Inclusion of Gabor textural transformations and hierarchical structures within an object based analysis of a riparian landscape

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INCLUSION OF GABOR TEXTURAL TRANSFORMATIONS AND
HIERARCHICAL STRUCTURES WITHIN AN OBJECT BASED ANALYSIS OF A
RIPARIAN LANDSCAPE

by

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ABSTRACT

Land cover mapping is an important part of resource management, planning, and economic predictions. Improvements in remote sensing, machine learning, image processing, and object based image analysis (OBIA) has made the process of identifying land cover types increasingly faster and reliable but these advances are unable to utilize the amount of information encompassed within ultra-high (sub-meter) resolution imagery.

Previously, users have typically reduced the resolution of imagery in an attempt to more closely represent the interpretation or object scale in an image and rid the image of any extraneous information within the image that may cause the OBIA process to identify too small of objects when performing semi-automated delineation of objects based on an images’ properties (Mas et al., 2015; Eiesank et al., 2014; Hu et al., 2010). There have been few known attempts to try and maximize this detailed information in high resolution imagery using advanced textural components.

In this study we try to circumnavigate the inherent problems associated with high resolution imagery by combining well researched data transformations that aid the OBIA process with a seldom used texture transformation in Geographic Object Based Image Analyses (GEOBIA) known as the Gabor Transform and the hierarchal organization of landscapes. We will observe the difference made in segmentation and classification accuracy of a random forest classifier when we fuse a Gabor transformed image to a Normalized Difference Vegetation Index (NDVI), high resolution multi-spectral imagery (RGB and NIR) and Light
Detection and Ranging (LiDAR) derived canopy height model (CHM) within a riparian area in Southeast Iowa. Additionally, we will observe the effects on classification accuracy when adding multi-scale land cover data to objects. Both, the addition of hierarchical information and Gabor textural information, could aid the GEOBIA process in delineating and classifying the same objects that human experts would delineate within this riparian landscape.
PUBLIC ABSTRACT

Land cover mapping is an important part of resource management, planning, and economic predictions. Improvements in remote sensing, machine learning, image processing, and object based analysis (OBIA) has made the process of identifying land cover types increasingly faster but these advances are unable to utilize the amount of information encompassed within ultra-high resolution imagery.

Previously, users have typically reduced the resolution of imagery in an attempt to more closely represent the interpretation or object scale in an image and rid the image of any extraneous information within the image that may cause the OBIA process to identify too small of objects when performing semi-automated delineation of objects based on an images’ properties (Mas et al., 2015; Eiesank et al., 2014).

In this study we try to circumnavigate the inherent problems associated with high resolution imagery by combining well researched data transformations that aid the OBIA process with a seldom used texture transformation in Geographic Object Based Image Analyses (GEOBIA) known as the Gabor Transform and the hierarchal organization of landscapes. We will observe the difference made in segmentation and classification accuracy of a random forest classifier when fused with several well-known spectral and LiDAR derivatives within a riparian area in Iowa. Additionally, we will observe the effects on classification accuracy when adding multi-scale land cover data to objects. Both, the addition of hierarchical information and Gabor textural information, could aid the GEOBIA
process in delineating and classifying the same objects that human experts
would delineate within this riparian landscape.
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Chapter 1- Background

INTRODUCTION

Land cover mapping is an important part of resource management, planning, and economic predictions. Improvements in remote sensing, machine learning, image processing, and object based image analysis (OBIA) has made the process of identifying land cover types increasingly faster and reliable but these advances lack to keep up with the growing availability of ultra-high (sub-meter) resolution imagery.

Previously, users have typically reduced the resolution of imagery in an attempt to more closely represent the interpretation or object scale in an image and rid the image of any extraneous information within the image that may cause the OBIA process to identify too small of objects when performing semi-automated delineation of objects based on an images’ properties (Mas et al., 2015; Eiesank et al., 2014; Hu et al., 2010). There have been few known attempts to try and maximize this detailed information in high resolution imagery using advanced textural components.

In this study we try to circumnavigate the inherit problems associated with high resolution imagery by combining well researched data transformations that aid the OBIA process with a seldom used texture transformation in Geographic Object Based Image Analyses (GEOBIA) known as the Gabor Transform. We will observe the difference made in segmentation and classification accuracy of a random forest classifier when we fuse a Gabor transformed image to a
Normalized Difference Vegetation Index (NDVI) and Light Detection and Ranging (LiDAR) derived canopy height model (CHM) within a riparian area in Southeast Iowa. Additionally, we will observe the effects on classification accuracy when adding hierarchical land cover data to objects.

BACKGROUND

The following chapter will cover the existing literature and research in geographic object based image analysis (GEOBIA) as it pertains to the progression of the various data sources used as well as segmentation uses. This will not be an exhaustive search due to the amount of creativity and the constantly evolving nature of GEOBIA but will, instead, focus on the background that is pertinent to this study. Emphasis will be given to the seminal papers that establish the support for the hypotheses of this study.

This chapter will first describe the framework of this type of analysis and how geography uses it to understand the environment. In this description, the individual steps of the analysis will be explained with elaboration of the details that make this study useful to the scientific community. Then, attention will be given to the timeline of new data that has contributed to GEOBIA and will provide support for the choice of data that was used within the methodology of this study. Chapter 2, will describe the purpose of this study, the methodology, and results. Chapter 3 will continue the discussion and how the findings of this study will help build future hypothesis and what could be done in future studies to extend this research.
Object based image analysis (OBIA) is a technique or method that intelligently exploits the information gathered within a raster image, a collection of data that is represented by a continuous surface of regular sized grids representing some real world scene. The goal of OBIA is to isolate and extract objects that a human viewer would consider as important or significant within an image by identifying groups of pixels that are similar in location and value, drawing some polygon, and then classifying what this object is. This could be a face, a pedestrian, a traffic sign, or landslides (Rowley et al., 2006; Yu et al., 2016; Chen et al., 2014, Booth et al., 2009). The applications are endless and continue to evolve with new data and image processing techniques.

Through object extraction and classification, an inventory can be made of the contents of any image. Objects as small as blood vessels to as large as galaxies can be identified and quantified in this type of analysis (Liu et al., 2003; Wang et al., 2015). At a landscape or regional level, land cover resources can be identified for utilization or conservation, quickly, when compared to taking field level measurements.

Landscape level images are being more readily available with the decreasing cost of sensors, increasing availability of quality satellite imagery, and the continued development of drones (Mookambiga & Gomathi, 2016; Fauvel et al., 2013; Feng et al., 2015). The use of OBIA on this scale makes it useful for anybody trying to understand an area’s spatial organization or contents such as natural resource planning, intelligence, hazard mitigation, or security (Booth et al., 2009; Hamilton et al., 2013; Ko, 2008). This focus on space and scale has
resulted in the development of Geographic Object Based Image Analysis (GEOBIA). The first identified instance of this was a hand demarcated land cover map created by Francis Marchner and the United States Department of Agriculture in 1950 (Marschner, 1950). Although this example does not utilize computer vision like most GEOBIA techniques use, aerial imagery was still used in the creation of this map and objects were subsequently identified from them.

Today, the steps taken for the extraction and classification of objects within an image are similar throughout GEOBIA’s domain. The first step is data collection or creating a topographic image from which to extract landscape level objects from. Then preprocessing or data preparation of the image is performed. There are several items that can be accomplished within this step that can dramatically affect the results of the analysis. Different goals of this step are accentuating features within the image, data fusion, and georectification & orthorectification. Following preprocessing, segmentation or feature extraction is the next step that uses various algorithms to group similar pixels together based upon a certain heterogeneity threshold set by the user. These parameters determine the size of the objects as well as how similar an object’s pixels need to be before they are considered separate. The last step, classification, will use this information to predict the object’s class. This is an iterative process and users will combine various data, transformations, segmentation techniques, and classification algorithms to come up with the best output from a given input.
Feature extraction or segmentation is an important part of the GEOBIA process that generally follows preprocessing where a semi-automated program attempts to delineate the same objects that a human observer would consider as its own entity separate from any other objects within an image. The algorithms used to achieve this step attempt to group similar pixels together in order to identify the boundary that establishes one object from another. These objects will contain metrics (mean, standard deviation, minimum, etc.) of each band within a given image as well as landscape metrics that represent the shape of an object such as the area, elongation, complexity, or convexness. These metrics are what will be used for estimating an object's class through data mining.

These objects and their subsequent landscape metrics created from feature extraction separates GEOBIA from pixel based classification, another method in land cover classification that only utilizes pixel values for classification. The following reasons are why we chose an object based approach instead of a pixel based approach. Without considering pixel to pixel relationships, the resultant classified image can suffer from the “salt-and-pepper” effect where classified land cover pixels appear pixelated. A pixel based approach also fails at identifying discrete objects like trees or buildings and generally does not support our conceived systems model that is composed of separate interconnected structures. There is also support that object based classification has better classification accuracies than pixel based classification within GEOBIA (Karami et al., 2015; Immitzer et al., 2012; Myint et al., 2011). Another problem with pixel-
based classification is that the signal that is sensed to derive the pixel value often comes from the land area surrounding the actual pixel due to the remote sensing instruments and atmospheric effects (Townshend et al., 2000). So, relying on homogeneous regions (i.e. segments) instead of single pixel value can limit issues coming from the defects of remote sensors.

SEGMENTATION ALGORITHMS

The varying segmentation algorithms that are used within GEOBIA approach the same problem in different ways. Most software like eCognition and ENVI does some form of averaging across the bands in an image to compute a gradient or intensity image for the standard watershed algorithm (Jin, 2012). Other methods include the thresholding method, region-growing, and the edge-based method (Otsu, 1979; Fan et al., 2001; Vincent & Soille, 1991; Galambos, Kittler and Mata, 2001). For this study, we used the watershed algorithm implemented by ENVI to compare segmentation results due to its ubiquitous use in common software within GEOBIA, ability to create a hierarchy of segmented objects, and general support within the literature (Jin, 2012; Sellaouti et al., 2012; Alonzo et al., 2013; Xiao et al., 2010, Meyer, 2012).

The intuitive explanation of the watershed algorithm is that the algorithm treats each pixel as a topographic elevation value. Low pixel values are considered lower elevation within the landscape and higher values, higher. This hypothetical landscape is then flooded. As the water level is lowered, the emerging high level pixels are treated as the boundaries. The "basins" where the
water collects are considered to be the objects. The amount of water that floods the landscape is a user-defined parameter, “scale.” This parameter determines the size of the objects by determining the amount of edges that emerge from the flooded image. To prevent over segmentation, the user can also dissolve these boundaries based on a user-set parameter “merge” which determines how similar two adjacent object’s attributes need to be in order to be considered the same object. These parameters are arbitrarily optimized until the user is satisfied with the output.

The watershed algorithm can use either a gradient image or intensity image for segmentation. A gradient image is created from a base image (transformed to grayscale by averaging the values across bands) where the values of pixels increase with an increase in a directional flow or contrast of the original image using a Sobel edge detection method to highlight the boundaries of objects (Jin, 2012). The intensity method simply averages the value of pixels across bands.

Over and under segmentation refers to the feature extraction either creating too large of objects or too small of objects, respectively, relative to the desired object size. There are several elements within an image that can cause this over/under segmentation within an image. One source of over segmentation within an image is having high local pixel values relative to neighboring pixels. This can be caused from too much detail beyond what is desired within an image, noise within an image, or inappropriate parameter values. For example, if a user is interested in identifying entire fields of row crop agriculture but the
resolution of imagery is high enough that it clearly represents single rows-the user may need to decrease the resolution in order to prevent individual rows of crops from being segmented and, rather, have the entire field segmented.

Conversely, under segmentation can be caused by too low of resolution preventing the algorithm from delineating objects or inappropriate parameters values. Not having the appropriate data for the objects you wish to delineate may also cause under segmentation. One band of imagery may not demarcate the boundary of an object that a user wishes to identify suggesting that a canopy height model, normalized difference vegetation index, or other indices should be introduced to highlight the object of interest. Depending on the image or dataset, you may also have over segmentation in one location and under segmentation in another.

Users can take several approaches to try and limit the amount of under/over segmentation that occurs. A common method to reduce over segmentation is to reduce the resolution of an image using a filter such as a low-pass, Gaussian, or median kernel (Mas et al., 2015; Eiesank et al., 2014; Hu et al., 2010). Due to the complexity of aerial imagery, under segmentation rarely becomes an issue but could be addressed with either a high pass filter, pan-sharpening which can increase the contrast within the image, or introducing new data. Although reducing image resolution through the use of filters can reduce the amount of extraneous details, these filters could be masking important information that could be used to classify the data. Another method of reducing segmentation errors is to introduce information beyond spectral data that human
observers may use when classifying land cover in order to improve segmentation results.

Data fusion is a method that has been widely used to aid in the segmentation and classification steps in GEOBIA where the user combines various sources of data (Mookambiga & Gomathi, 2016; Man et al., 2016; Geerling et al., 2007). The goal of fusing data is to enable the segmentation and classification algorithm to better differentiate land cover classes. There are several methods to combine data but the most ubiquitous pixel level fusion is to stack the layers and normalize or standardize the different data sources (Mookambiga & Gomathi, 2016; Geerling et al., 2007; Forzieri et al., 2007). One of the earliest applications of data fusion for land cover classification was texture (Haralick et al., 1973).

CLASSIFICATION & RANDOM FOREST

Classification is the prediction of an object or other unknown instance based upon known attributes of the object. These classification algorithms that predict class have evolved considerably since their realization in the early 19th century. Attention to such algorithm’s stemmed from interest in probability, statistics, and distribution of data. The Bayes Theorem, an 18th century concept and equation in probability, influenced much of the existing algorithms (Stigler, 1983). This theorem led to the creation of the naïve Bayes classifier which assumes that each attribute’s instance independently contributes to the conditional probability of any given class. This corresponded with interest in the
maximum likelihood classifier (which was not fully accepted as a valid classifier until R.A. Fisher in the 1930’s) (Stigler, 1983; Stigler, 2007). This is a widely used classifier in GEOBIA and data mining that utilizes the probability density function to determine an unknown instance’s class.

It wasn’t until the 1950’s that machine learning or artificial intelligence became a field with the creation of the single layer perceptron and the computer (Rosenblatt, 1958). This gave way for the multilayer perceptron or artificial neural network in 1986, a widely used classifier with many adaptations (McClelland et al., 1986). At this time the K-nearest neighbor also gained popularity and is still a popular classification method. This method, also known as a lazy classifier, uses the most similar training example/s to classify an object (Cover & Hart, 1967).

The next wave of classification procedures gained momentum in the 1990’s with the creation of support vector machines and logistic regression (Böhning, 1992; Cortes & Vapnick, 1995). Support vector machines (SVM) identifies the optimal separating surface, hyperplane, or boundary within a dataset that distinguishes one class from another in n-dimensional space, to separate classes within the set of possible values. Within GEOBIA, SVM are one of the most widely used classifiers behind Random Forest (Belgui & Dra, 2016).

To date, random forest (RF) has been identified as one of the best performing classification algorithms within GEOBIA due to its ability to deal with large, high dimensional datasets (Belgui & Dra 2016; Rodriguez-Galiano et al., 2012; Breiman, 2001). This classifier was developed by Leo Breiman in 2001 and is based off of classification and regression (CART) or decision trees (Breiman,
CART successively partitions the dataset into smaller, purer, subsets based off of the training data in an attempt to isolate the classes. Entropy is often used as the metric to select the split in a feature to identify the purest split of a feature in the dataset. Entropy is defined in equation 1 as;

\[ H(X) = - \sum_{i=1}^{n} P(X_i) \log_2 P(X_i) \]  

Where \( P(X_i) \) is the probability of event \( X \) occurring. There are numerous implementations of CART that vary by how they calculate entropy or InfoGain but C4.5 or J48 is the most current and widely used program that utilizes CART (Quinlan, 1993).

RF is an ensemble of CART’s that are randomly generated and successively partitions a training dataset into smaller subsets to identify an object’s class. An important distinction between RF and CART is that instead of partitioning features based on maximizing purity or information gain, RF randomly selects the features to split upon over the user defined amount of regression trees and RF uses bootstrap aggregating or bagging (Breiman, 2001). Bagging is used to create as many randomly selected subsets, with replacement, of the original dataset as the user defined number of desired trees. These subsets are the same size as the original number of observations but since there is replacement, some observations are selected more than once and some observations are not selected at all. Each tree will use a single subset and each split within the tree will use a subset of the prior subset to randomly split a feature. Based on majority voting of each randomly generated tree, a new instance or observation is predicted.
As previously stated, for each tree that is generated from a randomly selected subset, some observations or data points are left out. These left out observations are considered to be the out-of-bag (OOB) examples. These OOB examples are then artificially predicted using the tree that was generated that did not use the OOB examples. The average error percentage is generated by averaging the error rate across all of the trees in the ensemble of trees. This metric is called the OOB error rate and used to estimate the performance of RF classifiers instead of using a test set, cross fold validation, or a receiver operating characteristic (ROC) curve.

Belgiu & Dra (2016) aptly indicated that random forest handles high dimensional data, limits the Hugh’s phenomenon that arises from high-dimensionality, has the ability to classify non-linear data, is less affected by skew and noise within the dataset, and computation time is small compared to other classifiers. Other studies have consistently provided evidence that RF outperforms or is comparable to other classifiers within GEOBIA such as support vector machines, regression, and artificial neural networks. (Johnson, 2014; Belgiu & Dra, 2016; Cutler et al., 2007; Rodriguez-Galiano et al., 2012). A user typically determines two parameters within the RF algorithm- the number of trees produced and the number of attributes that are available to be used when splitting the randomly generated CART’s. Some implementations of random forest, such as R, can provide feature importance metrics indicating which features contributed most in predicting an object’s class by observing the amount of change in OOB error with and without the selected feature (Liaw & Wiener,
This can provide evidence to whether or not a Gabor filter can aid in classification. These characteristics of random forest will aid in identifying the highly detailed and wide datasets that will be created from the segmentation of the datasets that will be analyzed within this study.

DATA FUSION

Texture

Texture within an image is a set of characteristics that describe the composition or variance within an image on a local, neighborhood, global or object based scale. Metrics for texture analysis was created in the mid 1950’s but it wasn’t until the 1970’s that computers were able to handle the algorithms used to utilize these metrics in a digital format (Kaizer, 1955; Andrews et al., 1972). It was Haralick et al. (1973) that first used these metrics for land cover classification purposes. They used linear discriminant analysis to create a set of hyperplanes or decision boundaries within their dataset to classify on a pixel by pixel basis of gray scale imagery. They computed their texture metrics on a neighborhood level using average and standard deviation values. Recently, texture has proven to be highly valuable for accuracy in GEOBIA of high resolution imagery. For example, Feng et al. (2015) increased classification accuracy by 17.1% through the use of texture metrics as opposed to without. They used imagery gathered from an ‘off-the-shelf” camera on a UAV platform of a vegetated suburban landscape using a random forest classifier. Feng et al. (2015) and many others use the common second order Grey-Level Co-
Occurrence Matrix (GLCM) to compute their desired textural features (Laliberte et al., 2009; Szantoi et al., 2013; Aguera et al., 2008; Haralick et al., 1973).

The GLCM is derived by the frequency of two similar or a neighborhood of gray-level intensity values occurring. The resulting matrix is used to compute the desired textural feature. In Haralick et al. (1973) original paper they defined 14 different textural features. Common examples of these features that can be derived from GLCM are entropy, homogeneity, contrast, standard deviation, and mean.

Gabor Textural Transformation

There are four different categories that textural information can be gathered: structural, statistical, model based, and transformation (Li et al., 2014). GLCM would be considered a statistical texture extraction method but this study is primarily concerned with the transform category as it deals with wavelet transformations. Wavelets are transformations that use a repeated signal such as a sine wave and a mathematical conversion to alter image’s pixels in a preferred way. Many wavelet transforms (discrete, continuous, Fourier) are used to reduce noise within an image which can prevent over segmentation or to bring out hidden patterns within the data which may be helpful for object detection (Hu et al., 2010; Mookambiga & Gomathi, 2016; Booth et al., 2009; Samiappan et al., 2016).

Gabor filters are a particular type of wavelet transform or band pass filter that was influenced from the Fourier transform but differs because its wavelet is
Gaussian modulated by a complex sinusoidal wave (Gabor, 1946; Daugman, 1985). These Gabor transformed wavelets are parameterized by the angle at which they alter the image and the frequency of the wavelet. As opposed to smoothing an image out at the cost of losing detail through Fourier transforms or median filters, Gabor transformed images identify the repeated pattern of localized pixels and gives them similar values if they are a part of the same repeated pattern allowing the Gabor transforms to be a textural feature. It has been identified that the Gabor filters can emulate the way that the visual cortex's of mammalian brains utilize texture to identify objects which provides support that this may be helpful in automatically segmenting an image in the same manner a human expert would manually segment an image (Marcelja, 1980; Daugman, 1985). This is based on the evaluation of neurons associated with the cortical vertex respond to different images or light profiles (Maffei et al., 1979). Marcelja, 1980 identified that cortical cells responded signals that are localized frequencies of light similar to what is represented by the Gabor transformations. Within the frequency domain, the Gabor transform can be defined in equation 2 by:

\[
G(u, v; f, \theta) = e^{\frac{-\pi^2}{\gamma^2} (f(u' - f)^2 + n^2 v'^2)}
\]

Where \( f \) is the user-determined frequency; \( \theta \) is the user-determined orientation at which the wavelet is applied to the image; \( \gamma \) and \( n \) are the standard deviations of the Gaussian function in either direction (Wang et al., 2010; Gabor, 1946). These parameters define the shape of this band pass filter and determine the effect it has on a one dimensional signal. Daugman (1946), created a 2-D application of this filter in equation 3;
\[
g(x, y) = \frac{1}{2\pi \sigma_x \sigma_y} \exp \left\{ -\frac{1}{2} \left[ \left( \frac{x}{\sigma_x} \right)^2 + \left( \frac{y}{\sigma_y} \right)^2 \right] + j(u_0x + v_0y) \right\}
\]

[3]

Where \( u' = uc \cos \theta - vsin \theta \) and \( v' = us \sin \theta - vc \cos \theta \)

In Samiappan et al. (2016), they compared Gabor filters to other texture features (grey-level co-occurrence matrix, segmentation-based fractal texture analysis, and wavelet texture analysis) for the automatic segmentation and classification of a wetland area using sub-meter resolution multispectral imagery. Gabor filters performed comparably in overall classification accuracy and Kappa coefficients with other texture features but were outperformed by GLCM metrics, segmentation-based fractal texture analysis, and wavelet texture analysis texture features. In this study they did not use any other data for analysis though raising questions of the performance of Gabor filters when paired with other data sources such as spectral, NDVI, or LiDAR derivatives (Samiappan et al., 2016; Xiao et al., 2015;). Wang et al. (2010) paired this Gabor transformation with a fast Fourier transform for edge detection on an urban landscape image that contained uniform textures. Wang et al. (2010) and Xiao et al.'s (2010) results support that implementing Gabor transform can improve segmentation. Within GEOBIA, there has been no identified studies that has used the textural information created from Gabor filters for classification purposes (Xiao et al., 2010).
Landscape Metrics

Spatial patterns heavily influence the factors that shape natural systems and thus, if quantified, can be significant predictors for features in the landscape. One can intuitively see that a river or stream will follow a linear or serpentine path while a building, road, or even an agricultural field will likely be planar and rectangular. The geometry of these specific features across a landscape are consistent enough to be predictors for classification. Using geometric features as a defining characteristic of a land cover type comes from the axiom that the landscape is organized in a pattern that is determined by the attributes of its parts. Since a single pixel does not contain this spatial information, a classification algorithm may not be able to separate the difference from a low slope pixel from a road or a building edge with the same slope angle, for example (Ferraz et al. 2014; Hill & Thomson, 2005). Across scales, these patterns and attributes may change, but the theory expresses itself across these scales nonetheless.

Within modern times, interest in this topic began in the early 20th century, but measuring and using this theory to characterize the landscape gained momentum with publications by Monica Turner and Formon & Godron (Gleason, 1917; Turner, 1989; Forman & Godron, 1981). With the help of work done by others, they aided in developing a field that is known as landscape ecology (Romme & Knight, 1982; Hoover, 1986). Landscape ecology looks at the patterning, heterogeneity, and how these variables influence the flows of energy across the landscape (Turner, 1989). This field has created a set of landscape
metrics used to analyze the heterogeneity of land cover classes. These metrics can either describe the global landscape, a local patch, or a class of objects. Generally, landscape metrics describe edge complexity, the size of the objects, and how objects or patches relate to one another. An informal review of the different metrics that can be used can be found here, McGarigal, *Landscape Metrics for Categorical Map Patterns* such as differences between landscape and patch centric metrics, area vs. edge metrics, and various distribution metrics.

Ferraz et al. (2014) relied upon landscape metrics in order to detect road segments within a forested mountainous region. They used a digital terrain model and a slope model derived from a LiDAR image. The Random forest model was able to identify that the objects with long lengths, short widths, minimum slopes, and minimum change in elevation within the object as roads with acceptable accuracy. With pixel based classification it would be likely that any pixel with little slope or similar elevation as the training information could be misclassified as a road.

Topographic Data

The next wave of data to test the capabilities of classifiers in GEOBIA were topographic information. Intuitively, different landscapes and land covers will have different elevation, slopes, and aspects. Floodplains will be located in the lower valleys of a landscape and prairies will establish themselves on flat or low-slope stretches of land. These characteristics and more can be captured through the use of topology and elevation. The first identified use of elevation in
GEOBIA was by Wilson & Franklin (1992). They used Spot satellite imagery fused with geomorphometric information gathered from stereoscopic analysis in a mountainous region of the Yukon Territory in Canada. The different variables they created and applied to their maximum likelihood classifier was solar incidence, elevation, and slope. They increased their classification accuracies of vegetated landcovers by 11% to 85% with the use of topographic data.

The advent of LiDAR has made topographic information more accessible for most GEOBIA users. Beyond the topographic models previously discussed, multi-return LiDAR can aid in developing models of vegetative structure. This utilizes the property of LiDAR that multiple returns of a single column or laser pulse can be reflected off of different targets at different times due to an object’s structure. The first identified paper in GEOBIA to utilize LiDAR was Hill & Thompson (2005). They created a canopy height model derived from LiDAR and 126-band spectral data to classify woodland vegetation. Many others have reported kappa coefficients or accuracies above 80% when using LiDAR information in their GEOBIA analysis (Geerling et al., 2007; Rahman et al., 2013; Forzieri et al., 2013; Debes et al., 2014).

Juel et al. (2015) provided valuable insight into their object based analysis of a coastal area in Denmark using similar data fusion techniques as our study. They used high resolution (<20 cm) multispectral Red, Green, Blue (RGB), Near-Infrared (NIR) imagery, GLCM derived textural information, and LiDAR derived topographic information including a CHM. Using random forest, they were able to achieve accuracy’s of up to 92%. Their variable importance indices reveal that
spectral data were most valuable for prediction accuracy, while several landscape metrics, LiDAR derived metrics, then GLCM derived texture metrics followed in importance. CHM was not the most important LiDAR variable but they conceded that CHM would likely be of higher importance if the LiDAR resolution was higher (below 24 m). This provides support that we should expect better accuracy with higher resolution LiDAR when fused with spectral data than without.

Hierarchical Organization

As stated earlier, one of GEOBIA’s goals is to automatically identify objects within an image as a human viewer would identify. This goal creates an optimization problem to match the scale, size, and objects that the human viewer would perceive as important. An observer or user may be looking for objects across scales such as for trees and forests, cells and tissues, the center line of a road and the boundary of the road causing a single scale of objects to be too simplistic of a model. An inherent flaw of the segmentation process is only being able to key in on a single size or homogeneity of objects given the scale and merge parameters. The user will likely either oversegment, identify too large of objects, or undersegment, identify too small or too many objects. Few have looked at the question of using multiple scales to either optimize the segmentation parameters or to increase classification accuracies.

This ability to look at objects of different scales offers a unique way to look at a widely recognized and studied phenomenon in ecology; hierarchical
organization. C.S. Holling describes this type of organization in a landscape as “...a hierarchy that contains breaks in object sizes, object proximities, and texture at particular scales” (Holling, 1992). It appears that GEOBIA has failed to implement hierarchical organization and therefore neglects a well supported idea that landcover types can be highly influenced by the higher tier of organization (Turner, 1989; Turner et al., 2001). An obvious approach to utilizing a hierarchical approach is to perform a classification on a courser segmented image with a broader classification scheme then apply these classification results to a finer segmented image with a more acute classification scheme.

The closest identified papers to bridge this gap are by Zhang et al., (2015) and Antunes et al., (2003). Zhang et al. (2015) created super-pixels, conglomerated pixels of similar values, to segment upon. This created a courser image to segment upon which has the effect of reducing noise and the salt-and-pepper effect from segmentation as well as limiting the problems of over/under segmentation. This methodology did not not however use the hierarchy in biological systems in their classification procedure. Antunes et al. (2003) utilized the varying scales of segmentation to increase their classification accuracies. They successively classified larger to smaller objects using a fuzzy rule-based classifier meaning they classified objects in either one of two classes and based the next, smaller scaled, objects based on their super-objects classification. Demarchi et al., (2016) also implemented a similar rule based classifier into their classification scheme of fused high resolution imagery and LiDAR derived data. Several others since Antunes et al. (2003) have attempted to use multiple scales
during the segmentation to either decrease noise or to optimize scaling parameters (Zhang et al., 2016; Laliberte et al., 2007; Gianinetto et al., 2014).

The addition of Gabor filters in combination with other well supported data sources in GEOBIA (i.e. CHM, NDVI), could more closely align segmentation results of natural land cover types with what human experts would hand delineate. The textural information gathered from a Gabor transform could also improve the classification accuracies of semi-automated delineated objects. Attributing hierarchical organization of land cover types to objects could also greatly increase classification accuracies using the random forest algorithm. In this study, we will observe if the addition of a Gabor transformed image will improve segmentation accuracies as compared to expert human subjects, increase classification accuracies of objects, and if a hierarchal scheme of land cover types and the use of super-objects and sub-objects will increase classification accuracies.
Chapter 2 - Study

INTRODUCTION

Detecting objects within a landscape through various forms of above-ground imagery provides valuable information to land management decisions. To date, image texture has been proven to be valuable information for the automated delineation and classification of imagery while hierarchical structures has been given little attention within the literature for increase classification accuracy. Image texture has generally been estimated by using matrix transformations but wavelet transformations have rarely been used as a way to measure texture, particularly the Gabor Transformation. Utilizing the hierarchical structure of natural land cover classes have also rarely been researched as an attribute for predicting an object’s class. Increasing the accuracy of object detection of landscape level imagery can improve the timeliness and effectiveness of land management understanding and decisions. Within this report, we will explore the impact that Gabor textural transformations and hierarchical structure attributes have on the detection of features within landscape level imagery.

Ultra-high resolution (sub-meter) imagery is often reduced to a lower resolution in order to increase processing time and reduce errors coming from over segmentation when performing geographic object based image analysis (Mas et al., 2015; Eiesank et al., 2014; Hu et al., 2010). Object based image analysis (OBIA) is an image processing process that takes an inventory of a raster image through the delineation of groups of homogeneous pixels to create
polygons that are to be classified using their characteristics that are derived from
the pixel and shape values. The OBIA process has been used to identify faces,
pedestrians, traffic signs, and landslides (Rowley et al., 2006; Yu et al., 2016;
Chen et al., 2014). At a landscape or regional level, this can be important for
assessing land cover and the type of resources that can be utilized or conserved.
Landscape level images are being more readily available with the decreasing
cost of sensors, increasing satellite imagery availability and quality, and the
continued development of drones (Mookambiga & Gomathi, 2016; Fauvel et al.,
2013; Feng et al., 2015).

The focus on space and scale results in the creation of Geographic Object
Based Image Analysis (GEOBIA) and this processes performance varies widely
across different landscapes. Landscapes with high pixel-to-pixel contrast
amongst their land cover types are more easily delineated than a landscape (or
project goal) that attempts to delineate objects that are not as drastically
separated class wise. This issue is heightened when the objective tries to identify
more than a couple land cover types. For example, in many object based image
analyses of urban areas, classification accuracy will likely be above 90% (Feng
et al., 2015; Man et al., 2015; Sugumaran & Voss, 2007; Myint et al., 2011; Li et
al., 2014) while within a natural landscape with little human influence it is
expected that the accuracy will be below 90% (Bork et al., 2007; Dalponte et al.,
2012; Dalponte et al., 2008; Forzieri et al., 2010; Johansen et al., 2007; Li et al.,
2014). Natural landscapes’ (e.g. riparian, brush, forested) spectral, height,
textural and geometrical metrics do not have considerable differences between
classes. This creates the challenge of maximizing the differences that do exist in order to prevent confusion between classes.

Generally, optimal segmentation and classification results would be to delineate and classify the same pixels that a human observer would delineate. Humans will typically utilize several forms of information in order to interpret their environment or to gather intelligence from an image. This can be color, distance or height, environmental relationships, and/or texture. In order to obtain or get close to perfect segmentation, GEOBIA would need to incorporate similar information into the segmentation and classification process that a human observer would utilize to delineate objects within an image.

GEOBIA has typically replicated this process of human object recognition using various contextual information, but still requires further development for better segmentation performance and improved classification accuracy. The Gabor textural transformation has been lauded as a method to replicate the same textural information that humans use to identify objects but little research has been conducted into the use of this transformation for object based image analysis (Marcelja, 1980; Daugman, 1985). Another group of information that is rarely included within research is hierarchical information, a typical way humans understand and interact with their environment. Both of these types of information are adequately exemplified in the metaphor of a human gradually descending in a hot-air balloon. As they are descending, they will begin to notice different patterns within the landscape which will give way to quick changes due
to the different patterns becoming apparent due to different perceptive scales (Forman, 1995).

In this paper, we attempt to utilize the amount of detailed information that can be stored in 7.6 cm resolution imagery to obtain better classification and segmentation results of complex floodplains by combining well researched data transformations that aid the OBIA process with a seldom used texture transformation in Geographic Object Based Image Analyses known as the Gabor Transform. We will use a random forest classifier, Normalized Difference Vegetation Index (NDVI) and Light Detection and Ranging (LiDAR) derived canopy height model (CHM) within a riparian area in Southeast Iowa to observe the difference in segmentation and classification that a Gabor transform and hierarchical land cover data can provide to object based analysis.

BACKGROUND

Classification is the prediction of an object or other unknown instance based upon known attributes. To date, random forest (RF) has been identified as one of the best classification algorithms within GEOBIA due to its ability to deal with large, high dimensional datasets (Belgiu & Dra 2016; Rodriguez-Galiano et al., 2012; Breiman, 2001). RF is an ensemble of classification and regression trees (CART) that are randomly generated and successively partitions a training dataset into smaller subsets to identify an object’s class. Others have consistently provided evidence that RF outperforms or are comparable to other classifiers within GEOBIA. (Johnson, 2014; Belgiu & Dra, 2016; Cutler et al.,
2007; Rodriguez-Galiano et al., 2012). Some implementations of random forest, such as R, can also provide a feature importance indicating which features contributed most in predicting object’s class (Liaw & Wiener, 2002). This can provide evidence to whether or not a Gabor filter can aid in classification. These characteristics will aid in identifying the highly detailed and wide datasets that will be created from the segmentation of both sets of imagery that will be analyzed within this report.

Spatial patterns heavily influence the factors that shape natural systems and thus, if quantified, can be significant predictors for features in the landscape. One can intuitively see that a river or stream will follow a linear or serpentine path while a building, road, or even an agricultural field will likely be planar and rectangular. The geometry of these specific features rarely vary. Quantifying the shapes of ecosystems and features within a landscape and the field of study that analyzes these relationships, Landscape Ecology, became a respected characteristic of objects. Metrics such as compactness, roundness, rectangularity, and numerous others are used to study these relationships. Without this spatial information, a classifier may not be able to differentiate a pixel with low slope as either a road or a building or a high slope pixel as either a building edge or a tree edge (Ferraz et al. 2014; Hill & Thomson, 2005).

Pixel-based classification neglects to measure these characteristics of land cover classes and results in poorer results on two levels; accuracy and the basic human perspective that there exists single identifiable units or objects in our environment. Studies continue to support that object based analysis have
higher classification accuracies of land cover over pixel based analysis (Karami et al., 2015; Immitzer et al., 2012; Myint et al., 2011). Pixel based classification creates a “salt-and-pepper” effect where land cover classes appear in a non-continuous, intermixed fashion that does not support that land cover classes appear in continuous patches that are influenced by similar disturbances and influences (Watt, 1947; Turner, 1989; O’Neil et al., 1989).

Texture features such as grey level co-occurrence matrix (GLCM) derivatives traditionally have been beneficial for segmentation and classification yet the Gabor transform has seldom been used with remote sensing of the environment but has been used in other OBIA processes such as fingerprint enhancement and human iris detection (Daugman, 1993; Ganesan & Bama, 2006). Gabor filters are a particular type of wavelet transform or band pass filter that was influenced from the Fourier transform that identifies texture as intervals of a 3-D Gaussian modulated sinusoidal wave. This modulation differs the Gabor transform from the Fourier transform (Gabor, 1946; Daugman, 1985). These Gabor transformed wavelets are parameterized by the angle at which they alter the image and the frequency of the wavelet. As opposed to smoothing an image out at the cost of losing detail through Fourier transforms or median filters, Gabor transformed images identify the repeated pattern of localized pixels and gives them similar values if they are apart of the same repeated pattern allowing the Gabor transforms to be a textural feature. Gabor features can emulate the way that visual cortex’s of mammalian brains utilize texture to identify objects (Marcelja, 1980; Daugman, 1985). This is based on the evaluation of neurons
associated with the cortical vertex respond to different images or light profiles (Maffei et al., 1979). Marcelja, 1980 identified that cortical cells responded signals that are localized frequencies of light similar to what is represented by the Gabor transformations. Within the frequency domain, the gabor transform can be defined by equation 2:

$$G(u, v; f, \theta) = e^{\frac{\pi^2}{f^2}(v^2(u'-f)^2+n^2v'^2)}$$

[2]

Where $f$ is the user-determined frequency; $\theta$ is the user-determined orientation at which the wavelet is applied to the image; $\gamma$ and $n$ are the standard deviations of the Gaussian function in either direction (Wang et al., 2010; Gabor, 1946). These parameters define the shape of this band pass filter and determine the effect it has on a one dimensional signal. Daugman (1946), created a 2-D application of this filter with the following in equation 3;

$$g(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp\left\{-\frac{1}{2}\left[\left(\frac{x}{\sigma_x}\right)^2 + \left(\frac{y}{\sigma_y}\right)^2\right] + j(u_0x + v_0y)\right\}$$

[3]

Where $u' = uc\cos - vs\sin \theta$ and $v' = us\cos - vc\sin \theta$

In Samiappan et al. (2016), they compared Gabor filters to other texture features (grey-level co-occurrence matrix, segmentation-based fractal texture analysis, and wavelet texture analysis) within the GEOBIA process of a wetland area using sub-meter resolution multispectral imagery. Gabor filters performed comparably in overall classification accuracy and Kappa coefficients with the other texture features but were outperformed by all other texture features. In this study they did not use any other data for analysis though raising questions of the
performance of Gabor filters when paired with other data sources such as spectral, NDVI, or LiDAR (Samiappan et al., 2016; Xiao et al., 2015;). Wang et al. (2010) paired this Gabor transformation with a fast Fourier transform for edge detection on an urban landscape image that contained uniform textures with promising results. Within GEOBIA, there has been no identified studies that has used the textural information created from Gabor filters for classification purposes.

Utilizing hierarchical organization within ecosystems, a common approach within ecology to understand the environment, is another uncommon strategy to include within an object based analysis that could greatly improve classification accuracies. The primary instances of developing a tiered or hierarchical scheme into GEOBIA is to reduce segmentation errors by decreasing noise or attempting to increase classification accuracy using either a rule-based classifier or fuzzy classifier but never with a random forest classifier and ultra high resolution multispectral imagery (Zhang et al., 2016; Laliberte et al., 2007; Gianinnetto et al., 2014; Antunes et al., 2003; Zhang et al., 2015; Demarchi et al., 2016). Within landscape ecology, O’Neill et al. (1989), meta-analysis of hierarchal frameworks in biology stated that the various scales within an ecological system define or limit one another in a way that could support the axiom that a super-object could be a useful property in defining a sub-object within a landscape. If multiple classifications are performed at several scales, you could use the larger scaled objects (i.e. super-objects) as attributes for the smaller scaled objects (i.e. sub-objects) to potentially increase the classification accuracy of the sub-objects. The
training data that we have available allows us to perform a two tier classification because the human subjects that performed the segmentation used two object classification schemas; a broad 7-class scheme and a narrower 13-class scheme. Using these two schemas to train and base our classifications upon, we could increase the classification accuracy of the sub objects.

An additional feature we used to increase the possibility of having better classification and segmentation results is the normalized difference vegetation index (NDVI) due to its consistently proven benefit to GEOBIA processes (Johansen et al., 2007; Straatsma & Baptist, 2008; Zhang et al., 2008; Li et al., 2014). NDVI takes the normalized difference of a near infrared and red band of multispectral imagery in order to increase the spectral properties of photosynthetically active vegetation allowing us to differentiate objects based on their photosynthetic properties. This is a common index that is frequently used within GEOBIA.

DATA

The aerial imagery that was used for this paper is a three band (near-infrared, red, and green), .08 meter resolution using an Applanix 439 Digital Sensor System taken on May 18, 2014. This imagery was taken by the U.S. Fish & Wildlife Service, Region 3 office and the U.S. Geological Survey’s Upper Midwest Environmental Sciences Center. The CHM used in this paper came from the Iowa LiDAR Project (ILMP, 2009). LiDAR data was downloaded as several four km² tiles that encompassed the study area. These were initially downloaded
as .las files, an open source binary data format. This LiDAR data was collected on May 5, 2010. The files were then converted into last-return digital surface model (DSM) TIFF files using Lidar Analyst’s “point cloud to raster with filtering” tool. The CHM was then created by subtracting the DSM from the first return values. All imagery and vector files were projected and processed within the Universal Transverse Mercator zone 15 projection. Both sets of data were collected during leaf-on conditions. Reference polygons were hand delineated and classified by experts from US Fish and Wildlife Service Region 3, Port Louisa National Wildlife Refuge, and the USGS Upper Midwest Environment Sciences Center.

STUDY AREA

The Horseshoe Bend Division of the Port Louisa National Wildlife Refuge (NWR) is a mixture of grasses and wetland habitat along the Iowa River 4 miles upstream from the confluence of the Iowa and Mississippi River. This 2,606 acre NWR is composed of grassland, wet meadows, forest, and semi and permanently flood emergent wetland habitat. Prior to flooding in 1993, this land was primarily used for agricultural purposes and was protected from flooding by a levee along the Iowa River. Since 1993, the levee has broken along the upper reach where the Iowa River intersects the NWR allowing the land to be susceptible to frequent inundation. This study area is in Port Louisa County Southeast of Wapello, Iowa (see figure 1).
Figure 1: Study Area

Figure 1: Horseshoe Bend Division of the Port Louisa NWR (study area)
METHODOLOGY

Gabor Transform

In order to implement the Gabor filters on the multi-band spectral imagery we used Matlab's Gabor feature on the University of Iowa's Neon high performance computer (HPC) which had up to 512 GB of RAM. This HPC was required due to the large amount of RAM required for processing images in Matlab. The first implementation of Gabor filters were performed on a 1610 x 687 single band pixel array, a filter bank of 4 orientations and 8 wavelengths, on a 32 GB RAM computer took approximately 8 hours to complete. A filter bank is the set of Gabor filters with different parameters that is applied to the spectral image. A bank of filters is required in order to identify different textures with different orientations and frequency's. This was reduced to approximately one hour with an 8128 x 8128 single band pixel array by reducing the amount of wavelengths from 8 to 4 on the same 32 GB RAM machine. Using the HPC, this was reduced further to approximately 90 seconds using the same filter bank. Before implementing on the HPC, the original spectral image had to be divided into manageable subsets with overlap in order to prevent ‘edge-effect.’ These images were then converted to greyscale by averaging across the three bands. The parameters selected for the filter bank were influenced by Jain & Farrokhina (1990). The wavelengths that were used for the filter bank were selected as increasing powers of two starting from 2.82842712475 (4/√2) up to the pixel length of the hypotenuse of the input image. From this, we used only
2.82842712475, 7.0710678, 17.6776695, and 44.19417382. When wavelengths become too long they no longer attributed the textural information desired from the image and therefore added unnecessary computing time. The directional orientation was selected as intervals of 45 degrees from 0 to 180: 0, 45, 90, 135.

Sixteen magnitude response images were created using the Gabor Transform and the sixteen different combinations of parameters in the filter bank. To limit high local variance within the output Gabor texture image, a Gaussian filter was applied. The magnitude response values were normalized across the 16 different bands so a Principal Component Analysis (PCA) could be applied. The first principal component from the PCA from these Gabor transformed images was used for this study because it limited the amount of computation time it would have taken to process 16 separate Gabor features in addition to the other data sources while still retaining the most amount of information from the 16 different Gabor response features. The Gabor band that will be used for this study can be viewed in Figure 3.

Canopy Height Model (CHM) & Normalized Difference Vegetation Index (NDVI)

LiDAR data was downloaded as several four km² tiles that encompassed the study area as .las files, an open source binary data format. The files were then converted into last-return Digital Terrain Model (DTM) and first-return Digital Elevation Model (DEM) using the ArcGIS add-on, LiDAR Analyst. Although LiDAR Analyst is a black-box module and so it is uncertain what method it uses to extract above-ground features for the DTM, there are several different
parameters to change in order to optimize results. The parameters used for this report were “method 2: Point Clouds,” specified the cell size as 2 meters, and selected “Auto-detect no-data regions” and “remove spikes and pits before processing” within the pre-processing step. The CHM was then created by subtracting the DTM from the DEM using raster math. In order to reduce over segmentation in forested regions, we applied a 11x11 pixel or 22x22 meter median filter.

NDVI was computed by applying equation 4 to our spectral imagery where $NIR$ refers to the near infrared DN values and $Red$ refers to the red DN values of the multi-spectral imagery. These DN values were not true reflectance value but were representative of such. The CHM and NDVI can be viewed in figure 2.

$$\frac{(NIR-Red)}{(NIR+Red)} = NDVI$$  \[4\]

Segmentation

For this study, we used the watershed algorithm implemented by ENVI version 5.0 Feature Extraction tool to compare segmentation results due to its ubiquitous use in common software within GEOBIA, its ability to create a hierarchy of segmented objects, and support within the literature, and support within the literature as a reliable algorithm (Jin, 2009; Sellaouti et al., 2012; Alonzo et al., 2013; Xiao et al., 2010, Meyer, 2012). The watershed algorithm can either use a gradient image or intensity image for segmentation. Based on observed results, this study selected to use the intensity method. The intensity method simply averages the value of pixels across bands. A user-defined
parameter, scale, is selected to identify the threshold that decides if a given intensity value within the gradient image can be a boundary. This allows the user to decide the size of the objects created. A secondary user-defined parameter defines how similar adjacent objects need to be before being combined. The user arbitrarily selects the parameter value based on how it reduces under and over segmentation. The parameters selected for this study were visually chosen based on a compromise between over and under segmentation relative to the hand demarcated objects.

In order to compare segmentation of a riparian landscape with and without Gabor features, we conducted segmentation on two separate sets of data. One dataset was a normalized stacked layer of NDVI and CHM with the original multispectral image used as ancillary data and the other dataset differed only by the inclusion of the Gabor feature. For both instances, the bands were converted to an intensity image by averaging across bands as opposed to being converted into a gradient image for segmentation.

The merging of two separate objects or regions was based on the full lambda schedule within this study where the user selects a merging threshold $t_{i,j}$ which is defined by equation 5:

$$t_{i,j} = \frac{|O_i||O_j|}{|O_i|+|O_j|} \frac{\|u_i-u_j\|^2}{\text{length}(\theta(O_i,O_j))}$$  \[5\]

where $O_i$ is a region of the image, $|O_i|$ is the area of $i$, $u_i$ is the average of region $i$, $u_j$ is the average of region $j$, $\|u_i - u_j\|$ is the Euclidean distance between the
pixel values of $i$ and $j$, and $\text{length}(\theta(O_i, O_j))$ is the length of the shared boundary of $O_i$ and $O_j$.

In order to create a hierarchy of land cover classes, two sets of segmentation parameters needed to be selected for each dataset. One set of parameters would be selected to use for the sub-objects within the hierarchy and the other set of parameters would be selected to create the super-objects. All parameters used the intensity and full lambda schedule algorithms for the watershed method. The only setting that changed between the sub and super-objects for either datasets was the merge parameter in order to retain similar boundaries as much as possible. Boundaries could moderately change despite this due to the Euclidean distance between the pixel values of $i$ and $j$ changing due to the merging of objects causing $t_{i,j}$ to cross the threshold resulting in a new boundary to be drawn.

The dataset that included the Gabor features had a scale parameter set at 30 with merge settings at 95 and 95.7 for the sub and super-objects, respectively. The dataset that did not include the Gabor features had a scale parameter of 10 with merge settings at 95.6 and 98.5 for the sub and super-objects, respectively. A representation of these results can be viewed and visually compared to the hand demarcated objects in figure 5.

Training Data

The training data used for this section is the transfer of class attributes from the hand demarcated segments to the automatically segmented objects.
based on the majority overlap of the hand demarcated segments. The experts who classified the objects identified them using two different classification schemes coming from the General Wetland Vegetation Classification System (Dieck et al., 2015). One scheme within this classification system identified objects of either being forest, marsh, agriculture, developed, open water, grass/forbs, or sand/mud. The finer classification scheme identified objects of either being agriculture, developed, grass/forbs, open water, road/levee, sand/mud, scrub-shrub, shallow marsh, submerged aquatic vegetation, upland forest, wet forest, wet meadow, and wet shrub. Figure 4 illustrates both classification schemes across the study area.

ENVI’s feature extraction tool calculates several landscape, spectral, and textural metrics. These attributes will be used for each random forest classifier and can be shown in tables 1-3. The Gabor and Hierarchical features will be included selectively to be able to compare their contributions to the OOB classification errors.

Random Forest

The random forest classifier was implemented on R using the random forest module (Liaw & Wiener, 2002). The number of trees that we selected to randomly generate was large enough (n=250) to where the strong law of large numbers would be able to take effect as indicated by the decrease in changes of accuracy. R also generates two separate variable importance indices: mean decrease in accuracy and mean decrease Gini. Mean decrease in accuracy
refers to the accuracy change in the random forest when a single variable is left out. This is a useful metric to identify the usefulness of a variable. The Gini index measures the purity change within a dataset when it is split based upon a given variable within a decision tree.

Hierarchical Scheme

In order to attribute the hierarchical structure to the sub-objects we classified both sets of automated-segmented super-objects, with and without the use of the Gabor features, using the courser classification scheme. These classified super objects were then converted to raster in order to calculate the majority overlap of the sub-objects. This step gave the sub-objects an attribute that mimicked an organized hierarchical scheme such as that particular land cover classes in the finer classification scheme belonged to land cover classes in the courser classification scheme.

Segmentation Assessment

Most studies rely upon the accuracy assessment of their classifiers to provide support for their analysis results but this does not provide evidence to whether or not a new data fusion technique improves the ability to delineate objects of interest within an image. In order to assess the performance of our segmented polygons, this study will assess the segments created with and without the Gabor feature using a method highlighted in Xiao et al. (2010).
We will evaluate our segmentation results using an empirical discrepancy measure used frequently in image segmentation evaluation (Zhang, 1996, Carleer et al. 2005; Xiao et al. 2010). Discrepancy measures utilize some ground truth image that represents the “correct” delineated/classified image to compare the semi-automated image results to. In our study, this will be the objects that were delineated and classified by experts from the U.S. Fish and Wildlife Service that were also used for training our random forest classifier. The discrepancy measures that will be used is the percentage of right segmented pixels (PR) in the whole image. In order to calculate PR we converted the classified segmented polygons and the ground truth polygons to raster and measured the ratio of incorrect pixels to total amount of pixels and converted this ratio to a percentage.

RESULTS

The following will present the empirical results with comparisons of the results for the OOB error results from the random forest classification and segmentation discrepancy results.

Classification Results

Table 1 shows the OOB classification results from the random forest classifier of the super objects with and without the Gabor feature and all other features included (spectral, CHM, NDVI). These results were then used as the hierarchical features for the sub objects. The sub-object's OOB classification results can be viewed in Table 2. As shown, the only instance when the inclusion
of the Gabor feature improved classification results for both the super and sub-objects was when the hierarchical feature was included. The hierarchal feature improved accuracy in both instances that it was included but was improved further when combined with the Gabor feature resulting with the best performance of the four datasets.

Table 1: Out-of-Bag Error (Super)

<table>
<thead>
<tr>
<th>Feature</th>
<th>Out-of-Bag Error</th>
<th>Pr %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Without Gabor</td>
<td>16.15%</td>
<td>21.65%</td>
</tr>
<tr>
<td>With Gabor</td>
<td>18.59%</td>
<td>21.62%</td>
</tr>
</tbody>
</table>

Table 1: Out-of-bag error results from the random forest classifier and percentage of right segmented pixels (PR) in the whole image for the super-objects.

Table 2: Out of Bag (Sub)

<table>
<thead>
<tr>
<th>Feature</th>
<th>Out-of-Bag Error</th>
<th>Pr %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Without Gabor Without Hierarchy</td>
<td>22.53%</td>
<td>13.99%</td>
</tr>
<tr>
<td>With Gabor Without Hierarchy</td>
<td>23.01%</td>
<td>71.63%</td>
</tr>
<tr>
<td>Without Gabor With Hierarchy</td>
<td>16.11%</td>
<td>13.50%</td>
</tr>
<tr>
<td>With Gabor With Hierarchy</td>
<td>12.71%</td>
<td>69.50%</td>
</tr>
</tbody>
</table>

Table 2: Our-of-bag error results from the random forest classifier and percentage of right segmented pixels (PR) in the whole image for the sub-objects.

Segmentation Results

Similar to the classification results, table 1 shows the PR segmentation results of the super objects with and without the Gabor feature and all other features included (spectral, CHM, NDVI) and Table 2 similarly shows the PR segmentation results for the sub-objects. The inclusion of the Gabor feature for
the super objects made very little difference (.03%) in the segmentation results according to the PR metric. In the sub-object case, the inclusion of the Gabor feature dramatically decreased the segmentation performance.
Chapter 3 - Discussion

While this study can provide insight into the capabilities and limitations of the inclusion of hierarchical structure and Gabor textural information in the classification of segments as well as the delineation of objects, we have suggestions for future research. This chapter will discuss our results, what should be considered for future research, and ontological concerns about this area of research such as the measurement of segmentation performance.

Discussion

Out of the three instances that Gabor features were included in the classification of the objects only one provided better OOB error results while in both instances that hierarchical objects were included we observed lower OOB error results. Gabor features only provided better accuracy when paired with hierarchical features. This provides support that providing hierarchical relationships to sub-objects can increase classification accuracy but does not provide support that Gabor features increase classification accuracies.

These results are mirrored in Samiappan et al. (2016) where they too found that Gabor features were the poorest performing texture features when compared to GLCM features, segmentation based fractal texture analysis (SFTA), and wavelet texture analysis (WTA) features in a wetland environment with very high resolution imagery (5 cm). In this study they only used two orientation (45°, 90°) and one wavelength value (2) while our study used four orientations (0°, 45°, 90°, 135°) and four wavelengths (2.82842712475, 2.64575131106, 2.44948974278, 2.2360679775).
7.0710678, 17.6776695, 44.19417382). Our study used the first principal component of the outputs of this filter bank output. It is possible that the Gabor parameters chosen in both studies were insufficient at capturing the textural characteristics of the land cover types they were intended to represent. Although research should still be conducted into the optimization of Gabor’s filter bank parameters for object based analysis, it should be considered that Gabor features do not provide additional information that aid in the classification of objects derived from high resolution imagery.

R also generates two separate variable importance index’s: mean decrease in accuracy and mean decrease Gini. Mean decrease in accuracy refers to the accuracy change in the random forest when a single variable is left out. This is a useful metric to identify the usefulness of a variable in the classification of an unknown object. The Gini index measures the purity change within a dataset when it is split based upon a given variable within a decision tree. Figures 7, 10, and 11 in Appendix 1 demonstrate the impact the Gabor features had on the ability the random forest had on predicting these unknown objects. Gabor features are indicated by Band 1 (B1) of the viewable variables. According to the mean decrease in accuracy metric, the Gabor features had a large impact on predicting the super-objects (figure 7) but a negligible effect on predicting any of the sub-objects (figures 10-11). According to the Gini index, all instances of the inclusion of the Gabor features apparently had negligible effects. When these features were included for the super-objects and for the sub-objects when the hierarchical features were not included, their OOB error increased. A
possible explanation to this phenomenon is that the Gabor features introduced noise and confusion into the dataset. Several variable selection methods could be used in future applications in addition to the variable importance indices such as a PCA, sequential forward/backward selection, beam search, random search, or simulated annealing in order to select the best features. In the case that the Gabor features increase accuracy (figure 11), it appears that it added additional predictive information when in conjunction with the hierarchical features. There is no apparent reason for this without further research into the relationship between Gabor features and hierarchal features.

To this date, Gabor textural analysis has never been conducted on anything other than spectral imagery. There is still potential that Gabor transformations could increase segmentation and classification accuracy’s when performed upon single spectral bands, LiDAR derivatives, or other spectral transformations such as an NDVI. While our results provided more support to which extent Gabor metrics can contribute to GEOBIA, there is still a large body of image types that Gabor transformations can be applied to that could aid in object detection.

Our study provided valuable information to the inclusion of hierarchically organized vectors because it provided accuracy estimates of classified objects with and without the inclusion of hierarchal attributes. Of the identified papers that used some form of hierarchical segmentation, only a few included hierarchical attributes in the classification of their objects (Laiberte et al., 2004; Laiberte et al., 2007; Laiberte et al., 2009) and one included the accuracy
estimates with and without the inclusion of hierarchal attributes (Antunes et al., 2003). The other studies simply used one segmentation scale to guide the segmentation results of the next finer or courser scale (Zhang et al., 2016; Gianinetto et al., 2014; Zhang et al., 2015; Demarchi et al., 2016). Antunes et al. (2003) report was in agreement with our results in that the inclusion of hierarchical attributes increased classification accuracies considerably. Laiberte et al. (2004), Laiberte et al. (2007), and Laiberte et al. (2009) supported our findings by stating that including hierarchical attributes visibly improved their results based on their Laiberte et al. (2004) study. Each of these previously mentioned studies (except Zhang et al. 2016) used the region growing method of segmentation that is utilized within the eCognition software as opposed to the watershed method utilized within ENVI+IDL suggesting more research should be conducted using this watershed approach.

Observing both variable importance indices, the Gini and mean decrease in accuracy index, for each instance the hierarchical features were included as an attribute (indicated as “Majority” in figures 9-10) for the sub-objects, the hierarchical features were indicated as providing substantially more predictive power relative to the other included features. This coincides with the increase in accuracy when these features were included and thus does not provide evidence that the hierarchical feature introduce noise into the dataset but rather valuable predictive information. This is contrary to the results observed when Gabor features were included in the random forest for predicting the super-objects, the
mean decrease in accuracy index indicated high predictive power for the Gabor features, and the OOB error increased.

Although Gabor features did not provide additional information to increase classification accuracies, they did improve segmentation results according to the sub-objects PR metric. The super-objects PR metric decreased negligibly when Gabor features were included in the segmentation step. If a conclusion could be made about the effect of including Gabor features into the segmentation step it would come from PR metrics taken from the sub-objects. The PR metrics for the sub-objects display a significant increase in segmentation accuracy when the Gabor features are included. This could support the notion that Gabor texture analysis emulates the way that the cortex's of mammalian brains utilize texture to identify objects because the segments generated with the use of the Gabor features more closely align with the segments delineated by human experts (Marcelja, 1980; Daugman, 1985). Based on these results, Gabor features should be included within the segmentation step of the GEOBIA process but should not be included as part of the classification of the resulting segments unless hierarchical features are included.

This analysis of the segmentation results should be taken lightly for multiple reasons. First, metrics to evaluate segmentation results are still being developed and are not widely used. Most segmentation evaluations within geography use some discrepancy measure based off a classified ground truth image (Zhang, 1996; Zhang, 2001; Zhang, 2009; Carleer et al. 2005; Xiao et al. 2010). These measures depend on the correct classification of the objects which
relies too heavily on the accuracy of the classifier instead of measuring the quality of boundaries created by an algorithm. One proposed method is to measure the distance between the ground truth boundaries and the boundaries generated by the proposed algorithm.

Second, most empirical methods for segmentation evaluation are based on ground truth generated by human subjects who subjectively delineate image object boundaries. Human subjects can be inconsistent, biased, and differ from subject to subject despite any expert status. One reason object based analysis is widely used within the sciences is because it produces consistent, predictable, and reproducible results. Rather than relying on correctly classified pixels for segmentation evaluation, object based image analysis should begin using distance to reference boundaries (Cavallam et al., 2002). Third, most users conducting an object based image analysis to aid in decision making process will do a considerable amount of post-processing (i.e. dissolving small segments and holes, smoothing, merging) possibly causing the PR metric, and other metrics to observe segmentation results to change. To provide additional insight into the segmentation performance, Appendix 2 provides an auxiliary analysis into the similarities of the resulting landscape metrics calculated from each of the manual and automated segmentation instances.

Landscapes are complicated systems that have spatially interconnected parts that influence one another across space and scales. Not utilizing this information (i.e. pixel-based classification) or not identifying spatial or hierarchical relationships does not fully exploit the information that can be obtained from
delineation and classification of objects. Our results provided further support that providing hierarchical structure to objects offers contextual information that can increase classification accuracy to objects beyond what is provided by texture and spectral alone.

Textural information within an image has long been proven to be a helpful feature for segmentation and classification and this paper sought to provide evidence to the inclusion of another texture derived feature, Gabor textural transformations. The insights this study offers to the use of Gabor features in object based analysis is two-fold; Gabor features can increase segmentation accuracy and they can introduce confusion or noise into the dataset to cause lower classification accuracy. The use of Gabor features within object based analysis is fairly new and more research should be conducted into the optimization of its parameters and its uses with other classifiers and segmentation algorithms.
Figure 2: CHM and NDVI

Figure 2: LiDAR derived canopy height model (top) and normalized difference vegetation index derived from original spectral image
Figure 3: Gabor Transformation

Gabor Transformed Image (1st PC)

Figure 3: Gabor transformed image derived from original image using the first principal component of all images created from the filter bank parameters of the study surrounding areas.
Figure 4: Hand Delineated Objects

Hand Delineated Objects

Super-Objects
- Agriculture
- Developed
- Forest
- Grass/Forbs
- Marsh
- Open Water
- Sand/Mud

Sub-Object Classification
- Agriculture
- Developed
- Grass/Forbs
- Open Water
- Road/Levee
- Sand/Mud

Figure 4: Hand delineated objects of both scales.
Figure 5: Juxtaposition of hand delineated, sub-objects, and super-objects for segments generated using the Gabor features.
Table A.3: Description of spatial attributes as defined by the ENVI 5.0 Help Manual

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area (FX_AREA)</td>
<td>Total area of the polygon, minus the area of the holes. Values are in map units.</td>
</tr>
<tr>
<td>Length (FX_LEGNTH)</td>
<td>The combined length of all boundaries of the polygon, including the boundaries of the holes. This is different than the MAXAXISLEN attribute. Values are in map units.</td>
</tr>
<tr>
<td>Compactness (FX_COMPACT)</td>
<td>A shape measure that indicates the compactness of the polygon. A circle is the most compact shape with a value of ( \frac{1}{\pi} ). The compactness value of a square is ( \frac{1}{2\sqrt{\pi}} ). ( \text{COMPACT} = \sqrt{\frac{4 \times \text{AREA}}{\pi}} / \text{outer contour length} ).</td>
</tr>
<tr>
<td>Convexity (FX_CONVEX)</td>
<td>Polygons are either convex or concave. This attribute measures the convexity of the polygon. The convexity value for a convex polygon with no holes is 1.0, while the value for a concave polygon is less than 1.0. ( \text{CONVEXITY} = \frac{\text{length of convex hull}}{\text{LENGTH}} ).</td>
</tr>
<tr>
<td>Solidity (FX_SOLID)</td>
<td>A shape measure that compares the area of the polygon to the area of a convex hull surrounding the polygon. The solidity value for a convex polygon with no holes is 1.0, and the value for a concave polygon is less than 1.0. ( \text{SOLIDITY} = \frac{\text{AREA}}{\text{area of convex hull}} ).</td>
</tr>
<tr>
<td>Roundness (FX_ROUND)</td>
<td>A shape measure that compares the area of the polygon to the square of the maximum diameter of the polygon. The &quot;maximum diameter&quot; is the length of the major axis of an oriented bounding box enclosing the polygon. The roundness value for a circle is 1, and the value for a square is ( \frac{4}{\pi} ). ( \text{ROUNDNESS} = \frac{4 \times \text{AREA}}{\pi} / (\pi \times \text{MAXAXISLEN2}) ).</td>
</tr>
<tr>
<td>Form_Factor (FX_FORMFAC)</td>
<td>A shape measure that compares the area of the polygon to the square of the total perimeter. The form factor value of a</td>
</tr>
</tbody>
</table>
circle is 1, and the value of a square is pi / 4. FORMFACTOR = 4 * pi * (AREA) / (total perimeter)^2

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elongation (FX_ELONG)</td>
<td>A shape measure that indicates the ratio of the major axis of the polygon to the minor axis of the polygon. The major and minor axes are derived from an oriented bounding box containing the polygon. The elongation value for a square is 1.0, and the value for a rectangle is greater than 1.0. ELONGATION = MAXAXISLEN / MINAXISLEN</td>
</tr>
<tr>
<td>Rectangular_Fit (FX_RECT_FI)</td>
<td>A shape measure that indicates how well the shape is described by a rectangle. This attribute compares the area of the polygon to the area of the oriented bounding box enclosing the polygon. The rectangular fit value for a rectangle is 1.0, and the value for a non-rectangular shape is less than 1.0. RECT_FIT = AREA / (MAXAXISLEN * MINAXISLEN)</td>
</tr>
<tr>
<td>Main_Direction (FX_MAIN_DI)</td>
<td>The angle subtended by the major axis of the polygon and the x-axis in degrees. The main direction value ranges from 0 to 180 degrees. 90 degrees is North/South, and 0 to 180 degrees is East/West.</td>
</tr>
<tr>
<td>Major__Length (FX_MAJAXLN)</td>
<td>The length of the major axis of an oriented bounding box enclosing the polygon. Values are map units of the pixel size. If the image is not georeferenced, then pixel units are reported.</td>
</tr>
<tr>
<td>Minor__Length (FX_MINAXLN)</td>
<td>The length of the minor axis of an oriented bounding box enclosing the polygon. Values are map units of the pixel size. If the image is not georeferenced, then pixel units are reported.</td>
</tr>
<tr>
<td>Number_of_Holes (FX_NUMHOLE)</td>
<td>The number of holes in the polygon. Integer value.</td>
</tr>
<tr>
<td>Hole_Area/Solid_Area (FX_HOLSOL)</td>
<td>The ratio of the total area of the polygon to the area of the outer contour of the polygon. The hole solid ratio value for a polygon with no holes is 1.0. HOLESOLRAT = AREA / outer contour area.</td>
</tr>
</tbody>
</table>

Table A.3: Description of spatial attributes as defined by the ENVI 5.0 Help Manual
Table A.4: Object Pixel Attributes

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spectral_Mean (AVG_Bx)</td>
<td>Mean Value of the pixels comprising in band x.</td>
</tr>
<tr>
<td>Spectral_Max (MAX_Bx)</td>
<td>Maximum value of the pixels comprising in band x.</td>
</tr>
<tr>
<td>Spectral_Min (MIN_Bx)</td>
<td>Minimum value of the pixels comprising the region in band x.</td>
</tr>
<tr>
<td>Spectral_STD (STD_Bx)</td>
<td>Standard deviation value of the pixels comprising the region in band x.</td>
</tr>
</tbody>
</table>

Table A.4: Description of slope, spectral, or gabor attributes within each object as defined by the ENVI 5.0 Help Manual

Table A.5: Object Textural Attributes

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Texture_Range (TXRAN_Bx)</td>
<td>Average data range of the pixels comprising the region inside the kernel (whose size you specify with the texture kernel size parameter in segmentation).</td>
</tr>
<tr>
<td>Texture_Mean (TXAVG_Bx)</td>
<td>Average value of the pixels comprising the region inside the kernel.</td>
</tr>
<tr>
<td>Texture_Variance (TXVAR_Bx)</td>
<td>Average variance of the pixels comprising the region inside the kernel.</td>
</tr>
<tr>
<td>Texture_Entropy (TXENT_Bx)</td>
<td>Average entropy value of the pixels comprising the region inside the kernel.</td>
</tr>
</tbody>
</table>

Table A.5: Description of texture attributes of the slope values within each object as defined by the ENVI 5.0 Help Manual
Figure A.6: Variable Importance, Super, No-Gabor

RF Variable Importance for Super-Objects, No-Gabor Features

Figure A.6: Variable importance indices for the random forest (RF) model for the super-objects when no Gabor features were included where B1 = NDVI, B2 = CHM, B3 = NIR, B4 = Red, and B5 = Green. Showing top 20 out of the 55 variable used.
Figure A.7: Variable Importance, Super, Gabor

Variable Importance for Super-Objects, With Gabor Features

Figure A.7: Variable importance indices for the random forest (RF) model for the super-objects when Gabor features were included where B1 = Gabor, B2 = NDVI, B3 = CHM, B4 = NIR, B5 = RED, and B6 = Green. Showing top 20 out of the 64 variable used.
Figure A.8: Variable importance indices for the random forest (RF) model for the sub-objects when no Gabor and no hierarchical features were included where $B_1 = \text{NDVI}$, $B_2 = \text{CHM}$, $B_3 = \text{NIR}$, $B_4 = \text{Red}$, and $B_5 = \text{Green}$. Showing top 20 out of the 55 variable used.
Figure A.9: Variable Importance, No-Gabor, Hierarchy

Variable Importance for Sub-Objects, No Gabor Features, With Hierarchical Features

Figure A.9: Variable importance indices for the random forest (RF) model for the sub-objects when no Gabor features were included and hierarchical features were included where B1 = NDVI, B2 = CHM, B3 = NIR, B4 = Red, and B5 = Green. Showing top 20 out of the 56 variable used.
Figure A.10: Variable Importance, Sub, Gabor, No Hierarchy

Variable Importance for Sub-Objects, With Gabor Features, No Hierarchical Features

Figure A.10: Variable importance indices for the random forest (RF) model for the sub-objects when Gabor features were included and no hierarchal features were included where B1 = Gabor, B2 = NDVI, B3 = CHM, B4 = NIR, B5 = RED, and B6 = Green. Showing top 20 out of the 66 variable used.
Figure A.11: Variable importance indices for the random forest (RF) model for the sub-objects when Gabor and hierarchal features were included where B1 = Gabor, B2 = NDVI, B3 = CHM, B4 = NIR, B5 = RED, and B6 = Green. Showing top 20 out of the 67 variable used.
Appendix 2

Within the results section of this report we illustrated the limitations of using a discrepancy metric for evaluating segmentation performance. In the following section, we offer an auxiliary analysis that briefly compares segmentation results on a practical or applied basis by observing the differences in landscape metrics between our automated results and the manually segmented results on a super and sub-object level. The goal of this addition is to provide a better understanding to whether or not any of our automated results can provide similar results to human manual segmentation efforts using the same metrics that are used to understand landscape patterns.

There are a variety of landscape metrics that are used to characterize landscape patterns. These are used to understand landscape change, fragmentation, as well as habitat suitability (Hamilton et al., 2013; Townsend et al., 2009; Cushman et al., 2013). If our automated results are similar to the metrics that are calculated for what is considered to be the correct segmentation results, the human delineated objects, then we can assume that they are representing similar landscapes.

Landscape metrics will be calculated using FRAGSTATS (McGarigal et al., 2012), an open source program commonly used for calculating landscape metrics. FRAGSTATS computes these metrics from thematic raster maps.
representing the land cover types of interest. The thematic classes used for this analyses were the classified objects at the super and sub-object level. Since we are not attempting to compare the segmentation results for any particular class or area, we will calculate metrics on a landscape level. If analyses were done on a class level, the number of metrics to visually compare could quickly become abundant with eight different segmentation instances, 13 different classes on the sub-object level and seven on the super-object level. Landscape metrics will represent the segmentation patterns for the entire study area.

FRAGSTATS is capable of calculating many different metrics representing different aspects of the landscape but the metrics decided upon for this analyses attempts to understand object geometry. The metrics calculated for this analyses are average and standard deviation of area (AREA), average and standard deviation of the fractal dimension index (FRAC), and average and standard deviation of the perimeter area ratio (PARA). Number of patches (NP) were also included for each result. In order to take a more landscape centric approach, area weighted mean was chosen over a simple average. The area (m²) weighted mean is the sum of all patches within a landscape multiplied by the proportional abundance of a patch. This uses total patch area instead of total landscape area. The fractal dimension index measures the shape or patch complexity by multiplying by 2 the logarithm of patch perimeter divided by logarithm of the patch area. This metric is resilient to raster biases in area and allows comparisons to be made across scales. Perimeter area ratio is the the ratio of the patch
perimeter to area. This metric also measures shape complexity but does not account for changes in the size of a patch.

These metrics are calculated on the patches that constitute the landscape which are defined by any continuous thematic pixel. Since these metrics do not include class as apart of their calculation, prediction error does not effect the results like it does on the discrepancy metric unless two segments of a similar class are adjacent. If two polygons of the same class are adjacent, they will be considered one continuous patch which could cause more dependency on the classification results.

In order to calculate these metrics in FRAGSTATS, two preprocessing steps had to be taken. First, all predicted polygons had to be converted to raster. This included two human segmented and six automated results including the super and sub-objects. Next, the resolution had to be resampled to .5 meters from the original .07 meters using bilinear convolution in order to have enough memory to process a single landscape.

The results can be viewed in table A2.1. The differences between sub and super objects are as expected with super objects having far fewer patches than the sub objects and the area weighted mean being larger for the super than the sub objects except for the sub objects created with the Gabor features. The sub objects created with the Gabor features had a much larger average area than any other of the results including the human segmented results. This is due to large continuous patches of wet forest that were predicted. These instances also
had the largest standard deviations indicating that there was a large mixture of large and small patches.

There are several explanations for why there could have been large continuous patches/segments of wet forest for the segments created using Gabor features. One reason is that close to half of the training sub objects (47%) were a single class (wet forest) causing the random forest classifier to over predict this single class when Gabor features were included. Similar to the findings within the discussion of this report, the Gabor features could have introduced confusion within the dataset causing the classifier’s default prediction to be the majority class if it became confused or misled enough. This too could cause continuous segments of a single object. Further statistical insight could provide information to why this phenomenon took place.

When observing these results, any time you compare two instances that used the same segments but had different classifications, you should expect very little changes in landscape metrics. For instance, when comparing the sub-object instances with and without hierarchical features, one can visually observe that there are little changes to calculated metrics. This is why it is more valuable to simply compare our automated results to the human segmented objects.

When observing the automated results for the super-objects, it appears that not including the Gabor features can provide more similar results to the human segmented objects than with the Gabor features. The only instance where the inclusion of Gabor features makes the segmentation more similar to the human segmented objects is the number of patches which can also be a
measure of landscape fragmentation. Average area and both measures of edge or shape complexity (FRAC and PARA) both show that the exclusion of Gabor features cause segments to be more similar to the human segmented objects.

Similar observations can be made for the sub objects as what was seen for the super objects. In most cases, the instances where the Gabor features were excluded had more similar landscape metrics to the human segmented objects. Similarly, the inclusion of Gabor features had more alike number of patches as the human segmented instances for the sub-objects. The exclusion of Gabor features seems to have severely over fragmented the landscape whereas the inclusion of Gabor features slightly under fragmented the landscape. The large continuous chains of wet forest likely had an impact on this under fragmentation.

It appears that the super objects with the exclusion of Gabor features had more similarities than the sub objects with excluded Gabor features did with the human delineated objects. The change in scale could make these comparisons less valid but the advantage of using the fractal dimension index is that you can make these comparisons across scales. The other metrics used in this analyses have more limitations when making comparisons across scales.

The observations made in this appendix alone provide very limited weight to which segmentation results were more accurate but can provide support when combined with the original analysis. The landscape metrics calculated here are contradictory to the findings supported by the PR metric. The PR metric supported that Gabor features improved segmentation accuracy whereas the
landscape metric observations supported the opposite. Out of these two metrics, the PR metric has been the only one supported in the past to evaluate segmentation performance but it would be expected that the results or trends of each metric would support the same conclusion. This reveals that either both metrics are inappropriate for segmentation evaluation or simply one is.

Undoubtedly, more efforts should be committed to coming up with a metric to evaluate segmentation performance. Without a more conclusive metric, results will appear unsatisfactory when comparing segmentation results.

Table A2.6: Landscape Metrics

<table>
<thead>
<tr>
<th></th>
<th>NP</th>
<th>AREA_AM</th>
<th>AREA_SD</th>
<th>FRAC_AM</th>
<th>FRAC_SD</th>
<th>PARA_AM</th>
<th>PARA_SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gab Super</td>
<td>62905</td>
<td>48.8303</td>
<td>0.9198</td>
<td>1.3848</td>
<td>0.3623</td>
<td>1382.5854</td>
<td>16912.9695</td>
</tr>
<tr>
<td>Gab Sub</td>
<td>87198</td>
<td>157.3637</td>
<td>1.4027</td>
<td>1.3448</td>
<td>0.3649</td>
<td>1215.0095</td>
<td>14595.7447</td>
</tr>
<tr>
<td>GAB Sub Hierarchy</td>
<td>87225</td>
<td>155.0374</td>
<td>1.3921</td>
<td>1.3425</td>
<td>0.3655</td>
<td>1216.4806</td>
<td>14717.948</td>
</tr>
<tr>
<td>NDVI super</td>
<td>51664</td>
<td>46.4862</td>
<td>0.9903</td>
<td>1.3659</td>
<td>0.3193</td>
<td>1166.5089</td>
<td>16133.0213</td>
</tr>
<tr>
<td>NDVI Sub</td>
<td>191050</td>
<td>16.4387</td>
<td>0.3062</td>
<td>1.3675</td>
<td>0.2905</td>
<td>2044.0821</td>
<td>12614.7237</td>
</tr>
<tr>
<td>NDVI sub hierarchy</td>
<td>189106</td>
<td>16.8922</td>
<td>0.312</td>
<td>1.3673</td>
<td>0.2898</td>
<td>2024.649</td>
<td>12638.2119</td>
</tr>
<tr>
<td>Control Super</td>
<td>87019</td>
<td>39.2243</td>
<td>0.701</td>
<td>1.3307</td>
<td>0.276</td>
<td>1096.1246</td>
<td>9329.8348</td>
</tr>
<tr>
<td>Control Sub</td>
<td>104549</td>
<td>20.3314</td>
<td>0.4604</td>
<td>1.2974</td>
<td>0.2594</td>
<td>1278.3324</td>
<td>10362.9513</td>
</tr>
</tbody>
</table>

Table A2.6: Calculated landscape metrics for human segmented objects and all instances of the automated segmented objects. NP=number of patches, AREA= square area of patch (m²), FRAC = fractal dimension index of a patch, PARA= perimeter area ratio of a patch, AM= area weighted mean, SD = standard deviation.
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