A Thesis

entitled

An Automated Method of Identifying the Location of Agricultural Field Drainage Tiles in Northwest Ohio

by

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Master of Arts Degree in

Geography

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Since the first European settlers arrived in Northwest Ohio in the 1800s, methods have been devised to drain The Great Black Swamp and turn it into farmland. Agricultural field tiles, buried three to four feet below the surface are the most common method used for drainage. Records of where those tiles have been installed are not complete, so methods have been devised to identify their location using satellite imagery which, given the right conditions, will show variations in soil moisture above the tiles. This thesis analyzes an automated method to identify the tile locations from aerial imagery, using an Object Based Image Analysis (OBIA) software called eCognition. Results were obtained that strongly correlated with results obtained from hand-digitizing tile locations, ranging from 53% to 78% agreement. However, attempting to use an unmodified version of the ruleset from one field to analyze a different field was only successful for one out of five fields. For the other fields, the time spent selecting new samples and adjusting the parameters was often the same amount of time, and occasionally more, than the time it took to draw the tiles by hand.
For Pete, Richele & Lizzy. Thanks for listening, advising and encouraging.
Acknowledgements

I owe a great debt to Dr. Kevin Czajkowski and Dr. April Ames, with whom I worked closely during this process of discovery. Thank you for all you have taught me. Thanks also to Dave Dean, who first taught me how to find field tiles on aerial images, and to Lanny Boes of Boes Quality Drainage for taking the time to educate me on the process of drainage tile installation. In addition I would like to thank the ladies who lunch, (April, Elyse, Isabelle, Karen, Krithica, and Sarah) for your moral support, and your laughter.
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Chapter 1

1 Introduction

1.1 History of Drainage in NW Ohio

Two hundred years ago, Northwest Ohio was covered by what was known as the Great Black Swamp, leading from the southwestern edge of Lake Erie toward the south and west, to approximately Ft Wayne, Indiana and encompassing more than three million acres of land (Fretwell, Williams, & Redman, 1996; Kaatz, 1955).

Figure 1-1: Extent of the Great Black Swamp (Kaatz, 1955)
In the 1840s and 1850s, Public Ditch Laws were developed with the intent of encouraging settlement in the area through large scale draining of the swamp (Ohio Department of Natural Resources Division of Soil & Water Conservation, 2009). The Swamp Land Act of 1850 granted more than 26,000 acres of swamp land to the state of Ohio, for the construction of levees and drains to reclaim it for farming and development (Fretwell et al., 1996).

Conversion of the swamp into useable agricultural land also necessitated the installation of drainage tile systems (otherwise known as field tile) to remove excess water from the soil. These were connected in regular patterns and flowed into the drainage channels that had been constructed alongside the fields. Originally the drain pipe was made of clay tile, either round or square (Figure 1-2), but since the 1960s it has been made of corrugated plastic with slits cut into the corrugations (Figure 1-3) (US Department of Agriculture Economic Research Service, 1987).
The first mechanized method of tile installation, called a steam ditcher, was invented in the late 1880s, allowing several hundred feet of tile to be placed in one day by a two man crew (Figure 1-4) (Hancock Historical Museum Association, 1988). Today’s methods can place tile at the rate of twenty- to thirty-thousand feet per day, depending on soil conditions (Error! Reference source not found.) (Boes, 2012).

Figure 1-4: Steam ditcher, circa 1900
(Photo: Courtesy Hancock Historical Museum)
The effect of these drainage systems is to prevent rainwater from standing on agricultural fields for too long by giving the water an outlet, after it percolates only a few feet into the soil. If this water were allowed to remain on the fields too long, it would make the fields impassable with farm equipment, and impair growth of the crops by causing the root system to grow too shallow. With tile drainage, crop production can be increased as much as twenty to thirty bushels per acre for corn, and by 7 to 14 bushels per acre for soybeans (Ohio Department of Natural Resources Division of Soil & Water Conservation, 2009).

In recent years, the environmental impact of this practice of installing tile drains has been called into question. Drainage tiles are being studied as a transport mechanism for fertilizer nutrients, specifically phosphorus and nitrogen that are not absorbed by the crops and soil. These nutrients then pass into adjacent drainage ditches and are carried into rivers and lakes. The Western Lake Erie watershed basin has seen significant environmental disruptions in recent years, specifically from toxic Microcystis algae. During the summer of 2011, the largest algae bloom ever recorded was present in Lake
Erie with additional outbreaks during the summers of 2012 and 2013 (Henry, 2014) (Figure 1-6).

Figure 1-6: MODIS satellite image of Lake Erie on March 21, 2012 (NASA, 2012)

1.2 Tile Identification

1.2.1 Why Do We Care Where The Tiles Are?

Knowing were the tiles are in a particular field can be useful information for many reasons:

- a farmer wishing to repair or extend the system of tiles, would need to know where to dig to access them
• local and regional organizations responsible for maintaining the public drainage ditches would be better informed about the potential flow into those ditches

• if there is an intended change in land use from agriculture to housing subdivision, it would be important to identify the tiles in order to remove or cap them to prevent basement flooding in the new houses

• researchers studying the contribution of fertilizers to the Lake Erie algae issue need to know the quantity of tile to calculate the volume of water contributed by them

• utility companies installing buried pipelines that cross an agricultural field are required to identify the location of any drainage tile in the field (Ohio Department of Natural Resources Division of Soil & Water Conservation, n.d.).

Modern practices now record the location of newly installed tile using GPS receivers and computerized mapping software mounted on the installation equipment. This allows accurate, detailed records to be kept (Boes, 2012). However, when the first of these drain tile systems were put into the ground, very few farmers kept any records of exactly where they were located or else the maps have been lost over the years. In these fields, identifying the tile locations can be difficult and time consuming.
1.2.2 Using Aerial Imagery to Identify Tile Locations

The use of aerial photography to identify the location of field tile has been attempted ever since reliable sources of imagery have become available. Photographs taken within a day or two after a rainfall of at least one inch will show differences in the spectral qualities of the fields above the locations of the drain tiles (Copenhaver, 2004). The water above the tile drains moves away faster than water between the tiles, leaving a very different soil moisture content. This difference is visible on aerial imagery as shown in Figure 1-7.

![Aerial photo of field showing visible signs of tile](“OSIP Data,” n.d.)

The process of manually reviewing a myriad of aerial photographs and hand digitizing the location of the tiles onto a GIS-based map has proven useful but is extremely time consuming. Often many images from different time frames must be examined to find the correct soil moisture conditions. Verma, et al. (1996) used a similar method to identify tile.
1.3 Problem Statement and Objectives

Identifying the location of underground field tiles without using destructive methods has always been a challenge. The advent of aerial imagery provides a more benign method for identification, but the process of hand-digitizing the location and length of field tiles requires a great deal of labor-hours to produce. An automated method to identify their location would significantly reduce the time needed, allowing valuable research time to be spent analyzing their impact rather than solely spent on identification.

The primary objective of this thesis is to use a software called eCognition to develop a method which will allow the automated distinction between dry and wet areas of a field which, if found in a regular pattern, would indicate the presence of field tiles. The eCognition software, which was first released in 2000 by Definiens Imaging GmbH, uses the digital processing technique of Object Based Image Analysis. It attempts to copy the way the human brain analyzes visual input, using shape, size, texture and local context, in addition to the spectral attributes, to identify and classify objects. A further objective is to then apply that same process to an image of a different field to see if it will identify the tile accurately. Ultimately, this ruleset could be applied, with minor modification, to a large swath of multiple fields to identify which fields contain tile and where those tile are located.

To quantify the accuracy of the eCognition results, a process of hand-digitizing the tile locations, through visual analysis, will be necessary on the same fields where the automated process is applied. A comparison will then be made of the two methods, highlighting the locations where eCognition correctly identified the tile and where it did not.
Chapter 2

2 Literature Review

2.1 Methods Used to Identify Tile in the Past

Since the first use of tile drains in this area of northwest Ohio, beginning about 1859 (Kaatz, 1955), farmers needed a method to identify where those tiles were if adequate records were not kept. The use of tile probes to locate them is time consuming and not very accurate. With the relatively recent advent of easily obtained aerial photography, several studies have been conducted to find a means of identifying tiles using these photographs.

Verma, et al. (1996) used color infrared (CIR) photographs as the basis for a study to locate drainage tiles in Vermillion County, Illinois. They chose photographs taken in spring, during “leaf-off” conditions, a few days after a heavy rain. The timing of the photographs in relation to the rain is critical. Under the right conditions, the soil above the tile drains will be drier than areas between tiles. This difference in moisture content can be observed as a difference in spectral reflectance of the soil on a CIR image.

The CIR images were scanned to a TIF (tagged image file) format then were geo-referenced and added to a Geographic Information System (GIS) database using IDRISI
software. Other layers added to this GIS were soil maps, contour maps, surface drainage maps and administrative boundaries, as well as black and white aerial photographs used to determine land use and vegetation cover. The software classified the images to show “wet”, “moist” and “drained” areas. Tile probes were used to field-verify the locations of the tiles as indicated by the “drained” areas in the processed images.

A study conducted by Sugg (2007) used a GIS to analyze land cover and soil data in eighteen states across the United States to define areas most likely to have sub-surface tile drains and areas that would benefit from installing drains. Soil information was obtained from the USDA/NRCS State Soil Geographic Database (STATSGO) and the county-level Soil Survey Geographic Database (SSURGO), while land use information came from the 1992 state National Land Cover Dataset (NLCD). The locations of the five poorest-drained soil types were then overlaid with row crop information to determine areas that could potentially have artificial drainage improvement. However, the tile identified by this method is not necessarily all tile drainage; it could be surface drainage.

Two studies of tile drainage were conducted by researchers at Purdue University. The first, by Naz, and Bowling (2008), used a decision-tree for evaluating land-cover, soil drainage class and topography data to determine potentially tile drained fields in the northwest part of Tippecanoe County, Indiana. They then processed the images using spatial convolution filtering techniques to enhance the edges of the tile lines. The images were further classified into “tile” and “non-tile” by a density slice classification. The classified images were then compared to the known tile locations in the areas being studied to determine the accuracy of the method. The Naz, et al., (2009) study used this
same decision tree analysis and image processing techniques to a study area within the Hoagland watershed in west-central Indiana.

In an earlier project here at the University of Toledo, Thompson (2010) evaluated “leaf on” imagery obtained from the National Agricultural Imagery Program (NAIP) for selected agricultural fields in Wood County, Ohio. An unsupervised classification was performed on the NAIP images giving twenty classifications, then an edge detection method was used to identify abrupt changes. Noise reduction techniques of Clump, Sieve, and Majority analysis were then used. Once the image processing was completed, “heads-up” digitizing was done in ArcMap 9.3 to visually identify individual tile lines in the study fields. These tile locations were then verified through comparison with blueprints of the actual locations of the tiles, obtained from the Wood County Soil and Water Conservation District.

2.2 Use of Object Based Image Analysis

With the advent of high resolution orthophotos and satellite imagery, the process of analyzing those images at a pixel level consumes vast amounts of computer resources. Additionally, using only spectral information of the pixels ignores any relationships based on location, shape or texture. Object Based Image Analysis (OBIA) uses a process called segmentation to group adjacent pixels based on all these characteristics in a manner attempting to copy the way the human mind classifies objects (Dezso, et al., 2012). These larger segments can then be classified without being as resource intensive. Hay and Castilla (2006), in their evaluation of OBIA, described it as a method “to replicate (and or exceed experienced) human interpretation of RS images in automated/semi-automated ways, that will result in increased repeatability and
production, while reducing subjectivity, labor and time costs.” Repeated iterations of the segmentation steps allow a hierarchy of classifications to be applied to the image (Dezso et al., 2012).

The segmentation of an image can be accomplished by two methods. Cut-based, or top-down segmentation, starts with the entire image as one segment then divides the image into smaller and smaller segments based on their differences. Alternately, merge-based, or bottom-up segmentation, begins with individual pixels which are then combined into segments based on their similar characteristics (Dezso et al., 2012).

The concepts behind OBIA were developed several decades before a practical user interface was developed which hindered its more widespread use. In 2000, Definiens Imaging GmbH released its eCognition software and it has become one of the most successful applications for OBIA (Campbell & Wynne, 2011). In 2003, Flanders, et al. published an evaluation of eCognition, which follows the segmentation methods described above, then uses fuzzy-logic algorithms to determine membership/non-membership of the segment to the defined classes. The classification of the segments can thus be improved by the use of characteristics such as shape, since these attributes are not affected by conditions of atmospheric haze or sun angle that complicate the interpretation of spectral information.

OBIA, and specifically eCognition has been used by a diverse group of researchers and government agencies to classify their imagery. Some examples include change detection of forest extent in Germany (Walter, 2004); detection of floodplain habitats along the Danube River (Wagner, 2009); mapping sugarcane cropland changes in Brazil (Vieira et
al., 2012); overall land use classification (O’Neil-Dunne, et al., 2011); and the Minnesota Department of Natural Resources, which used it to update their National Wetland Inventory for Minnesota (Smith, et al., 2012).

2.3 Environmental Effects of Tile Drainage

Recent studies looking into potential causes of environmental disturbances in waterways and in the Western Basin of Lake Erie in particular, have suggested that agricultural use of tile drains could be an important factor. Of particular concern are the recent, severe Microcystis algae blooms occurring in the lake. Phosphorus fertilizer is suspected of being a major contributor to these blooms. The fertilizer added to a field can enter the waterway not only from surface runoff but also through the tile drains if it is not adsorbed by the soil (Michalak et al., 2013; Nett, et al., 2008; Ohio Lake Erie Phosphorus Task Force, 2010; Ohio Lake Erie Phosphorus Task Force II, 2013).
Chapter 3

3 Methodology

3.1 Location

The area being analyzed is located in Northwest Ohio, in Madison Township of Sandusky County. The fields chosen for analysis were a subset of those used in a concurrent project at the University of Toledo, under the guidance of Dr. Kevin Czajkowski, analyzing the use of biosolids on agricultural fields permitted for such use by the Ohio EPA (Czajkowski et al., 2010). The portion of Dr. Czajkowski’s project completed by this author was to visually identify and hand-digitize the location of the agricultural field tile in designated fields, from aerial and satellite photos using ArcMap software. This thesis uses a subset of those same fields.

The initial visual analysis and hand-digitizing of the drainage tiles in the fields was completed using red/green/blue (RGB), color infrared (CIR) and black and white orthorectified county aerial mosaics from one foot to one meter per pixel spatial resolution acquired from the National Agricultural Imagery Program (NAIP), County Auditors, and the Ohio Statewide Imagery Program (OSIP). The age of the imagery used and its resultant pixilation created difficulties at times during the visual identification of the tiles. It was often difficult to distinguish between the tile lines and the lines created on
the field from plowing. The older the imagery, the more difficult this process was. Although it was acceptable to use the older imagery for the hand-digitizing done in the above referenced project, when it was used with eCognition, the problems proved to be insurmountable. As a result, it was decided to use more recent, high definition imagery that is currently available from the Ohio Statewide Imagery Program (OSIP). This new imagery necessitated repeating the hand-digitizing process for the fields studied herein. In order to be able to “see” the buried tile on an aerial photo, it needs to have been taken under just the right conditions, one to two days after a rainfall of more than one inch during leaf-off conditions (Copenhaver, 2004). Since the actual dates and conditions under which the images were taken are unknown when using publicly available OSIP data, they may not have been taken under these perfect conditions. Not all fields will show the presence of tile, even though it may be there. Therefore it was decided to only choose fields that obviously displayed the presence of tile drainage. The six fields chosen were ones that showed positive evidence of the presence of field tile on the images. This assumption is based on the premise that imagery is getting more refined and more prolific at an extraordinary rate right now so in the future freely-available, appropriate imagery will not be as difficult to find.
3.2 Imagery

The imagery used for this project was the imagery available in downloadable form from the State of Ohio in their Ohio Statewide Imaging Program (OSIP). The Sandusky County, 1 foot MrSID (.sid) County Mosaic (RGB) and 1 meter CIR County Mosaic images were downloaded. The RGB imagery had been collected in 2011 and the CIR in 2006, both during March-April. This March to April time frame is considered to be “leaf-off” conditions. However, in northwest Ohio agricultural areas, a certain number of fields will have an actively growing crop of winter wheat during this time period.

The images were trimmed to the boundaries of Madison Township and then further cropped to create six separate files at the boundaries of the individual fields to be analyzed. They were also converted from the .sid file format to a .tif format for use in eCognition, as the software does not recognize the .sid format. This preliminary image processing was done using ESRI ArcMap 10.1 software. This conversion process changes the spatial resolution of the imagery but it is not considered a factor in this analysis. A separate project was set up for each field, within eCognition, using the two images (RGB and CIR) for that field. Within eCognition, these two images display as six layers and were labeled as follows: RGB-red, RGB-green, RGB-blue, CIR-ir, CIR-red and CIR-green.

Since the imagery was taken during “leaf off” conditions while there were no crops growing in the fields that were analyzed, the color infrared (CIR) image layers didn’t show any evidence of tile lines beyond what was visible on the natural color (RGB) image and therefore were not used as layers during the segmentation and classification steps (Figure 3-1).
To create an automated system to identify the location of buried agricultural field tile it was decided to use eCognition software, which was originally launched in 2000 by Definiens Imaging GmbH, and is now owned by Trimble Navigation Ltd. The software is an Object-Based Image Analysis (OBIA) software that can use contextual information contained within a photographic image, in addition to the spectral information used by most land classification software. The version used for this study was eCognition Developer 8.7.

Within the software, a set of rules are created for processing the images. There are two major types of rules: segmentation and classification. The segmentation process cuts up
the visual image into portions based on certain parameters, then each of these segments can be classified into specific categories. This two-step process can be repeated as needed, with different parameters, to create various sizes and shapes of segments and multiple levels of classifications.

### 3.3.2 ArcMap

ESRI’s ArcMap 10.1 software was used for several steps in this study. The initial image processing, to crop the image and put it into a format recognized by eCognition, was completed using ArcMap. It was also used for hand-digitizing the tile lines and creating the buffer polygons used for data comparison, and then again for the comparative analysis between the hand-digitized polygons and those created by eCognition.

### 3.4 Developing Rulesets

The goal of the analysis with the eCognition software was to come up with segments of the image that isolate the dry areas from the wet areas with preliminary steps to exclude the non-field areas like houses and wooded areas. Much time was spent experimenting with the different choices for segmenting and classifying the images. There are more than 130 different algorithms that can be applied to the imagery in any combination of steps. Most of these algorithms can evaluate the imagery based upon nearly 300 different object features covering the layer values, geometry, position, texture, hierarchy, thematic attributes, point cloud features, class-related features, linked object features, scene features, process related features, region features and image registration features (Trimble Germany GmbH, 2012) These algorithms also have many other parameters with variable settings for each. Appendix A provides a list of available algorithms while Appendix B
lists the various features these algorithms can address, in version 8.7 of eCognition. All these choices lead to a seemingly infinite number of combinations to test.

### 3.4.1 Segmentation

The various segmentation algorithms initially evaluated included multiresolution segmentation, spectral difference segmentation, quadtree segmentation, chessboard segmentation and contrast split segmentation. After much trial and error testing of these algorithms and their parameters, the multiresolution segmentation proved to be the best means of creating useful segments for analysis since it takes into account the spectral properties of the image as well as the shape and size characteristics. Table 3.1 lists the parameters used in this multiresolution segmentation for each of the fields analyzed.

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<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
</tr>
</tbody>
</table>

Of the other algorithms evaluated but not finally used, spectral difference segmentation was tested as a follow-on to the multiresolution segmentation and it would sometimes deliver more appropriate segments. In other circumstances it would merge the segments too much, which defeated the purpose of the segmentation. The quadtree segmentation method created square segments that were not useful in defining the linear nature of the tile that was desired and the chessboard segmentation method by itself only gave uniform sized square segments which also were not useful. When the right size chessboard
segmentation was combined with contrast split segmentation it gave reasonably good segments, but was less effective than using the multiresolution segmentation while using twice the number of processing steps. This was not a significant amount of processing time for the small areas being analyzed here, but if the intent is to expand the scope to larger areas in the future, then processing time can become an important factor.

3.4.2 Classification

Within the classification algorithm, the object features evaluated were: mean brightness, area, border to, standard deviation, length/width, density and mean difference to neighbors. Three algorithms were found to be effective at classifying tile as separate from the background: mean brightness; standard deviation of each of the three RGB layers; and mean difference to neighbors of the RGB layers. The values used to delineate the classes needed to be changed for every field due to differences in the coloration of the soil itself. This was possibly due to changes in soil types within a field, or the method of plowing used and how recently the plowing was done on a field. The adjustments were made through a process of selecting samples for a classification then allowing the software to calculate the range of values for the parameters (Figure 3-2). In locations with significant differences across a field, as the values were adjusted to pick up more tiles in one area, it included too much of the not-tile areas in the brighter portions of the field. To circumvent this, it was necessary to segment several of the fields into parts, based on brightness of the soil, and then analyze each area separately. The parameters used for the classification algorithm, for each of the fields and their sections are listed in Figure 3-2: Locations "tile" samples were taken for Field 2
Figure 3-2: Locations "tile" samples were taken for Field 2

Table 3.2: Parameters for classification to “tile” used for each field

<table>
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<td>135.083 &lt; tile &lt; 159.372</td>
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<td>0.544 &lt; tile &lt; 2.914</td>
<td>0.36 &lt; tile &lt; 2.39</td>
<td></td>
</tr>
<tr>
<td>STD DEV - RGB-green</td>
<td></td>
<td>0.432 &lt; tile &lt; 2.313</td>
<td></td>
<td></td>
</tr>
<tr>
<td>STD DEV - RGB-blue</td>
<td>0.097 &lt; tile &lt; 6</td>
<td>0.440 &lt; tile &lt; 6.148</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MEAN DIFF TO NEIGHBORS - RGB-red</td>
<td></td>
<td></td>
<td></td>
<td>-4.878 &lt; tile &lt; 17.701</td>
</tr>
<tr>
<td>MEAN DIFF TO NEIGHBORS - RGB-green</td>
<td></td>
<td></td>
<td></td>
<td>-4.219 &lt; tile &lt; 18.274</td>
</tr>
<tr>
<td>MEAN DIFF TO NEIGHBORS - RGB-blue</td>
<td>-4.155 &lt; tile &lt; 16.955</td>
<td>0.635 &lt; tile &lt; 13.435</td>
<td>-0.635 &lt; tile &lt; 13.435</td>
<td>-0.727 &lt; tile &lt; 18.221</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>FIELD 3 LIGHT</th>
<th>FIELD 4</th>
<th>FIELD 5</th>
<th>FIELD 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>BRIGHTNESS</td>
<td>45.854 &lt; tile &lt; 163.31</td>
<td>142.404 &lt; tile &lt; 168</td>
<td>104.379 &lt; tile &lt; 119.809</td>
<td>130 &lt; tile &lt; 161</td>
</tr>
<tr>
<td>STD DEV - RGB-red</td>
<td></td>
<td>0 &lt; tile &lt; 5.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>STD DEV - RGB-green</td>
<td></td>
<td>3.833 &lt; tile &lt; 7.006</td>
<td></td>
<td></td>
</tr>
<tr>
<td>STD DEV - RGB-blue</td>
<td></td>
<td>3.70 &lt; tile &lt; 7.266</td>
<td></td>
<td>0.097 &lt; tile &lt; 6</td>
</tr>
<tr>
<td>MEAN DIFF TO NEIGHBORS - RGB-red</td>
<td>-3.396 &lt; tile &lt; 11.278</td>
<td>2.596 &lt; tile &lt; 15.019</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MEAN DIFF TO NEIGHBORS - RGB-green</td>
<td>-2.493 &lt; tile &lt; 10.795</td>
<td>2.773 &lt; tile &lt; 15.577</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MEAN DIFF TO NEIGHBORS - RGB-blue</td>
<td>-3.657 &lt; tile &lt; 14.293</td>
<td>0.973 &lt; tile &lt; 13.738</td>
<td></td>
<td>-4.55 &lt; tile &lt; 16.955</td>
</tr>
</tbody>
</table>

3.5 Hand-Digitized Lines

In order to evaluate the accuracy of the results obtained from the eCognition rulesets, hand digitized tile lines were drawn, based on visual analysis, using ArcMap software.
These provide a comparison between what eCognition algorithms see and evaluate on the image versus what the human eye sees. Since the image only shows the dry soil above the tile and not the tile itself, as represented by the hand-digitized linear feature, a ten foot buffer was created around the linear features to provide a representative polygon of the dry areas visible in the image. This was based on an average width of twenty feet for the dry areas visible in the six images.

### 3.6 Data Comparison

A comparison was made to determine how accurately the polygons exported from eCognition overlapped the hand-digitized polygons using the Symmetrical Difference function. The results of this comparison were grouped into four categories:

- Positive – areas designated as tile by both the hand analysis and eCognition
- Negative - areas where both the hand analysis and eCognition agreed were not tile
- False Positive – areas eCognition designated as tile but the hand analysis said were not tile
- False Negative – areas designated by eCognition as not tile but the hand analysis said were tile

The total area in square feet was calculated for the “field” region of each image, along with the area of each of the four result categories. These four areas were then expressed as a percentage of the entire area, which were presented in a confusion matrix. A percent
agreement value was calculated as the sum of the Positive and Negative spaces, and percent error as the sum of the False Positive and False Negative.

Percent Agreement = \( \frac{\text{positive area}}{\text{entire area}} + \frac{\text{negative area}}{\text{entire area}} \)

The kappa statistic was then calculated from these values.
Chapter 4

4 Results

4.1 Individual Field Results

After much experimentation with the various ruleset combinations, a basic group of rules was used as the starting point to analyze the 6 different fields being studied. This consisted of first performing a multiresolution segmentation using the parameters as shown in Table 3.1. This was then followed by a classification of those segments into classes of “tile” and “not tile” using the parameters as listed in Figure 3-2: Locations "tile" samples were taken for Field 2.

These parameters were set using the sample function in eCognition through which the user can select specific segments as typical of the “tile” and “not tile” classes. The final step was to merge the “tile” segments into one large segment that could then be exported and used for analysis in ArcMap.

Three of the fields (Fields 1, 3 and 6) needed preliminary processing to separate out different areas of the field. The images for all three of these fields have areas that were not agricultural – either wooded or residential. These sections were removed before the segmentation and classification steps to identify tile were performed. Fields 1 and 3 also
had significant variations in soil coloration and brightness across the field. This caused
great difficulty with setting the appropriate parameters in the segmentation and
classification steps. To alleviate this problem on Field 1, the non-field areas were
removed first using a multiresolution segmentation and classification process. The
remaining regions were subdivided into two sections (light and dark), based solely on
brightness. They were then processed as though they were separate fields and merged
again after processing. This approach did not work effectively for Field 3, where the
preliminary steps needed to be reversed before processing became effective. It was first
segmented into two regions, based solely on brightness, then the residential area was
removed from the dark region. Fields 2, 4 and 5 used the basic ruleset as is, with only
alterations in the parameters as shown in Table 3.1 and Figure 3-2: Locations "tile"
samples were taken for Field 2
4.1.1 Field 1

Field 1 (Figure 4-1) was first segmented and classified into “field” and “not field” areas (Figure 4-2, Figure 4-3), then the “field” areas were classified into "field-light” and “field-dark” areas, with brightness = 160 as the divide between light and dark (Figure 4-4). All “field” areas were then re-segmented into smaller pieces using the parameters in Figure 4-5 (Figure 4-5). The “field-dark” and “field-light” areas were then classified into “tile” and “not tile” using the parameters in Figure 3-2: Locations "tile" samples were taken for Field 2 (Figure 4-6, Figure 4-7) and the individual segments of each class were then merged (Figure 4-8).
Figure 4-2: Field 1 – Segmentation

Figure 4-3: Field 1 - Remove non-agricultural areas
Figure 4-4: Field 1 - Classify light and dark areas

Figure 4-5: Field 1 - Re-segment field portions
Figure 4-6: Field 1 - Classify dark area to tile/not tile

Figure 4-7: Field 1 - Classify light area to tile/not tile
Field 2 was segmented using the parameters in Table 3.1, then classified into “tile” and “not tile” using the parameters in Figure 3-2: Locations "tile" samples were taken for Field 2
(Figure 4-10, Figure 4-11) and the individual segments of each class were merged 
(Figure 4-12)

Figure 4-10: Field 2 - Segmentation

Figure 4-11: Field 2 - Classification

Figure 4-12: Field 2 – Final eCognition results
4.1.3 Field 3

As a first step, Field 3 was segmented and classified using the simple ruleset from Field 2 with no modifications (Figure 4-14). In the top, lighter portion of the field, it classified objects as tile but they did not accurately reflect the locations of the tile lines. In the lower, darker portion of the field, it did not capture the tile areas at all. This ruleset was then abandoned for Field 3 and as a next step the ruleset from Field 1 was attempted. This however did not accurately remove the “not field” areas, so processing with the Field 1 ruleset directly was not continued. Instead, the process was reversed and the image was segmented and classified into “field-dark” and “field-light” regions first (Error!)
Reference source not found.), then the “not field” areas were removed from the “field-dark” region (Figure 4-16). Both regions were then re-segmented into smaller pieces using the parameters in Table 3.1(Figure 4-17). Each of the regions were classified into “tile” and “not tile” areas using the parameters in Figure 3-2: Locations "tile" samples were taken for Field 2

(Error! Reference source not found., Figure 4-19). Finally the individual segments of each class were merged (Figure 4-20).

Figure 4-14: Field 3 - Segmented and classified using the ruleset from Field 2
Figure 4-15: Field 3 - Segment and classify in to "light" and "dark" regions

Figure 4-16: Field 3 - Remove "not field" areas from "dark" region
Figure 4-17: Field 3 - Re-segment “field-light” and "field-dark" areas

Figure 4-18: Field 3 - Classify “field-dark” to “tile” and “not tile”
Figure 4-19: Field 3 - Classify “field-light” to “tile” and “not tile”

Figure 4-20: Field 3 – Final eCognition results
Field 4 was first segmented and classified using the ruleset from Field 2 without modification (Figure 4-22). This unmodified ruleset did not accurately identify the locations of the field tiles. The parameters for segmentation and classification were then adjusted based on new samples for this particular field. The parameters used are listed in Table 3.1 and Figure 3-2: Locations "tile" samples were taken for Field 2.

The segmentation step and final results after classification are shown in Figure 4-23 and Figure 4-24.
Figure 4-22: Field 4 segmented and classified using the ruleset from Field 2

Figure 4-23: Field 4 - Segmentation
Figure 4-24: Field 4 – Final eCognition results
4.1.5 Field 5

An analysis was completed on Field 5 using the rulesets from each of the prior fields, with no modification. None of them could identify any tile at all on a field with such a dark soil color and prominent plowing lines (Figure 4-26, Figure 4-27, Figure 4-28, Figure 4-29). Field 5 was then segmented using the parameters in Table 3.1, and classified using the parameters in Figure 3-2: Locations "tile" samples were taken for Field 2

, developed through the use of samples specific to this field (Figure 4-30, Figure 4-31).
Figure 4-26: Field 5 segmented and classified using the rulesets from Field 1

Figure 4-27: Field 5 segmented and classified using the ruleset from Field 2

Figure 4-28: Field 5 segmented and classified using the rulesets from Field 3
Figure 4-29: Field 5 segmented and classified using the ruleset from Field 4

Figure 4-30: Field 5 – Segmentation
Figure 4-31: Field 5 - Final eCognition results
Field 6 was the only field where the application of a ruleset from a prior field without modification successfully identified the location of the tile. The field was first segmented and classified into “field” and “not field” using the same steps as were used in Field 1 (Figure 4-33). The “field” area was re-segmented using the parameters in Table 3.1, then classified into “tile” and “not tile” using each of the parameters developed for Field 1-dark and -light areas. The Field 1-light classification rules did not identify the tiles (Figure 4-35), but the Field 1-dark rules as listed in Table 3.2 did successfully identify them (Figure 4-36).
Figure 4-33: Field 6 - Segmentation and classification into "field" and "not field"
Figure 4-34: Field 6 - Re-segment "field" area

Figure 4-35: Field 6 - Classification using ruleset from "light" area of Field 1
4.2 Comparisons to Hand-Digitizing

Once the results were obtained from eCognition they were exported to a polygon shapefile. ArcMap was then used to compare the areas of these polygons to the polygons obtained from the hand digitizing process. This comparison divided the field into four distinct areas. The Positive and Negative are those regions where eCognition and the hand-digitizing produced results that agreed on what is “tile” and what is “not tile” respectively, and is represented by the values for Percent Agreement. The Percent Agreement for the six fields ranged from 53% to 78% with an average of 70%. The complete results are shown in Table 4.1. The detailed confusion matrix and kappa statistic (K) for each of the fields and a summary are shown in Table 4.2 through Table
4.8. Looking at these statistics, Field 4 (K=0.48) and Field 6 (K=0.42) showed the best agreement, while the least consistent results were for Field 2 (K=0.16). The biggest factor affecting these results appears to be the homogeneity of the field. Fields 4 and 6 are both very homogeneous across the entire field in terms of lightness and darkness of the field. For Fields 1 & 3, that difference was accounted for with some degree of success, but it did not equal the results from a homogeneous field. For Field 2, the right hand side of the field appears to have dried faster than the left side, blurring the location of the field tiles in that portion. Field 5 was homogeneous but the results may have been affected by the fact that a small amount of crop growth was observable on what was expected to be a “leaf-off” field.
Figure 4-37: Visual results of comparison between eCognition and hand-digitizing
Table 4.1: Results comparison

<table>
<thead>
<tr>
<th></th>
<th>Entire Area</th>
<th>Positive (blue)</th>
<th>Positive %</th>
<th>Negative (green)</th>
<th>Neg Space %</th>
<th>False Positive (purple)</th>
<th>False Pos %</th>
<th>False Negative (orange)</th>
<th>False Neg %</th>
<th>% Agreement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Field 1</td>
<td>3,980,256</td>
<td>617,961</td>
<td>15%</td>
<td>2,213,440</td>
<td>56%</td>
<td>803,856</td>
<td>20%</td>
<td>344,999</td>
<td>9%</td>
<td>71%</td>
</tr>
<tr>
<td>Field 2</td>
<td>872,808</td>
<td>130,207</td>
<td>15%</td>
<td>332,509</td>
<td>38%</td>
<td>384,466</td>
<td>44%</td>
<td>25,626</td>
<td>3%</td>
<td>53%</td>
</tr>
<tr>
<td>Field 3</td>
<td>1,706,607</td>
<td>375,352</td>
<td>22%</td>
<td>774,120</td>
<td>45%</td>
<td>462,214</td>
<td>27%</td>
<td>94,921</td>
<td>6%</td>
<td>67%</td>
</tr>
<tr>
<td>Field 4</td>
<td>1,369,315</td>
<td>254,129</td>
<td>19%</td>
<td>813,419</td>
<td>59%</td>
<td>156,169</td>
<td>11%</td>
<td>145,598</td>
<td>11%</td>
<td>78%</td>
</tr>
<tr>
<td>Field 5</td>
<td>1,850,778</td>
<td>121,409</td>
<td>7%</td>
<td>1,299,800</td>
<td>70%</td>
<td>355,173</td>
<td>19%</td>
<td>74,396</td>
<td>4%</td>
<td>77%</td>
</tr>
<tr>
<td>Field 6</td>
<td>1,642,755</td>
<td>559,824</td>
<td>34%</td>
<td>613,609</td>
<td>37%</td>
<td>310,418</td>
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<td>158,904</td>
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<td>71%</td>
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<tr>
<td>Average</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>70%</td>
</tr>
</tbody>
</table>
Table 4.2: Confusion Matrix - Field 1

<table>
<thead>
<tr>
<th>Field 1</th>
<th>Hand-digitized</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>tile</td>
<td>not tile</td>
<td>total</td>
</tr>
<tr>
<td>eCognition</td>
<td>0.15</td>
<td>0.20</td>
<td>0.35</td>
</tr>
<tr>
<td>not tile</td>
<td>0.09</td>
<td>0.56</td>
<td>0.65</td>
</tr>
<tr>
<td>total</td>
<td>0.24</td>
<td>0.76</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Field 1 K = 0.31 = fair agreement

Table 4.3: Confusion Matrix - Field 2

<table>
<thead>
<tr>
<th>Field 2</th>
<th>Hand-digitized</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>tile</td>
<td>not tile</td>
<td>total</td>
</tr>
<tr>
<td>eCognition</td>
<td>0.15</td>
<td>0.44</td>
<td>0.59</td>
</tr>
<tr>
<td>not tile</td>
<td>0.03</td>
<td>0.38</td>
<td>0.41</td>
</tr>
<tr>
<td>total</td>
<td>0.18</td>
<td>0.82</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Field 2 K = 0.16 = slight agreement

Table 4.4: Confusion Matrix – Field 3

<table>
<thead>
<tr>
<th>Field 3</th>
<th>Hand-digitized</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>tile</td>
<td>not tile</td>
<td>total</td>
</tr>
<tr>
<td>eCognition</td>
<td>0.22</td>
<td>0.27</td>
<td>0.49</td>
</tr>
<tr>
<td>not tile</td>
<td>0.06</td>
<td>0.45</td>
<td>0.51</td>
</tr>
<tr>
<td>total</td>
<td>0.28</td>
<td>0.72</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Field 3 K = 0.33 = fair agreement

Table 4.5: Confusion Matrix - Field 4

<table>
<thead>
<tr>
<th>Field 4</th>
<th>Hand-digitized</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>tile</td>
<td>not tile</td>
<td>total</td>
</tr>
<tr>
<td>eCognition</td>
<td>0.19</td>
<td>0.11</td>
<td>0.30</td>
</tr>
<tr>
<td>not tile</td>
<td>0.11</td>
<td>0.59</td>
<td>0.70</td>
</tr>
<tr>
<td>total</td>
<td>0.30</td>
<td>0.70</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Field 4 K = 0.48 = moderate agreement
Table 4.6: Confusion Matrix - Field 5

<table>
<thead>
<tr>
<th>Field 5</th>
<th>Hand-digitized</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>tile</td>
</tr>
<tr>
<td>eCognition</td>
<td>tile</td>
</tr>
<tr>
<td></td>
<td>not tile</td>
</tr>
<tr>
<td></td>
<td>total</td>
</tr>
</tbody>
</table>

Field 5 $K = 0.26 = $ fair agreement

Table 4.7: Confusion Matrix - Field 6

<table>
<thead>
<tr>
<th>Field 6</th>
<th>Hand-digitized</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>tile</td>
</tr>
<tr>
<td>eCognition</td>
<td>tile</td>
</tr>
<tr>
<td></td>
<td>not tile</td>
</tr>
<tr>
<td></td>
<td>total</td>
</tr>
</tbody>
</table>

Field 6 $K = 0.42 = $ moderate agreement

Table 4.8: Summary Confusion Matrix

<table>
<thead>
<tr>
<th>Summary</th>
<th>Hand-digitized</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>tile</td>
</tr>
<tr>
<td>eCognition</td>
<td>tile</td>
</tr>
<tr>
<td></td>
<td>not tile</td>
</tr>
<tr>
<td></td>
<td>total</td>
</tr>
</tbody>
</table>

Summary $K = 0.34 = $ fair agreement
Chapter 5

5 Conclusions

The process of creating rulesets within eCognition did successfully produce results that correlated with the results obtained from hand-digitizing. The Kappa statistic ranged from a high of 0.48 for Field 4 to a low of 0.16 for Field 2 with an average of 0.34 for all fields combined. However, even after a basic ruleset was developed, a certain amount of time was needed to “tweak” the parameters when moving to a new field. Attempting to use an unmodified version of the ruleset from one field to analyze a different field was only successful for one field, that of using the Field 1 dark area ruleset on Field 6 with a resulting kappa value of 0.42. The time spent selecting new samples and adjusting the parameters was often the same amount of time, and occasionally more, than the time it took to draw the tiles by hand. In addition, the same visual analysis process performed by a person is needed to determine how to adjust the parameters. The major factor that seems to affect the results is the homogeneity of the field itself. If this variation could be accounted for, possibly through the use of soil maps added as a layer in eCognition, more successful results might be obtained.
The imagery shows some locations with likely broken tiles, appearing as spacing between the linear segments of tile that are lined up. Visually, the human brain can connect these tiles into one single line, but this analysis did not reveal a means of telling the software how to accomplish that.

There are very subtle differences between the dry and wet areas and smaller segments will allow the classification step to look at these differences. When larger segments were used, it created larger, more rounded segments instead of highlighting the long linear nature of the tiles. In fields where there were crisscrossing tile lines, the linear effect was impossible to isolate. While the human brain can interpret the nature of crisscrossed tile lines, a computer cannot. It is like the difference between individual lines drawn separately for a tic-tac-toe game versus the image of a hashtag that is stamped all as one. The eye can tell a difference and distinguish them as separate entities, eCognition cannot.

As discussed in Section 3.1, imagery must be obtained that has been taken during just the right soil moisture conditions. This significantly limits the usefulness of the identification process for both eCognition and the hand digitizing process, unless resources are available to purchase custom photogrammetry specifically for a project. The increasing availability of high-resolution imagery will lessen this problem in the future.

Context information, such as shape and distance from another object is a benefit of eCognition and OBIA software in general. For example, eCognition can distinguish between trees that are part of a residential area vs. those in a woods by looking at the proximity to another classification called house. This thesis did not allow for the use of
those powerful tools because the analysis was being done on too limited of a region. These fields are just square with straight lines of light and dark, so there is no context to compare anything. There was only “tile” and “not tile” so it was not useful to use a relational algorithm such as “it’s ‘tile’ if it’s next to ‘not tile.’” It’s a waste of a lot of the power of eCognition.

In general, while this research generated what appear to be good results from eCognition, it is not really a good use of resources at this time to use eCognition for identifying drainage tile.
Chapter 6

6 Further Research

There were several obstacles confronted during this research project, which would benefit from further study. Continued better imagery over time will likely have better resolution, and more powerful computers will be able to process larger areas of study in a shorter period of time. An additional benefit of more high-resolution imagery will improve the chances that images will be found where soil moisture conditions are appropriate for this analysis.

When it comes to determining dry from wet soil, different soil types affect how quickly certain areas of a field will drain any water into the tile. This leaves different stretches of tile with narrowly drained areas and some other spots with wide sections of dried soil. Further research could tie in Soil Survey Geographic Database (SSURGO) maps to the analysis and develop different rulesets based on what type of soil. Since the brightness of the field changes from location to location, based on the soil type, the evaluation of whether it’s tile or not requires tweaking of brightness values to evaluate by. As of this writing, a new version of eCognition (version 9) has just been released. It appears that it
has enhanced capabilities for handling thematic, or vector, layers. This may allow the integration of a soil map into the analysis with more ease

Further experimentation with the available algorithms in eCognition may also reveal additional useful steps. The ability to compare areas of light vs. dark as relative values instead of absolute numbers would simplify the transfer of a ruleset from one area to another. Another aspect to examine would be the use of the edge extraction algorithms to give a sharper delineation between those light and dark areas.

If the problem with needing to make adjustments to every field can be overcome, an obvious next step would be to expand the geographical area analyzed. Instead of encompassing only one field, one square mile or an entire township could be studied. To accomplish this, the preliminary steps would need to be improved in order to effectively remove all non-agricultural areas such as houses, roads and woods. Combining this larger area with improved steps for analyzing the soil type could prove to be a powerful combination.
References


Appendix A

eCognition Algorithms Available

- **Process related operation**
  - execute child processes
  - execute child as series
  - if
  - then
  - else
  - throw
  - catch
  - set rule set options

- **Segmentation**
  - chessboard segmentation
  - quadtree based segmentation
  - contrast split segmentation
  - multiresolution segmentation
  - spectral difference segmentation
  - multithreshold segmentation
  - contrast filter segmentation

- **Basic Classification**
  - assign class
  - classification
  - Hierarchical classification
  - remove classification
- **Image layer operation**
  - distance map
  - create temporary image layer
  - delete layer
  - convolution filter
  - layer normalization
  - median filter
  - sobel operator filter
  - pixel trace filter
  - pixel min/max filter (prototype)
  - edge extraction lee sigma
  - edge extraction canny
  - edge 3d filter
  - surface calculation
  - layer arithmetics
  - line extraction
  - abs mean deviation filter (prototype)
  - contrast filter (Prototype)
  - pixel filter sliding window
  - fill pixel values

- **Thematic layer operation**
  - assign class by thematic layer
  - synchronize image object hierarchy
  - read thematic attribute

- **Interactive operations**
  - show user meeting
  - set active pixel
  - create/modify project
  - manual classification
  - configure object table
  - select input modes
  - start thematic edit mode
  - select thematic objects
  - finish thematic edit mode
  - polygon cut
  - select image object
  - save/restore view settings
  - display map
  - define view layout
  - set custom view settings
  - change visible map
  - change visible layers
  - show scene
  - ask question
  - set project style
  - show/hide help
  - configure manual image equalization
  - show/hide class
  - display features in image object information

- **Parameter set operations**
  - apply parameter set
  - update parameter set
  - load parameter set
  - delete parameter set file
  - update action from parameter set
  - update parameter set from action
  - actions to array
  - apply active action to variables
- Sample operation
  - Classified image objects to samples
  - Cleanup redundant samples
  - Nearest neighbour configuration
  - Delete all samples
  - Delete samples of classes
  - Disconnect all samples
  - Sample selection
- Image Registration
  - Image registration
  - Delete landmarks
  - Set landmark
- Text Operations
  - Split string (prototype)
- Point Cloud
  - LiDAR file converter
  - Precalculating LiDAR file metrics
Appendix B

eCognition Analytical Features
To neighbors
- Mean Diff. to neighbors
- Mean Diff. to neighbors (abs)
- Mean diff. to darker neighbors
- Mean diff. to brighter neighbors
- Number of brighter objects
- Number of darker objects
- Rel. border to brighter objects

To super-object
- Mean diff. to super-object
- Ratio to super-object
- StdDev diff. to super-object
- StdDev Ratio to super-object

To Scene
- Mean diff. to scene
- Ratio to scene
- Hue, Saturation, Intensity
  - Create new 'HSI Transformation'

Geometry
  Extent
  - Area (Px)
  - Border length (Px)
  - Length (Px)
  - Length/Thickness
  - Length/Width
  - Number of pixels
  - Rel. Border to Image Border
  - Thickness (Px)
  - Volume (Px)
  - Width (Px)

Shape
  - Asymmetry
  - Border index
  - Compactness
  - Density
  - Elliptic Fit
  - Main direction
  - Radius of largest enclosed ellipse
  - Radius of smallest enclosing ellipse
  - Rectangular Fit
  - Roundness
  - Shape index

To super-object
- Rel. area to super-object
- Rel. rad. position to super-object
- Rel. inner border to super-object
- Distance to super-object center
- Elliptic distance to super-object center
- Is end of super object
- Is center of super-object
Based on Polygons
- Number of right angles with edges longer than
- Area (excluding inner polygon) (Pd)
- Area (including inner polygon) (Pd)
- Average length of edges (polygons) (Fx)
- Compactness (polygons)
- Length of longest edge (polygons) (Pd)
- Number of edges (polygons)
- Number of inner objects (polygons)
- Perimeter (polygons) (Fx)
- Polygon self-intersection (polygons)
- Stdev of length of edges (polygons) (Fx)

Based on Skeletons
- Number of segments of order
- Number of branches of order
- Average length of branches of order
- Number of branches of length
- Average branch length (Pd)
- Average area represented by segments (Pbx)
- Curvature/length (only main line)
- Degree of skeleton branching
- Length of main line (no cycles) (Fx)
- Length of main line (regarding cycles) (Fx)
- Length/Width (only main line)
- Maximum branch length (Pd)
- Number of segments
- Stdev of Curvature (only main line)
- Stdev of area represented by segments (Pbx)
- Width (only main line) (Fx)

Position
- Distance
  - Distance to line
    - Distance to scene border (Pxl)
    - T distance to first frame (Fx)
    - T distance to last frame (Fx)
    - X distance to scene left border (Pxl)
    - X distance to scene right border (Pxl)
    - Y distance to scene top border (Pxl)
    - Y distance to scene bottom border (Pxl)
    - Z distance to first slice (Pd)
    - Z distance to last slice (Pd)
  - Coordinate
    - Is at active pixel
      - Time (Fx)
      - Time Max (Pd)
      - Time Min (Pd)
      - X Center (Fx)
      - X Max (Fx)
      - X Min (Fx)
      - Y Center (Fx)
      - Y Max (Fx)
      - Y Min (Fx)
      - Z Center (Fx)
      - Z Max (Fx)
      - Z Min (Fx)
  - Is object in region
    - Create new 'is object in region'
- Class-Related features
  - Relations to neighbor objects
    - Existence of
    - Number of
    - Border to
    - Rel. border to
    - Rel. area of
    - Distance to
    - Mean diff. to
    - Overlap of two objects
  - Relations to sub objects
    - Existence of
    - Number of
    - Area of
    - Rel. area of
    - Clark Aggregation Index
  - Relations to super objects
    - Existence of
  - Relations to Classification
    - Membership to
    - Classified as
    - Classification value of
    - Class name
    - Class color
    - Assigned class
- Linked Object features
  - Linked objects count
  - Linked objects statistics
  - Link weight to PPO

- Scene features
  - Scene Variables
  - Map Variables
  - Class-Related
    - Number of classified objects
    - Number of samples per class
    - Area of classified objects
    - Area percentage of
    - Layer mean of classified objects
    - Layer stddev of classified objects
    - Statistic of object value (prototype)
    - Histogram of object value (prototype)
  - Scene-Related
    - Existence of object level
    - Text processing (prototype)
    - Existence of image layer
    - Existence of thematic layer
    - Existence of map
    - Mean of Scene
    - StdDev
    - Smallest actual pixel value
    - Largest actual pixel value
- Validity of region
  - Active pixel t-value
  - Active pixel x-value
  - Active pixel y-value
  - Active pixel z-value
  - Is active vector layer changed
  - Map origin T (Pxl)
  - Map origin X (Pxl)
  - Map origin Y (Pxl)
  - Map origin Z (Pxl)
  - Map size T (Pxl)
  - Map size X (Pxl)
  - Map size Y (Pxl)
  - Map size Z (Pxl)
  - Number of image layers
  - Number of maps
  - Number of objects
  - Number of pixels in scene
  - Number of samples
  - Number of thematic layers
  - Original Scene ID
  - Original Scene Name
  - Scene ID
  - Scene Magnification
  - Scene Name
  - Scene Pixel Size
  - Scene Resolution
  - Scene bit depth
  - Second Level Scene Name
  - Slice distance (Pxl)
  - Time-series distance
  - Top Scene ID
  - Top Scene Name
  - User name
Appendix C

Rulesets
School - Field & Analysis
- Cleanup
  - delete 'SP500'
  - delete Field'
  - at SP500: remove classification
  - at Field: remove classification
- Segment to separate different areas of field
  - 500 [shape:0.5 compact:0.9] creating 'SP500'
- Classify on mean brightness to remove wooded & residential areas from 'field'
  - at SP500: field
  - unclassified at SP500: not field
- Re-segment field portions & classify
  - field at SP500: 20 [shape:0.1 compact:0.9] creating 'Field'
    - with Existence of super objects field (1) = 1 at Field: field
    - with Existence of super objects not field (1) = 1 at Field: not field
    - field at Field: tile
  - field at Field: merge region