>
<th>Total</th>
<th>Producer Accuracy</th>
<th>Error of Omission</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blueprint tiles</td>
<td>28</td>
<td>153</td>
<td>181</td>
<td>15.5%</td>
<td>84.5%</td>
</tr>
<tr>
<td>No blueprint tiles</td>
<td>7</td>
<td>0</td>
<td>7</td>
<td>0%</td>
<td>100%</td>
</tr>
<tr>
<td>Total</td>
<td>35</td>
<td>153</td>
<td>188</td>
<td></td>
<td></td>
</tr>
<tr>
<td>User Accuracy</td>
<td>80%</td>
<td>0%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Error of Commission</td>
<td>20%</td>
<td>100%</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

TABLE 4.2 Tile line detection accuracy for 2006 NAIP imagery

<table>
<thead>
<tr>
<th></th>
<th>Detected Tiles</th>
<th>No Detected Tiles</th>
<th>Total</th>
<th>Producer Accuracy</th>
<th>Error of Omission</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blueprint tiles</td>
<td>10</td>
<td>263</td>
<td>273</td>
<td>3.7%</td>
<td>96.3%</td>
</tr>
<tr>
<td>No blueprint tiles</td>
<td>10</td>
<td>0</td>
<td>10</td>
<td>0</td>
<td>100%</td>
</tr>
<tr>
<td>Total</td>
<td>20</td>
<td>263</td>
<td>283</td>
<td></td>
<td></td>
</tr>
<tr>
<td>User Accuracy</td>
<td>50%</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Error of Commission</td>
<td>50%</td>
<td>100%</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 4.3 Tile line detection accuracy for 2009 NAIP imagery

<table>
<thead>
<tr>
<th></th>
<th>Detected Tiles</th>
<th>No Detected Tiles</th>
<th>Total</th>
<th>Producer Accuracy</th>
<th>Error of Omission</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blueprint tiles</td>
<td>0</td>
<td>225</td>
<td>225</td>
<td>0</td>
<td>100%</td>
</tr>
<tr>
<td>No blueprint tiles</td>
<td>45</td>
<td>0</td>
<td>45</td>
<td>0</td>
<td>100%</td>
</tr>
<tr>
<td>Total</td>
<td>45</td>
<td>225</td>
<td>270</td>
<td></td>
<td></td>
</tr>
<tr>
<td>User Accuracy</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Error of Commission</td>
<td>100%</td>
<td>100%</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4.4 Tile line detection accuracy totaled for three years of imagery

<table>
<thead>
<tr>
<th></th>
<th>Detected Tiles</th>
<th>No Detected Tiles</th>
<th>Total</th>
<th>Producer Accuracy</th>
<th>Error of Omission</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blueprint tiles</td>
<td>38</td>
<td>641</td>
<td>679</td>
<td>5.1%</td>
<td>94.9%</td>
</tr>
<tr>
<td>No blueprint tiles</td>
<td>62</td>
<td>0</td>
<td>62</td>
<td>0</td>
<td>100%</td>
</tr>
<tr>
<td>Total</td>
<td>100</td>
<td>641</td>
<td>741</td>
<td></td>
<td></td>
</tr>
<tr>
<td>User Accuracy</td>
<td>38%</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Error of Commission</td>
<td>62%</td>
<td>100%</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The eleven subsets used for crop, tillage, and soil classification analysis are shown in Figures 4.17 to 4.28 for the 2005, 2006 and 2009 imagery. The following images are grouped by year (2005, 2006, and 2009) and vertically by field number. Each field for each year is represented by four images, beginning with the aerial photograph. The aerial photograph is a subset from the NAIP imagery for Wood County. The second image is the 20 class unsupervised classification for that specific field. The third image is the edge detection which shows where the differences in pixel values are located. The fourth image is the vector format line detection. This image is created from the preceding raster imagery and serves as a tile map for that specific field. The red box around certain fields indicates an area where a tile drainage blueprint was available for validation.
FIGURE 4-17: 2005 subset areas one, two, and three (columns, left to right); aerial photograph, 20 class unsupervised classification image, edge detection image, and line detection feature class (rows, top to bottom).
FIGURE 4-18: 2005 subset areas four, five, and six (column, left to right); aerial photograph, 20 class unsupervised classification image, edge detection image, and line detection feature class (rows, top to bottom).
FIGURE 4-19: 2005 subset areas seven, eight, and nine (columns, left to right); aerial photograph, 20 class unsupervised classification image, edge detection image, and line detection feature class (rows, top to bottom).
FIGURE 4-20: 2005 subset areas ten and eleven (columns, left to right); aerial photograph, 20 class unsupervised classification image, edge detection image, and line detection feature class (rows, top to bottom).
The tile detection process for the 2005 images found reasonable tile drain patterns in all eleven areas. Areas one and two had large sections of trees that were not detected. Area eleven had a large quarry in the northeastern portion of the image which was also not detected. Both of these “non detections” are good for the detection process because those are two less inaccuracies to be concerned with. Areas three, four, and six had many smaller fields within the boundaries which seemed to cause some inaccuracies by detecting the individual field boundaries as tile lines. This is caused by the difference in crops planted in the fields as well as the difference in tillage practices between the fields.
FIGURE 4-21: 2006 subset areas one, two, and three (columns, left to right); aerial photograph, 20 class unsupervised classification image, edge detection image, and line detection feature class (rows, top to bottom).
FIGURE 4-22: 2006 subset areas four, five, and six (columns, left to right); aerial photograph, 20 class unsupervised classification image, edge detection image, and line detection feature class (rows, top to bottom).
FIGURE 4-23: 2006 subset areas seven, eight, and nine (columns, left to right); aerial photograph, 20 class unsupervised classification image, edge detection image, and line detection feature class (rows, top to bottom).
FIGURE 4-24: 2006 subset areas ten and eleven (columns, left to right); aerial photograph, 20 class unsupervised classification image, edge detection image, and line detection feature class (rows, top to bottom).
The tile detection process for the 2006 imagery yielded very similar results to the 2005 imagery. Similar to 2005, areas one and two did not have the large amounts of trees in the area detected and area eleven did not have the quarry detected. Again however, areas three, four, and six had some erroneous lines detected representing the boundaries between fields. The tile lines that were detected seemed to be very reasonable and part of drainage patterns for the most part. Area nine yielded the best results, showing many tile lines that formed relative drainage patterns. Compared to 2005, the results were very similar except 2006 seemed to have less tile lines detected overall, especially in areas one through six. This is most likely because of the moisture content of the soil in relation to the date the imagery was collected as compared to the 2005 imagery collection date.
FIGURE 4-25: 2009 subset areas one, two, and three (columns, left to right); aerial photograph, 20 class unsupervised classification image, edge detection image, and line detection feature class (rows, top to bottom).
FIGURE 4-26: 2009 subset areas four, five, and six (columns, left to right); aerial photograph, 20 class unsupervised classification image, edge detection image, and line detection feature class (rows, top to bottom).
FIGURE 4-27: 2009 subset areas seven, eight, and nine (columns, left to right); aerial photograph, 20 class unsupervised classification image, edge detection image, and line detection feature class (rows, top to bottom).
FIGURE 4-28: 2009 subset areas ten and eleven (columns, left to right): aerial photograph, 20 class unsupervised classification image, edge detection image, and line detection feature class (rows, top to bottom).
The tile detection for the 2009 imagery yielded results that were different than the 2005 and 2006 imagery because of the significantly lower amount of individual line segments detected. Many of the same fields had lines detected within their boundaries as they did in 2005 and 2006, but the segments were shorter and more detached. The lower number of line segments detected reduced the inaccuracies caused by the presence of many fields in areas three, four, and six. Area eleven had no tile lines detected at all in 2009. The lack of tile line detection could be caused by the soil being too dry or too moist to see a clear difference in soil reflectance between tile drained soil and non drained soil.

4.2 Crops

For this analysis, the eleven subset areas were used to analyze the influence of crop type on tile detection. The fields with the most tile lines detected in their boundaries were consistently fields with corn and soybean planted on them through 2005, 2006, and 2009. In 2005, corn and soybean fields were very comparable with corn covering four “tiles detected” fields and soybean covering five “tiles detected” fields. In 2006 the trends continued with corn and soybean representing the most “tiles detected” fields except soybean covered over three times more fields than corn (4 and 13 respectively). In 2009, corn and soybeans still covered the most fields that had tile lines detected within their borders. Corn covered eight “tiles detected” fields and soybeans covered eight “tiles detected” fields as well. In addition to corn and soybeans, hay covered one “tiles detected” field in 2006 as well as 2009. Wheat covered one “tiles detected” field in 2009 but none in 2005 or 2006.
Looking further than “tiles detected,” the main crops still cover most fields with tile lines detected in the form of “tiles detected” and “some tiles detected.” In 2005, tile lines were detected in fourteen of nineteen corn fields and ten of twenty soybean fields. Tile lines were detected in one of ten wheat fields and two of four hay fields but these lines were questionable and fell into the “some tiles detected” category. In 2006, tile lines were detected in eight of nineteen of corn fields and on thirty three of thirty eight soybean fields. The corn field tile detection was down from 2006 but, the soybean field detection was a lot higher, still representing the two dominant crops for tile detection. Tiles were detected on one of seven wheat fields and one of three hay fields. In 2009, tile lines were detected on fourteen of eighteen corn fields and eleven of twenty one soybean fields. Wheat fields had a better detection rate of five of eleven but hay fields were one of two.

Table 4.5: Crop and tile detection totaled for 2005, 2006, and 2009

<table>
<thead>
<tr>
<th>Crop</th>
<th>Fields w/ Tiles Detected</th>
<th>Fields w/ Some Tiles Detected</th>
<th>Total Fields</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corn</td>
<td>15</td>
<td>20</td>
<td>51</td>
</tr>
<tr>
<td>Soybeans</td>
<td>26</td>
<td>18</td>
<td>69</td>
</tr>
<tr>
<td>Wheat</td>
<td>1</td>
<td>6</td>
<td>28</td>
</tr>
<tr>
<td>Hay</td>
<td>2</td>
<td>3</td>
<td>9</td>
</tr>
</tbody>
</table>
4.3 Tillage

For all three years, no till was the tillage practice that yielded the most detected tile lines but was also the most common practice. In 2005, tile lines were detected (either “tiles detected” or “some tiles detected”) on twenty two of thirty one no-till fields. In the same year, tile lines were detected on three of five mulch till fields, one of seven ridge till fields, and one of six conventional till fields. The fields that actually had clear “tiles detected” traits were found on no-till lots (eight fields) and conventional till lots (one field). In 2006, tile lines were detected on twenty two of thirty one no-till fields, again encompassing a large amount of the fields with data available. Tile lines were also detected on two of three mulch till fields, four of eight ridge till fields, and six of ten conventional till fields. Clear patterned fields, “tiles detected,” were detected on no-till (eleven fields), mulch till (two fields), ridge till (two fields), and conventional till (three fields). In 2009, tile lines were detected on seventeen of thirty no-till fields, two of three mulch till fields, five of nine ridge till fields, and six of eleven conventional till fields. “Tiles detected” areas included no-till areas (ten fields), mulch till areas (one field), ridge till areas (five fields), and conventional till areas (two fields).

4.6: Tillage and tile detection totaled for 2005, 2006, and 2009

<table>
<thead>
<tr>
<th>Tillage</th>
<th>Fields w/ Tiles Detected</th>
<th>Fields w/ Some Tiles Detected</th>
<th>Total Fields</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Till</td>
<td>29</td>
<td>31</td>
<td>95</td>
</tr>
<tr>
<td>Mulch Till</td>
<td>3</td>
<td>4</td>
<td>11</td>
</tr>
<tr>
<td>Ridge Till</td>
<td>8</td>
<td>5</td>
<td>24</td>
</tr>
<tr>
<td>Conventional Till</td>
<td>6</td>
<td>8</td>
<td>27</td>
</tr>
</tbody>
</table>


4.4 Soils

Hoytville clay loam (HgA), Nappanee loam (NnA), Rimer and Tedrow loamy fine sands (RfA), Wauseon fine sandy loam (way), Hoytville silty clay (HvA), and Mermill sandy clay loam (MeA) were the six soil series that were prominent throughout all three years of interest. In total, these soil series comprised 67.3% of total land in the eleven subset areas. In 2005, these six soil series plus the significant presence of the Mermill loam (MdA) soil classification totaled 80.5% of total tile line segments (2,486) for the year. HgA represented 911 segments while no other soil series represented more than 300 segments individually. In 2006, the six main soil series comprised 86.5% of total segments (2,888) for the year. Again, HgA represented the most segments at 1,440 with the next highest, HvA, representing 435 segments. In 2009, the six main soil series plus the additional presence of the Mermill-Aurand Complex (MfA) soil series represented 82.5% of total segments (3,693) for the year. HgA represented 1,547 segments with the next highest total being HvA, at 494 segments.

Table 4.7 shows the percentage of each subset area composed of the individual soil series of interest. Hoytville clay loam covers 45 percent of the subset areas totaled while the other soils combined total approximately 30 percent of the subset areas. Tables 4.8, 4.9, and 4.10 show the amount of tile line segments detected per acre of that particular soil series. In 2005, all of the soil series show up less than one segment per acre except for Mermill sandy clay loam which had 4.168 line segments visible per acre of soil. For 2006 and 2009, the soils followed the same trend as the 2005 soils did.
Table 4.7 Area of each soil series with relation to subset area

<table>
<thead>
<tr>
<th>Soil Series Abbreviation</th>
<th>Soil Series Full Name</th>
<th>Soil Series Area in Acres</th>
<th>Percentage of Subset Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>HgA</td>
<td>Hoytville clay loam</td>
<td>7,273.8</td>
<td>45.0</td>
</tr>
<tr>
<td>NnA</td>
<td>Nappanee loam</td>
<td>514.7</td>
<td>3.2</td>
</tr>
<tr>
<td>RfA</td>
<td>Rimer and Tedrow loamy fine sands</td>
<td>353.8</td>
<td>2.2</td>
</tr>
<tr>
<td>WyA</td>
<td>Wauseon fine sandy loam</td>
<td>257.3</td>
<td>1.6</td>
</tr>
<tr>
<td>HvA</td>
<td>Hoytville silty clay</td>
<td>2,203.5</td>
<td>13.7</td>
</tr>
<tr>
<td>MeA</td>
<td>Mermill sandy clay loam</td>
<td>257.3</td>
<td>1.6</td>
</tr>
<tr>
<td>MdA (2005)</td>
<td>Mermill sandy clay loam</td>
<td>64.3</td>
<td>.4</td>
</tr>
<tr>
<td>MfA (2009)</td>
<td>Mermill-Aurand complex</td>
<td>1,077.6</td>
<td>6.7</td>
</tr>
</tbody>
</table>

Table 4.8 Soil variation of tile detection for 2005

<table>
<thead>
<tr>
<th>Soil Series Abbreviation</th>
<th>Soil Series Full Name</th>
<th>Number of Tile Line Segments Detected per Acre of Soil Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>HgA</td>
<td>Hoytville clay loam</td>
<td>.125</td>
</tr>
<tr>
<td>NnA</td>
<td>Nappanee loam</td>
<td>.419</td>
</tr>
<tr>
<td>RfA</td>
<td>Rimer and Tedrow loamy fine sands</td>
<td>.317</td>
</tr>
<tr>
<td>WyA</td>
<td>Wauseon fine sandy loam</td>
<td>.486</td>
</tr>
<tr>
<td>HvA</td>
<td>Hoytville silty clay</td>
<td>.121</td>
</tr>
<tr>
<td>MeA</td>
<td>Mermill sandy clay loam</td>
<td>.408</td>
</tr>
<tr>
<td>MdA</td>
<td>Mermill sandy clay loam</td>
<td>4.168</td>
</tr>
</tbody>
</table>
Table 4.9 Soil variation of tile detection for 2006

<table>
<thead>
<tr>
<th>Soil Series Abbreviation</th>
<th>Soil Series Full Name</th>
<th>Number of Tile Line Segments Detected per Acre of Soil Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>HgA</td>
<td>Hoytville clay loam</td>
<td>0.198</td>
</tr>
<tr>
<td>NnA</td>
<td>Nappanee loam</td>
<td>0.478</td>
</tr>
<tr>
<td>RfA</td>
<td>Rimer and Tedrow loamy fine sands</td>
<td>0.297</td>
</tr>
<tr>
<td>WyA</td>
<td>Wauseon fine sandy loam</td>
<td>0.470</td>
</tr>
<tr>
<td>HvA</td>
<td>Hoytville silty clay</td>
<td>0.197</td>
</tr>
<tr>
<td>MeA</td>
<td>Mermill sandy clay loam</td>
<td>0.595</td>
</tr>
</tbody>
</table>

4.10 Soil variation of tile detection for 2009

<table>
<thead>
<tr>
<th>Soil Series Abbreviation</th>
<th>Soil Series Full Name</th>
<th>Number of Tile Line Segments Detected per Acre of Soil Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>HgA</td>
<td>Hoytville clay loam</td>
<td>0.212</td>
</tr>
<tr>
<td>NnA</td>
<td>Nappanee loam</td>
<td>0.470</td>
</tr>
<tr>
<td>RfA</td>
<td>Rimer and Tedrow loamy fine sands</td>
<td>0.486</td>
</tr>
<tr>
<td>WyA</td>
<td>Wauseon fine sandy loam</td>
<td>0.921</td>
</tr>
<tr>
<td>HvA</td>
<td>Hoytville silty clay</td>
<td>0.224</td>
</tr>
<tr>
<td>MeA</td>
<td>Mermill sandy clay loam</td>
<td>0.769</td>
</tr>
<tr>
<td>MfA</td>
<td>Mermill-Aurand complex</td>
<td>0.147</td>
</tr>
</tbody>
</table>
Chapter Five

Discussion

After analyzing the results of the subsurface tile drainage system line detection process, further research was performed to determine why certain fields had tile lines detected while others did not have any lines detected. Crop cover, tillage practices, and soil classifications all play a part in which fields have detected lines and which fields do not.

5.1 Accuracy

The validation performed on the detected tile lines did not show a strong confidence in using the method of detection for locating subsurface tile drainage systems described in Chapter 3. Statistically, the 2005 image had the best results of the three years. 28 line segments matched the in situ map while 153 segments from the in situ map were not accurately detected. Of the 35 total segments detected, 28 were accurate, yielding 80% user accuracy. The 2006 image was not as accurate as the 2005 image, detecting 10 tile lines that matched the in situ map while 263 segments from the in situ maps were not detected. Of the 20 total segments detected in 2006, 10 were accurate,
yielding 50% user accuracy. The 2009 image did not result in any accuracy, detecting 0 tile lines while 225 in situ segments were left undetected. Overall, for the three years combined, the producer accuracy was 5.1% and the user accuracy was 38%.

Tile line accuracy was measured for fields that had both detected tile lines and blueprint maps. The assessed spatial accuracy was 3.25 meters. That error may result from the registration of the blueprint maps and the georeferenced or the edge detection method itself. That much error may not tell the researcher exactly where the tile drains are to a specific spatial coordinate, but it does indicate that lines detected there are from drainage systems and that the field has functioning tile lines. The cause of this inaccuracy may be the use of an edge detection method in remote sensing software that causes slight inaccuracies by the nature of the function. When edge detection finds a significant difference between two pixels in a raster image, it adds the pixels of each value, straddling the line of difference, to the edge. The edge is then two pixels wide which can cause a shift in the actual placement of the tile line. The actual tile line may be at the center of a 10, 20, or 30 foot wide dry soil area (Ale et al 2007 and Naz and Bowling 2008).

There is also an issue with the NAIP imagery referencing system that may cause inaccuracies in the detected tile lines. In the 2005 and 2006 NAIP metadata, it says that the imagery is rectified using pre-established base points but in 2009, it does not have a rectification system described (NAIP metadata). Although all three years of imagery are using the same projected coordinate system and geographic coordinate system, the rectification discrepancies of the imagery from one year to the next may cause enough of
a shift to throw off the tile maps if they are referenced to one specific year like they were for this project. The 2005 and 2006 imagery lined up very well but the 2009 had some slight variations that may be enough to create a visible shift in the location of the detected tile lines. The maps that were used to serve as an accuracy assessment also have many variables. Not all of the maps were created by the same person so information available and formatting becomes an issue. Also, the availability and accuracy of benchmark points to reference the map are limited and inconsistent. For example, one of the \textit{in situ} maps was referenced using a concrete marker by the property owner’s driveway and a number of feet away from the center of the intersection to the southeast of the property. These are both makers that would be easy to determine in person, but difficult to decipher in aerial imagery.

After executing the tile detection process for these images, some fields showed up with clear tile patterns that did not match the patterns represented by the \textit{in situ} maps obtained from the Wood County Soil and Water Conservation office. This raises a question about old installation versus newer installation. Fields 4, 6, and 8 all had this problem in one year or another. While the use of the maps for accuracy says that these detected lines are inaccurate, the detected lines and pattern found say that the \textit{in situ} map lines are not the only drainage present.

\textbf{5.2 Crops}

The timing of the aerial photos plays a large role in the amount of tile lines that will be detected. When looking at crops in the aerial photographs, it is important to realize that not all fields are planted at the same time and due to location, growth cycles
could be affected causing non-uniform fields to study. The common crop cycle in Wood County, is corn, soybeans, and then wheat. Corn and soybeans are typically planted at similar times during the year and harvested at a similar time. However, wheat is planted in the winter and harvested in the spring or early summer. Hay is also a crop that was analyzed in this research but does not fit the common cycle and is typically found on land that is unprofitable to plant one of the more common cash crops. Alfalfa and other types of hay are planted and harvested multiple times throughout the spring and summer, making its growth cycle much more difficult to compare to other crops. The NAIP photographs that were used for this research were processed on September 10th for the 2005 image, November 7th for the 2006 image, and October 10th for the 2009 image. These dates do not necessarily represent the time of data collection however, just the date that the imagery was processed and made available for public use. We can extrapolate from these dates that the photographs were collected at different times during the growing season. The difference in collection dates could explain some of the consistencies in the data. The wheat crop may have just been harvested, revealing only the recent harvester tracks that could be inaccurately identified as tile lines.

Also related to the timing of the imagery collection is the growth stage of the individual crop when being compared to the same crop in a different year. Research conducted by Adams and Arkin (1977) concluded that ground cover can be calculated by looking at the amount of light that is intercepted by plant canopy. The light interception can then be converted into the percentage of soil that is shaded by that same plant canopy. Their research covered multiple crops including corn and soybeans. They found that corn ground cover ranged from 10% to 70% while soybean ground cover ranged
from 10% to 80% (Figures 5.1 and 5.2) (Adams and Arkin 1977). These numbers can be related to the growth stages of the individual crop, with younger corn covering 10% of the ground while more mature corn covers 70% of the ground. Burstall and Harris (1983) had similar conclusions while analyzing the growth cycle of potatoes and studying the amount of light they intercepted with their growth rate. This research shows that more mature plants may affect the amount of light that reaches the soil and in turn the amount of energy returned from the soil. Muller and Decamps (2000) recommend detecting soil moisture and reflectance relationships on soil that has recently been prepared for sowing and is uniformly bare. This would avoid errors or missing data from intercepted energy.

FIGURE 5-1: Corn growth stages with relation to the percentage of visible soil as the crop matures. (Photo attributed to University of Illinois Extension Service)
FIGURE 5-2: Soybean growth stages with relation to the percentage of visible soil as the crop matures. (Photo attributed to University of Illinois Extension Service)

The nature of the transect data can also affect the outcome of tile line location analysis by being skewed towards a specific crop. For 2005, 2006, and 2009, corn and soybeans are sown on more fields than either wheat or hay which could indicate that the number of detected tile lines on corn and soybean fields is skewed because there are more fields of that type available to study. When looking at the percentages of fields with tile lines detected, it becomes clear that corn and soybeans are more prominent, however on a larger scale with more transect points included, wheat and hay fields may show up with more tile lines detected.
5.3 Tillage

The tillage practices recorded throughout this research were no till, mulch till, ridge till, and conventional till. The way these tillage practices are performed may cause inaccuracies in the tile line detection process. No till farming leaves the residue from the previous crop in place and after the crop has been harvested, that residue may be spread to cover even more of the soil than before harvest. No till farming may not allow enough of the soil to be seen to determine the moisture level through soil reflectance, similar to what was discussed with ground cover percentages. Mulch till may have a similar effect because it incorporates so much organic material that the soil moisture reflectance relationship may be affected or inconsistent. Ridge till farming may be the most deceiving practice when investigating soil moisture. The ridges may appear dry because the soil is slightly higher than the lower areas between ridges. The purpose of the trenches between the ridges is to hold organic material and moisture. This may cause a pattern to be detected that is of a different orientation than the tile lines. Conventional till farming may be the best method to see soil moisture reflectance because the soil is turned over completely and after the field is prepared for planting, it appears homogeneous. Muller and Decamps (2000) found that they could detect a significant difference on homogeneous fields when they were prepared for planting. After only the plow had been used on the field, the heterogeneous nature of the soil clumps made the soil moisture difficult to detect, but after the disc was used to smooth the soil for planting, the soil moisture became more visible after rainfall.
Similar to the skewing effects of the crop data from the transects, where one crop may show up more than other crops, effecting the appearance of accuracy, tillage practices were affected in a similar way. No till farming was represented on 34 of 63 fields in 2005, 31 of 63 fields in 2006, and 30 of 63 fields in 2009. It comes as no surprise then when no till fields also have the most fields with tile lines detected within their boundaries. It would be beneficial to find more fields that use mulch till, ridge till, and conventional till practices in order to get a larger sample and determine if no till farming really results in more accurate detection of tile lines. This may be a difficult task however, with the rise in concern for water quality and more responsible, conservative farming practices, no till farming is becoming the most popular form of tillage with some states even paying farmers money to not till their fields before planting.

5.4 Soils

The most common soil series with tile lines detected on them in this research were HgA, NnA, RfA, WyA, MeA, and HvA. In 2005, MdA showed a significant amount of tile lines detected and in 2009, MfA showed a significant amount of tile lines detected. All eight of these soil series fit the characteristics previously outlined for soils that would benefit from having artificial drainage installed.

The soils that had the most tile lines detected on them in 2005, 2006, and 2009 can be broken into three groups based on their physical characteristics. One group consists of the Hoytville soils which are the most common soils in the region, HgA and HvA. Another group consists of Mermill and Wauseon soils, including MfA, MdA, MeA, and Way. The third group consists of Nappanee and Rimer-Tedrow soils,
including NnA and RfA. The Hoytville soils both come from a wave-planed till parent material and can be found in depressions, drainage ways, and extensive lake plain flats. The permeability of these two soil series is a direct result of their high clay content. Both soils have a moderately slow permeability in the solum, reducing to a slow permeability in the lower solum, and a very slow permeability in the substratum. Drainage can also result of the clay content, with both soils having very poorly drained soil. The seasonal water table and cropland considerations are related for these soils because the seasonal water table can reach the surface of the soil. Artificial surface and subsurface drainage systems are recommended to remove excess water year round but, especially during seasonal high water levels. Another interesting consideration for the Hoytville silty clay, HvA, is the use of deep rooted cover crops to improve soil structure and help water movement into the tile drainage system. Water flow can be restricted in this soil because of the high clay content and potential soil compaction of field activity. These soils were most likely the soils that have tile drainage lines detected because artificial drainage is very common and usually necessary to make the fields profitable (Wood SSURGO). Also, according to Muller and Decamps (2000) soils with higher clay content are easier to determine differences in moisture related reflectance variations.

Very similar to the Hoytville soils in group one was the second group consisting of Mermill, Mermill-Aurand, and Wauseon soils. The main differences were the parent material, permeability, and clay content. The parent materials of these soils are loamy glaciolacustrine deposits and underlying till for the Mermill soils and loamy and sandy glaciolacustrine deposits and overlying till for the Wauseon soil. All of these soils are located in depressions, drainage ways, and extensive lake plain flats, similar to the
Hoytville soils. The permeability ranges from moderate in the upper solum to slow and very slow in the lower solum and substratum, resulting from the lower clay content than group one soils. These soils are very poorly drained and have a seasonal water table at the surface of the soil. Artificial surface and subsurface drainage systems are recommended to remove excess water, especially during the seasonal high water periods (Wood SSURGO). Obviously, these soils would have subsurface tile drainage lines detected, because they need artificial drainage to be profitable. Muller and Decamps (2000) found that soils that are mostly sand or clay were easier to compare moisture reflectance levels than silty soils or silty clay soils. This carries true here as well with these soils as they are sandy clay loams, loams, and fine sandy loams. These sand and clay contents make the soils easier to detect tile lines in because of the more obvious soil moisture reflectance relationships (Muller and Decamps 2000).

The third group of soils differed from the other two groups for many reasons including their slope which was 0 to 2 percent, location in landforms, permeability, and reason for artificial drainage. The parent materials for this group of soils were different for each soil with Rimer-Tedrow (RfA) having a sandy glaciolacustrine deposits and underlying till material while the Nappanee (NnA) had a wave-planed till material. The permeability of these soils was both slow and very slow in the lower solum and substratum but, the RfA soil was rapid in the upper solum. This difference is related to the loamy fine sand surface texture of the RfA soil which has a faster permeability than silt and clay soils. These soils are somewhat poorly drained and the seasonal water table depth was similar to the other soils, but on average, approximately six inches to one foot lower than the surface. Artificial subsurface drainage is
recommended to reduce the seasonally high water table and the use of artificial drainage in the Rimer-Tedrow soil may be ineffective if too much sand builds up in the drainage pipe (Wood SSURGO). With the drainage and permeability ratings of these two soils, it is surprising to find them being some of the most commonly detected soils with tile lines present. As discussed earlier, not all soils absolutely need artificial drainage but still have it installed to push the soil to maximum productivity. Again, these soils fit the theory of Muller and Decamp (2000) because of their high sand contents (RfA) and their balanced sand and clay content (NnA) making their soil moisture and reflectance relationship easier to discern.
Chapter 6

Conclusions

After the analysis of detected subsurface tile drainage system lines, many questions arise such as what is the best method to detect tile lines, what is the best soil to see tile lines on, what role does weather play on tile line detection? Although more research needs to be done for regions with different characteristics than Wood County, Ohio, there are some conclusions that can be drawn from this research.

The accuracy of this tile line detection process was difficult to quantify because of the lack of complete and up to date data but, the validation blueprints were used anyway. 2005 tile detection yielded a user accuracy of 80%, a producer accuracy of 15%, and an overall accuracy of 18%. 2006 tile detection yielded a user accuracy of 50%, a producer accuracy of 3.7%, and an overall accuracy of 7.1%. The 2009 tile detection was by far the worst for tile line identification because although there were lines detected, none could be validated with the validation blueprints.

It is difficult to judge the accuracy of this detection method or any other method due to the lack of historical data that tells the location of tile systems. In this research, the accuracy was not perfect but, some tile systems were detected where maps were also
located showing that the basis of this research has substance. More tile maps need to be used to clearly judge accuracy as well as putting multiple years of imagery together to get an idea if one series of detected lines was likely accurate or a single year anomaly.

Concerning crop relationships to tile line detection, corn and soybean fields are the best to detect tile lines on. 68% of fields with corn planted on their soil had at least some tile lines detected, while 63% of soybean fields had some tile lines detected. This is likely due to their leaf canopy and ground coverage. The timing of the imagery plays a large role in this because NAIP imagery is collected during “leaf on” periods, which is generally the spring and early summer. If the imagery is collected late in the year, the crops may have matured to a point where their canopies close and the soil cannot be clearly analyzed. The imagery used for this project was processed between September and November, indicating the photographs were collected a short amount of time before their processing dates. The may be late in the year to see the soil through the crop cover or residue after harvest. Imagery other than “leaf on” NAIP imagery can be used to avoid the ground coverage of crops. This may help detect more lines but, will be very difficult to find a perfect time to collect the imagery because not all farmers practice the same planting and harvesting schedule.

From this research, it appears that no tillage and mulch tillage are the best practice when detecting tile lines. According to Muller and Decamps (2000) a homogeneous cover is the best for detecting soil moisture and reflectance relationships which would indicate that conventional tillage would be a better surface to detect tile lines. Actually, the results in this research show that there is practically no difference in detection based
on tillage practice with tile lines being detected on no till fields 63%, on mulch till fields 63%, on ridge till fields 54%, and on conventional till fields 52%. Either of these tillage practices can be efficient as long as the soil can be clearly seen. This is why mulch tilling of cover crops and ridge tilling can not be used in detecting tile lines. Mulch till farming leaves too much living vegetation cover on the soil and blocks the soil and ridge tilling can hold moisture in patterns that deceive the tile detection process.

Concerning soils, most soils in Wood County should have artificial drainage for two reasons. The first reason is the emphasis placed on agriculturally related economics in the county and the second is the high clay content of most of the soil. The soils that showed up most commonly with tile lines detected on them fit the criteria of having a relatively flat surface, low permeability, poor drainage, and a general need for artificial drainage. These characteristics coupled with farmers pushing their land to be as productive as possible means that most soil series in Wood County, Ohio will have a high chance of having subsurface tile drainage systems installed. One soil that fit these criteria and was by far the most common soil with tile lines detected was Hoytville Clay Loam. In 2005, Hoytville Clay Loam represented 911 detected line segments, nearly 3.5 times the next highest represented soil, Mermill Sandy Clay Loam. In 2006, Hoytville Clay Loam represented 1,440 detected line segments, nearly 3.5 times the next highest represented soil, Hoytville Silty Clay. In 2009, Hoytville Clay Loam represented 1,547 detected line segments, 3 times the next highest represented soil, Hoytville Silty Clay.

To conclude, this type of research cannot be carried out for a large area in one year, but should instead be a project covering multiple years of imagery and ground
truthing techniques. Using multiple years will help eliminate error and validate lines that are consistently detected. Using multiple times of year will eliminate ground covered by closing crop canopies and provide a broader range of weather patterns and how they effect the detection of tile lines. One approach that keeps coming up is the detection of soil moisture on homogeneous land by Muller and Decamps (2000). This theory can be applied to soil, crop, and tillage practices as well. The researcher can select similar crop covers to detect tile lines on simultaneously while eliminating the other coverage for that year or do the same for tillage practices or soil series.
References


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A Validation Field Blueprints

FIGURE A-1: Blueprints used for Validation Field 1
FIGURE A-2: Blueprints used for Validation Field 2

FIGURE A-3: Blueprints used for Validation Field 3
FIGURE A-4: Blueprints used for Validation Field 4

FIGURE A-5: Blueprints used for Validation Field 5
FIGURE A-6: Blueprints for Validation Field 6

FIGURE A-7: Blueprints for Validation Field 7
FIGURE A-8: Blueprints for Validation Field 8