Geographic Object Based Image Analysis for Utility Scale Photovoltaic Site Suitability Studies

by

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Abbreviations

AVHRR	Advance very high resolution radiometer
EPA	Environmental Protection Agency
GIS	Geographic information system
GISci	Geographic information science
GUI	Graphical user interface
MRS	Multi resolution segmentation algorithm
MW	Megawatt
OBIA	Object based image analysis
PV	Photovoltaic
RS	Remote sensing
SEIA	Solar Energy Industry Association
SSI	Spatial sciences institute
TVA	Tennessee Valley Authority
USC	University of Southern California
USGS	United States Geological Survey
USSE	Utility scale solar energy
VHR	Very high resolution

Abstract

As our country grapples with the long term negative effects that traditional electrical generation methods have on the environment, such as nuclear with a 50 year average decommissioning time, natural gas and the methane emissions associated with it, and coal which is not clean, there is a renewed focus on solar energy. This renewed focus is partially fueled by advancements in photovoltaic cell technology and favorable regulatory conditions, resulting in a decrease of solar energy production costs. This has led to the installed solar energy production capacity of the United States to grow from 7.33 gigawatts in 2012 to 51.45 gigawatts in 2018. As the industry matures and solar energy is adopted in new markets, the available land suitable for development has subsequently been reduced. A result of this is the industry has shifted its focus to identify suitable sites in areas that have been otherwise overlooked or discounted. To remain competitive, potential sites must be screened to identify site conditions that can increase costs or render a site undevelopable. This project identified that OBIA can successfully be used to identify a multitude of features that are encountered during the development of USSE projects, but the complexity and variability of the process makes it currently unsuitable to be deployed at scale. OBIA can however, be used to assess current site suitability analyses by generating otherwise unknown attribute data about a site to target locations wherein to look.

Chapter 1 Introduction

A combination of advancements in photovoltaic (PV) cell performance, shifting cultural attitudes towards the use of fossil fuels, government mandates, and a reduction in capital expenditures has created an energy market in which electricity generated by PV can compete on cost. In the first quarter of 2020, a record 3.6GW of solar PV was installed with another 5.4GW of utility scale projects being announced. Cumulatively 14.4GW of utility scale solar is expected to be installed in the United States in 2020 (SEIA, 2020). Simultaneously, the cost to develop utility-scale PV has decreased by two-thirds since 2009 (U.S. Department of Energy, 2017). With the increase in installation numbers, comes increased competition to identify and acquire land suitable for projects up to thousands of acres in size.

Typically, identifying ideal sites for USSE developments is a straightforward process when there is ample land available. Criteria like aspect, slope, solar radiation, and zoning are available as sources of data readily inputted into a GIS, however, this process does not apply to all situations. When evaluating sites in areas categorized by less favorable conditions, such as hilly terrain or areas prone to flooding, traditional methods used to identify sites with conditionals suitable for the development of utility scale PV becomes a time-intensive process. This is a result of the need to manually evaluate and vet each site for surface conditions and possible natural or manmade features that may be present, but are not accounted for in the vector data employed. Manual review is done to identify features on sites such as tree stands, wetlands, buildings, or roads; that lead to increased construction costs and restricts where on the sites USSE can be developed. While it may seem relatively straightforward to identify sites, a decrease in ideal sites requires a more precise approach to site selection, which has historically been done manually. This research aims to identify whether object-based image analysis can be used to accurately identify common construction impediments encountered on less-viable USSE sites, and if so, provide a conceptual workflow on how one could incorporate these findings into their site selection process.

The term utility-scale has multiple definitions (SEIA, 2020; U.S. Department of Energy, 2017). The Solar Energy Industries Association (SEIA) defines utility-scale PV as any project that has an offtake agreement with a utility, regardless of project size. Conversely, financiers of PV development define utility-scale by the amount of investment required to construct the site. For the purposes of clarity, this research defines utility-scale is as a PV development that is 5mw or larger in size (US Department of Energy, 2012). Each megawatt (MW) produced requires, on average, 8-10 acres of developable land (Mulvaney, 2019).

1.1. Site Review Process

A typical USSE site selection process is relatively standardized, which is convenient to those involved. However it lacks accuracy by relying on datasets such as the National Wetland Inventory (NWI) and the Federal Emergency Management Agency (FEMA) 100 Year Floodplains that are dated. Since 1996 the Fish and Wildlife Service (FWS) has been updating the NWI at a rate of 2% of the total land area of the lower 48 states per year (US Fish and Wildlife Service, n.d.). Research that closely parallels this project, conducted in 2019, relies on wetland datasets from 2002 and a landside risk dataset from 1991 in the site selection process (Guaita-Pradas et al, 2019). These data sets have since become outdated, as the wetland morphology has changed significantly in years since. As a result, inaccuracies are introduced into models.

The site selection process begins with the exclusion of land deemed undevelopable. The reason land can be deemed undevelopable can be grouped into two categories, topographic and regulatory. Topographic constraints on development include aspect, slope, soil composition, and wetlands. Regulatory constraints include protected lands, areas of environmental concern, and zoning. Undevelopable land is removed from the original parcel geometry resulting in a new parcel geometry that is representative of only the developable areas within a given site. This is done by loading parcel data into a model created in ArcGIS Model Builder that erases wetlands, floodplains and slope greater than 10%. In this example two parcels from the study area were selected and used as the input to the model. The output of the model is the new parcel geometry with only the developable land remaining. Figure one illustrates this process, it is important to note that the total developable land decreased from 227.6 acres to 194.67 acres for Example A and from 241.50 acres to 184.67 acres for Example B. This reduction of available developable land only accounts for the above criteria and falls short of fully quantifying the sites conditions such as roads, buildings, vegetation, irrigation channels and retention ponds.

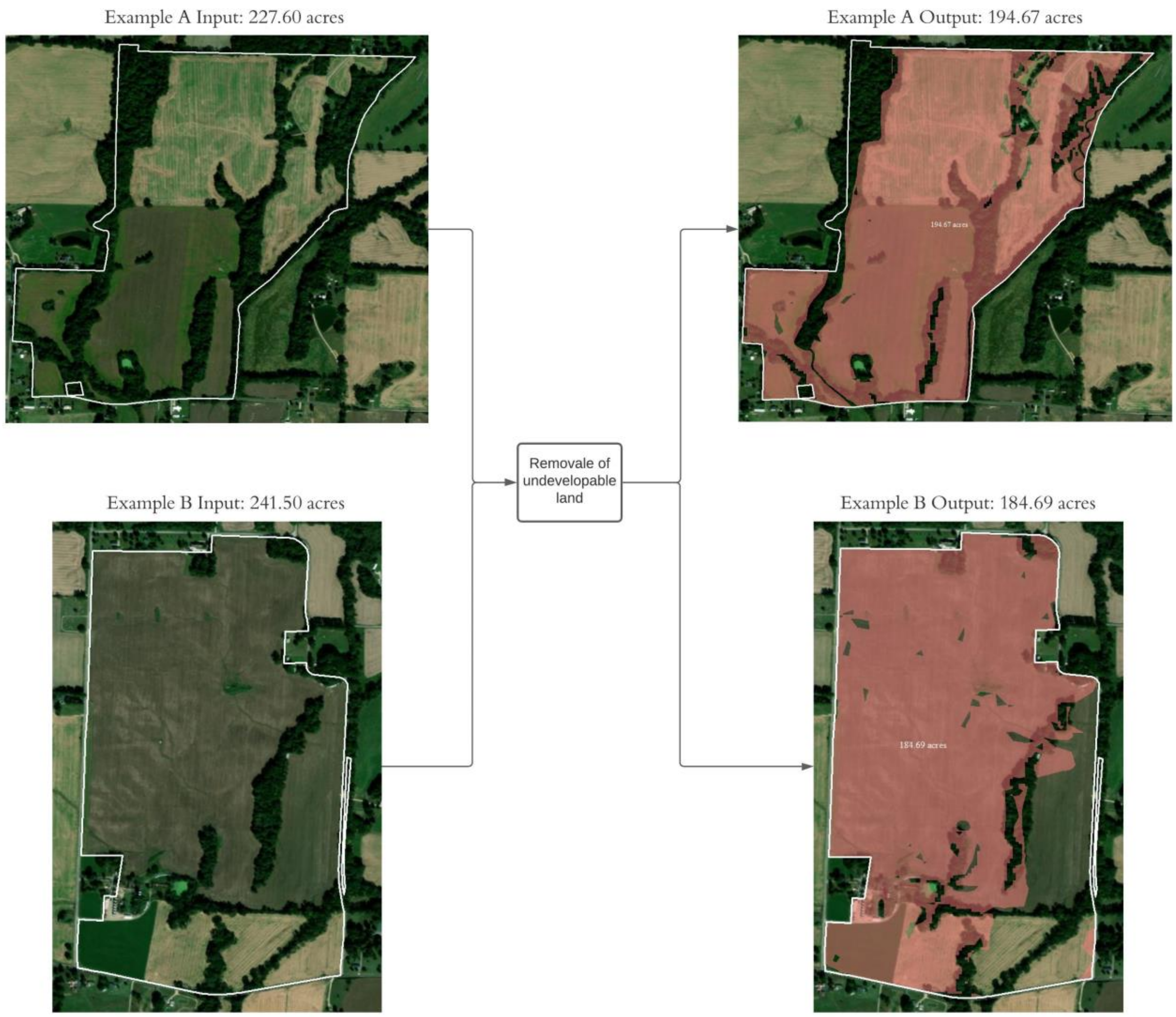

Figure 1: Example sites A and B's parcel boundary (white) is used as the input for the model. The model removes slope greater than 10%, NWI, and FEMA 100 year floodplain from the parcel's geometry.. The output of this process only leaves the remaining developable land (rust color) remaining.

Figure 1 illustrates one problem with the current selection process. In Figure 1, Example A has 194.67 acres of developable land after the initial screen compared to Example B with 184.69. However, the unaccounted for tree stands intersecting the developable land in Example A create a break along the eastern edge of the parcel. To mitigate the impact of the trees, the developer would need to clear them in advance. If this was not an option, the site would either have to be designed around the trees or built at a smaller scale, by not developing the smaller of the two areas. All of the options available increase capital expenditures or result in a smaller project, thus producing less revenue. This is also true of buildings and roads, although in these cases the impediments cannot always be moved or cleared. The earlier in the development process these features are identified, the earlier they can be accounted for to allow for accurate cost estimation and site planning to be conducted.

The number of potential sites remaining after the removal of the slope, wetlands, and floodplains varies and is determined by the size of the area of the target market, the size of the project, and the complexities of the local topography. A site for a 5MW project requires approximately 50 developable acres, while a 50MW project requires upwards of 500 developable acres. Due to this, there are fewer potential sites as a project size increases. That said, these numbers run in the thousands. It is necessary to run the models at this scale because not every landowner is willing to sell or lease their land for USSE development; it can be assumed that only 5-10% of contacted landowners will be interested. Of the projects that make it past this initial phase, still less will make it through the full development cycle and be placed in service (Mulligan, 2020).

When faced with making decisions that are difficult to automate, a GIS technician uses their spatial reasoning and logical assumptions to assess the impacts, not only of a single feature, but all of a site’s features in relation to one another. Two sites of 100 acres can both have the same number of buildings, roads, and trees, with only one being be suitable for development. For example, one site may have a road running along the property line to a home in the corner of the property, versus a site with a road that leads to a house surrounded by trees situated in the middle of a property. In the first case, the layout of the features does not impact the overall site. By relying on human reasoning and spatial analyses, the process gains precision and the GIS-based site selection process is improved upon. However the process cannot be scaled or replicated, which makes it time-consuming in nature, potentially causing delays in the selection process. Further, human judgement, while it has the potential to increase precision, can also introduce the element of human error. Ultimately, no two GIS technicians will evaluate a site's suitability in the same way, even though they may agree on many of the key characteristics and concepts of the site selection process

1.1.1. Incorporating Object Based Image Analysis

During the site selection process, a GIS technician is identifying, categorizing, and quantifying the objects present on the site based on shape, texture, spectral properties, and spatial relationship to other objects present (Rizvi et al, 2019). The goal of this research is to identify if this process can be mimicked by using OBIA to identify and classify objects, rather than being done manually by a GIS technician. OBIA first groups pixels into objects based on their spectral, textural, or spatial similarities; the objects are then identified using rule based classification. OBIA was specifically chosen for this project as it "…applies a logic intended to mimic some of the higher order logic employed by human interpreters, who can use the sizes, shapes, and textures of regions, as well as the spectral characteristics used for conventional pixel based classification." (Campbell and Wynne 2012, 371). The assumption is, if OBIA can accurately identify and classify construction impediments, similarly to how a technician would, this process can be partially or fully automated. This could then be scaled in size to increase the overall efficiency of the site selection process. The ensuing benefits of this improvement will be the expedition the site selection process, granting a competitive advantage over developers employing time consuming methods, and a decrease in the associated labor costs.

1.2. Study Area

Each environment presents its own unique conditions and challenges. In the desert regions of the American Southwest, shallow bedrock leads to increased costs associated with driving the pilings needed to support PV arrays. In the Pacific Northwest, there is extensive tree cover and difficult topography. The study area select for this research is located in the southwest corner of Weakly County, TN, within the Tennessee Valley Authority (TVA) electric service territory. This area was purposely chosen for its diverse topography and the interplay between agricultural land and forest or rural infrastructure, which increases the likelihood that impediments will be found. Selecting a study area devoid of any impediments would not fulfill the need of this research. Because the very high resolution (VHR) image that will be used is being provided free of charge from a third party, this research was limited to acquiring only one image. As such it was important to purposively select a study area that would provide enough examples of impediments of interest.

1.2.1. Tennessee Valley Authority

The TVA service territory was selected for this study for multiple reasons. One being that the market expected to see an increase in the construction of utility scale projects. Based on the TVA’s integrated resource plan (IRP) published in 2019, the utility plans on installing an additional 14 gigawatts of PV generating capacity over the next 20 years (St. John, 2019). The TVA’s electric service territory has approximately 16,000 miles of transmission lines that span roughly 80,000 square miles (TVA, 2020). This area covers all of Tennessee as well as parts of Southern Kentucky, Southern Virginia, Eastern North Carolina, Northern Georgia, Northern

Alabama, and Northern Mississippi. Figure 2 shows TVA's territory as well as the study area for this project.

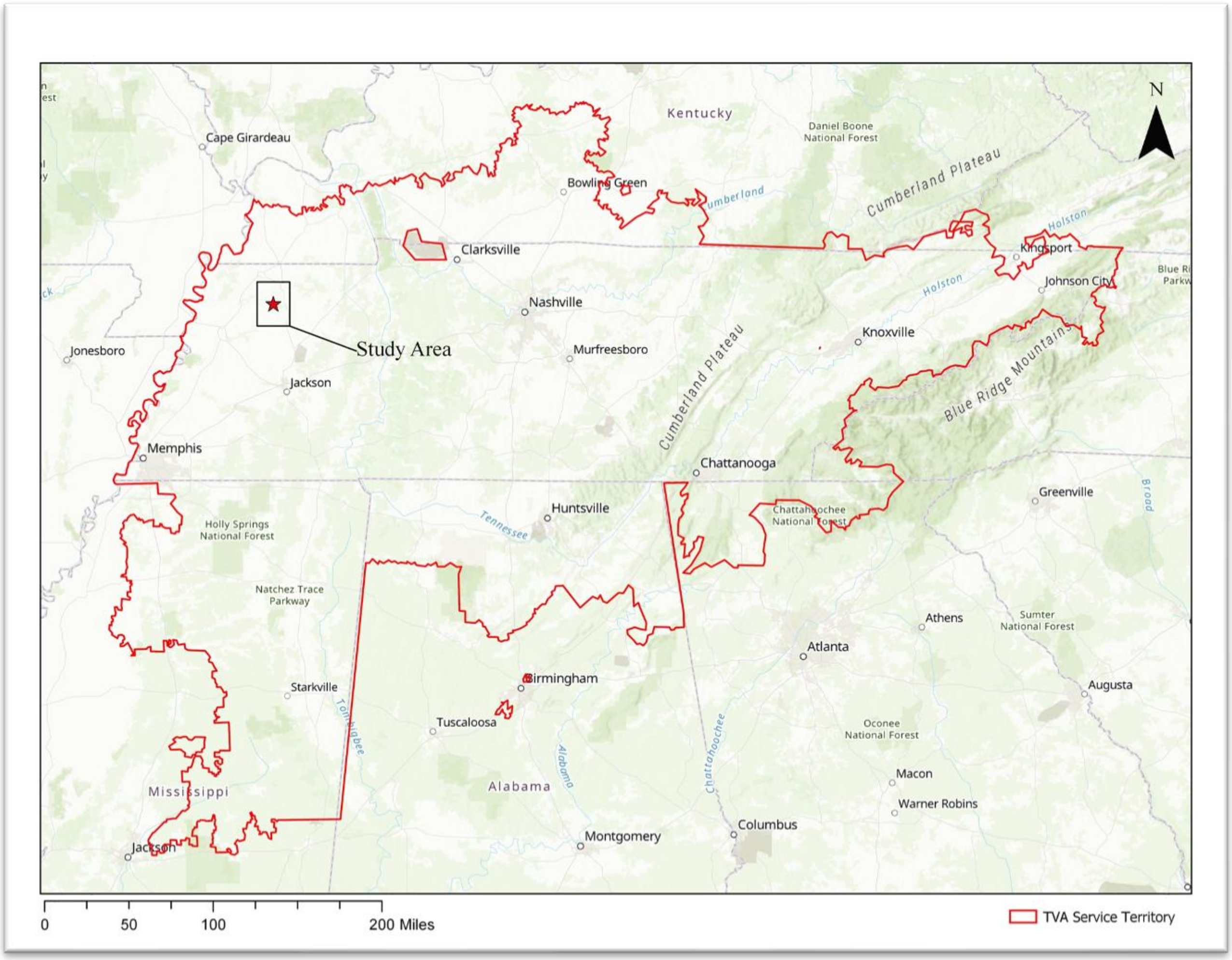

Figure 2 : TVA service territory and study area.

1.2.2. Study Area Selection

The selection of the study area was based on a number of factors. For a utility scale project to succeed, it is necessary to be in proximity to load centers, or areas that consume large amounts of energy such as cities, as well as a large amount rural or undeveloped land. The area needed to have the topographic qualities associated with utility scale solar. These areas are primarily flat and free of wetlands, floodplains, and high slopes.

The study area for this project lies within an area known as the Mississippi Valley Loess Plains that comprises the western edge of Tennessee. This area is on average between 250 – 500 feet in elevation and known for loess deposits that can be up to 50 feet thick in some areas (Environmental Protection Agency, n.d.). This area has a large number of river systems and floodplains that transect the area. Historically the area was covered in oak and hickory tree stands and floodplain forests, but much of this has been cleared and converted for agricultural or livestock use (Environmental Protection Agency, n.d.). Figure three shows in greater detail the location and features of the study area.

Figure 3: Study Area within the USGS 7.5 minute Garder, Tennessee Quadrangle.

After a visual review, the location of the study area was selected using base map satellite imagery within ArcGIS. One critical criteria were that it contained the necessary features within a 60 km^2 area. The size limitation was a result of the need for VHR imagery. Due to the high costs of obtaining VHR imagery, 60 km^2 is the maximum size provided for academic use by the vendor. This will be discussed in further detail in Chapters 2 and 3. The study area also had to contain sites where a USSE project could feasibly be developed. After running an initial screen on the whole state of Tennessee by removing slope greater than 10%, wetlands, and floodplains, the forest cover of the sites was tabulated using the National Land Cover Database. The final study area was selected because it contained potential sites with established forest cover within a 60 km^2 area.

1.3. Summary of Project Objectives

The objective of this project is to identify if OBIA can be used to more effectively identify objects on a potential solar site that may cause additional time and cost despite what may appear, via traditional methods, to be suitable sites. A literature review was conducted to identify related works and research, and to ensure that this idea of research was a novel one. Related works, discussed in Chapter 2, provide the framework on which this research project was designed. The related works section informed the requirements of this project, such as the need for VHR imagery and a means of measuring the accuracy of the process. Chapter 3 describes the methodology used for this project. It explains and describes the sources for data used in the project. In addition, the software utilized for OBIA, Harris Geospatial ENVI Feature Extraction, will be discussed and explained. Chapter 4 discusses and assesses the accuracy of the OBIA process. Chapter 5 concludes the paper by providing recommendations on how this research can be expanded upon as well as its broader importance within the context of industrial solar development, within the TVA, nationally, and globally.

Chapter 2 Related Works

This literature review did not identify previous research on the application of OBIA for USSE site selection process. This is likely due to the fact that only recently have user interfaces been developed that allow for routine or practical application of OBIA, while much the theoretical and conceptual data was completed in previous decades (Campbell and Wynne, 2012). This chapter introduces and defines common construction impediments encountered in the study area, reviews research related to identifying features that share similarities with the features of interest to this project, and the related research on how OBIA can be used to identify these features. It will also discuss the spatial and spectral resolutions required for OBIA, and the importance they have in achieving accurate results. The chapter concludes by providing sample workflows that can be replicated or modified to suit the needs of other studies.

2.1. Utility Scale Photovoltaic Construction Impediments

There are many definitions of what constitutes a utility scale PV development. For the purposes of this study, utility scale is defined as a PV development that is 5mw or larger in size (US Department of Energy, 2012). Each megawatt (MW) produced requires, on average, 8-10 acres of developable land (Mulvaney, 2019). Using this formula, a 100mw PV development will require 800-1000 acres of suitable land. Due to their size, utility scale PV developments are most often found outside of urban centers in rural areas with large flat tracts of contiguous land, free from impediments such as trees, buildings, roads, and water. Site impediments are conditions or features on the ground that can increase construction costs or prohibit construction altogether (Guaita-Pradas et. al, 2019). By identifying these features and assessing their impact on a potential site, developers can make actionable decisions using temporally relevant data. Table 1 contains common impediments found within the study area, and previous research on using OBIA for their identification.

Table 1. Common Impediments and Related Works

Impediment	Examples	Previous Research	Method(s)	Platform(s)	Study Area
Road	• Street • Driveway • Access Road	• (Medhi and Saha, 2019)	• Nearest Neighbor • Rule Based • Multiresolution Segmentation Algorithm	• Resourcesat-II • 5.8m Multispectral • Kompsat • 2.8m Multispectral • 0.7m Panchromatic	• Jorhat District; Assam, India
Building	• House • Barn • Silo	• (Attarzadeh and Momeni, 2012)	• SEaTH • SEperability • THresholds	• QuickBird • 2.4m Multispectral • 0.6m Panchromatic	• Isfahan, Iran
Vegetation	• Tree Stands	• (Chubey et al, 2006) • (Rizvi et al, 2019)	• eCognition • Multiresolution Segmentation Algorithm	• IKONOS-2 • 4.0m Multispectral • 1.0m Panchromatic	• Rocky Mountains; Alberta, Canada

2.1.1. Roads

Roads are a common impediment found on sites within the TVA service territory and cause problems to solar development interests by fragmenting the useable area on a site. The fragmentation caused by roads is especially relevant in utility scale PV developments because it is often necessary to create an assemblage of parcels with different owners to acquire the acreage needed to develop a USSE project (US Department of Energy, 2012). Being that roads were put in place without consideration for future development, their placement fragments the developable area. This introduces the need to build around the roads, introducing gaps in the site design where solar panels cannot be placed, leading to an increase in construction costs. Removing or moving the location of the roadway will increase both engineering and construction costs. Additionally, roads on private property are not readily available as a vector layer, making identifying them individually on each site a laborious task. If OBIA can identify roads at scale then they can be incorporated into the site screening process.

2.1.2. Buildings

Buildings are impediments that contribute to construction costs for a number of reasons, some shared and others specific to building type. Common buildings found on rural sites in the TVA include houses, mobile homes, barns, stables, and silos. All buildings create a physical impediment to construction, as the site must be built to accommodate their locations. Many homes are occupied and have connecting infrastructure such as sewers lines, water lines, and the electrical grid. The height of silos can often create large swaths of shading leading to areas with a decreased production capacity. All buildings present unique challenges to a site and can be constructed in short time, and the geometric shape and often uniform spectral returns make them very compatible with OBIA methodologies.

2.1.3. Vegetation

Due to their size, the impact of utility scale solar developments on sites existing vegetation must be considered. Developing utility scale solar involves the clearing and disturbance of vegetation on the site. This can have negative effects on both the biological environment and a create community opposition, resulting in the increased chance of a project not making it to completion. These effects are manifested in a variety of ways and are related to the type of vegetation in question.

From an environmental standpoint, the development of utility scale solar risks habitat loss, effects groundwater runoff, pollution of local streams, and even alters the location where aquatic insects lay their eggs (Mulvaney 2019, 171). The simple act of clearing wildflowers on a site can negatively affect the local pollinator population. One study linked the deaths of between 16,200 and 59,400 birds in 2016 caused by the land use changes of utility scale solar developments in Southern California (Walston et al, 2016). One of the most visible changes solar can have on the landscape is the clear cutting of large swaths of trees.

The presence of trees on a site presents unique challenges with respect to the siting and execution of a project. While solar developers traditionally target agricultural land, the conflict between solar development and existing forests will only increase as less agricultural land becomes available for development. For example, the Massachusetts Department of Energy Resources estimates that 2,500 acres of trees have been cleared in the past 10-15 years within the state to make way for solar development (LeMoult, 2019). Clear cutting can also generate opposition within the community, leading to a project's failure. This can also be the case even if the clearing of the trees is not happening within the local community. Georgetown University's planned solar farm has faced sharp criticism from the student body for their plan to clear 240 acres of trees in in Charles County, MD to make way for the development of the project (Dance, 2019). Lastly, the costs associated with clear cutting forests to prepare a site for development, while dependent of the thickness of the forest and its location, estimate between \$3,000 and \$5,600 per acre (O'Keefe, 2020). For a site such as Georgetown University's, this can equate to between a \$720,000 and \$1,344,000 increase in construction costs.

2.2. Platforms

Selecting the platform to be used is determined by the size of the object being identified. If the spatial resolution results in pixels larger than the object being analyzed, this requires per-pixel or sub-pixel analysis and are not suitable for use in OBIA (Blashke, 2010). The launch of IKONOS-1 in 1999 ushered in the era of commercially available VHR satellite imagery providing 0.8m panchromatic and 4.0m multispectral spatial resolution (Chen and Hossain, 2019). Since IKONOS' launch, advances in sensor technologies are now producing VHR images with <1m spatial resolution, which is required for accurate OBIA.

2.2.1. Spatial Resolution

Accurate segmentation, or the grouping of individual pixels into objects, is dependent on the spatial resolution of the input image. While image segmentation has been applied to remotely sensed (RS) data since the launch of Landsat-1, it was the launch of IKONOS that finally provided an opportunity for researchers to apply these techniques to VHR images (Chen and Hossain, 2019). For the purposes of this study it is important to ascertain the spatial resolution that will be suitable to use for segmentation on objects of varying size. Prior research has established minimal thresholds required for accurate segmentation. Medhi and Salah (2019) compared three segmentation techniques applied to images collected by the Resourcesat-II and Kompsat satellites. An accuracy assessment was performed on the results and it was found that by using a multiresolution segmentation algorithm (MRS) on Kompsat 0.7m Panchromatic imagery resulted in 56% accuracy rate, compared to a 15% accuracy rate when using Resourcesat-II 5.8m multispectral imagery (Medhi and Salah, 2019).

Past research has identified the minimum threshold required for segmentation and identification. Attarzadeh and Momeni (2012) used QuickBird 2.4m multispectral imagery to identify building outlines. Their workflow accurately identified 80% of the buildings in the image. To achieve this accuracy, the authors ran multiple segmentation iterations to first identify the proper scale level for segmentation. Their research also demonstrated the importance of rule development; because of the variation in color, texture, and size, even among like objects such as buildings, a rule designed to identify buildings with light color roofs can inadvertently exclude buildings with dark roofs. Attarzadeh and Momeni note that their accuracy was limited as a result of a rule they developed because the spectral threshold set excluded buildings with light colored roofs. Additional research applied a semiautomated OBIA workflow to National Aerial Image Program (NAIP) 1.0m multispectral images. This approach resulted in 95% of buildings being accurately identified (Caggiano et. al, 2016).

Research on the use of OBIA for vegetation detection and classification has generally been focused on plant species classification for environmental monitoring and inventory (Blashke, 2010). Trees alone do not create an impediment to solar site construction, however, tree stands and heavily forested areas do, as they require clearcutting and stump removal to prepare the site for the driving of the piles and instillation of the solar panels. Chubey et. al applied Trimble's eCognition MRS module to IKONOS-2 4.0m multispectral imagery and were able to identify 81 of 86 tree stand image objects in the dataset (Chubey et. al, 2006). This suggests that 4.0m multispectral imagery can be suitable for tree stand identification using OBIA.

2.3. OBIA Segmentation and Classification Workflows

There is a robust amount of research available on the topic of OBIA and the workflows that provide the most accurate results in identifying specific feature within an image. This research intended to create an iterative workflow suitable for identifying the most common impediments found in the TVA service territory. To achieve this, a literature review was conducted to identify workflows that have demonstrated to be able to achieve the desired outcomes of this paper. A key determinate in selecting the workflows to be analyzed was there was potential to be replicated using Harris Geospatial ENVI + IDL software and the accompanying ENVI Feature Extraction Module (ENVI FX) (Xiaoying, 2009). The ENVI + IDL and ENVI FX software will be discussed in detail in Chapter 3 of this paper.

2.3.1. Segmentation

The first step in OBIA is segmentation. Segmentation is the process of grouping pixels with similar spectral properties into objects, which represent real world features. The accuracy of the segmentation process has a direct effect on the accuracy of the classification process. The primary segmentation algorithm used in the studies reviewed is the Multiresolution Segmentation Algorithm (MRS). MRS has been shown to be more accurate than other segmentation algorithms, such as the watershed transformation, by up to 18% (Kavzoglu and Tonbul, 2017). MRS works by grouping pixels with similar spectral attributes until the variance parameter threshold, also known as the scale parameter, is reached, at which point the segmentation process ceases.

A workflow created by Belgui and Dragut involved using an MRS algorithm run in eCognition to identify buildings. After the image was segmented, unsupervised classification was ran with an overall accuracy rate of 82.3%. The same segmented image was run through a supervised classification with overall accuracy of 86.4% (Belgui and Dragut, 2014). Being that the difference in accuracy between the two classification methodologies is 4.1%, this workflow shows promise for being semi-automated. MRS algorithms have shown promise not only in identifying buildings, but across a range of features including water and trees.

MRS algorithms have been used to accurately segment water features in VHR images. Moffett and Gorelick identified a workflow for water feature extraction using MRS ran in eCognition. To optimize the accuracy of the segmentation process, the authors recommended that a heavy emphasis is placed on spectral properties while de-emphasizing the object (Moffett and Gorelick, 2012). Further research has shown that the use of MRS in OBIA workflows for water feature extraction are more accurate that those that rely on pixel-based classification, with one study achieving 90% accuracy (Kaplan and Avdan, 2017).

As previously discussed, MRS has proven to be successful in the identification of tree stands using IKONOS-2 imagery (Chubey et al, 2006). Further research has expanded on the work done by Chubey et al (2006) by using eCognition's MRS algorithm on WorldView-2 0.5m pan-sharpened imagery. While the researchers utilized imagery with considerably better spatial resolution, their results were less accurate and attributed to over-segmentation (Sinaga et al, 2019). The over-segmentation of VHR imagery when using MRS is a problem identified in previous research and is expected to be encountered in the course of this research (Chubey et al, 2006; Culvenor, 2003). To mitigate the problem of over segmentation, multiple segmentation iterations are run at different scales and merge levels until the desired results are achieved. An exhaustive literature review did not identify any automated solutions to over segmentation. Harris Geospatial's ENVI software offers the user the ability to preview their segmentation results on a small subset of the image in real time, which is one reason this software was used for this project.

2.4. Findings

The purpose of this literature review was to examine OBIA workflows and establish which segmentation methodology would be best suited for the purpose of this research. Based on the findings, it was determined that achieving the most accurate results across all of the listed impediments would require sub-meter resolution multispectral images (Blashke, 2010). In all cases, except for the identification of forest stands, it was shown that imagery with a higher spatial resolution yield results with a higher rate of accuracy. The related works also identified MRS to be a strong candidate to successfully segment the impediments this project focused on. By using the ENVI + IDL and ENVI FX module, this study intends ascertain if OBIA can be used to identify impediments to construction on potential utility scale solar sites at scale, to replace the work currently performed by a human.

Chapter 3 Data and Methods

This project used a combination of vector data and VHR imagery to identify construction impediments on potential USSE developments. Wetlands, FEMA 100 year floodplains, and slope greater than 10% were erased from the parcels within the study area to remove land widely considered unsuitable for development. The output of this process creates a mask, in the form of a shapefile, that is used in the OBIA; this limits the segmentation and classification to only sites that meet the minimum requirements for USSE developments. The mask created in the previous step was uploaded, along with the VHR image of the study area, to Harris Geospatial's ENVI. Using ENVI's Feature Extraction module, the image was first segmented and merged to create objects. With the objects, rules were then created based on the attribute data created during the segmentation process. Based on the rules, the classification process was initiated to identify all similar objects within the image. The classification process creates a shapefile of all the objects boundaries, which is then fed back into ArcMap to further delineate impediments within the study area and the sample sites. This process and its inputs and outputs are described in detail within this chapter.

3.1. Data Collection and Preparation

Prior to aggregating the data for this analysis, the researcher first identified a suitable location for the study area within the area eliminated from future analysis via the basic site suitability described in the last chapter. The further requirements of the study area are that it contained a mixture of impediments on developable land within an area of less than 60 km^2. The size constraint on the study area was due to the costs associated with VHR imagery, which was provided free of charge by Hexagon Geospatial via their Hexagon Imagery Program (HxIP). If this project were forced to pay for the same image it would cost $251.48. The final study area selected is 56.34 km^2 of primarily agriculture land within Weakley County, TN, and can be seen in Figure 3. Traditionally, the first step in identifying PV sites is to map the electrical infrastructure required for a utility scale project to interconnect. As the focus of this research was on OBIA, this step was omitted in favor of finding an ideal study area from a topological standpoint.

3.1.1. Data Sets and Sources

The data required for this project consisted of both vector and raster data. While the majority of the datasets are publicly available, both the satellite imagery and parcel data are proprietary datasets produced by private companies. Table 2 shows the datasets, their description, and sources.

Table 2: Datasets and Sources

Dataset	Data Type	Description	Source	Location
National Wetland Inventory	Polygon Feature Class	This dataset contains delineated wetland boundaries. It is produced by having a investigator use satellite imagery to identify and delineate wetland boundaries and types.	US Fish and Wildlife Service	https://www.fws.gov/wetlands/data
National Flood Hazard Layer	Polygon Feature Class	This dataset contains the boundaries for the Special Flood Hazard Area (SFHA). SFHA are areas that have a 1% chance of annual flooding, also known as 100-year flood zones. This layer is produced by FEMA for use in the Flood Insurance Rate Map.	Federal Emergency Management Agency	https://msc.fema.gov/portal/home
Slope	Polygon Feature Class	This dataset is produced by merging the study area DEMs into one raster that covers the study area. A raster calculator is used to group the slope into buckets 0-5%, 5-10%, 10-15%, 15-20%, and 20% +. The raster is then converted into a feature class in ArcMap.	United States Geological Survey	https://www.sciencebase.gov/catalog/item/530f4226e4b0e7e46bd2c315
Parcel	Polygon Feature Class	This proprietary dataset contains parcel geometry and associated attribute data such as owner name, parcel APN, tax ID, address, use code, zoning, and acreage.	Digital Map Products	https://www.digmap.com/
Satellite Image	GeoTIFF	Spatial Resolution: 30cm Projection: NAD83 Format: GeoTIFF AOI size: 56.34km^2	Hexagon Geospatial	https://www.hexagongeospatial.com/resources/resource-library/content-providers/hexagon-imagery-program

3.1.2. Wetlands

Due to their ecological sensitivity and physical characteristics, land that has been identified as wetlands are not considered for development. The National Wetland Inventory (NWI), produced by the US Fish and Wildlife Service (USFWS), is used to remove wetlands from a parcel geometry. This is done by using the erase tool in ArcMap 10.6.

3.1.3. Floodplains

Floodplains, specifically Special Hazard Flood Areas (100-year floodplains), introduce risk and delays into a project. The increased risk of flooding, and the insurance required to build within these areas, increase project costs. These factors alone and in combination make developing utility scale PV on floodplains impractical and difficult. Hence, these areas were also excluded from development by using the erase tool in ArcMap 10.6.

3.1.4. Slope

The impacts that slope has on a potential site are difficult to quantify and are different from site to site. Unlike wetlands and floodplains, there is no consensus as to the most appropriate slope on which to develop industrial solar. For example, a site with an even 20% slope with a southern aspect would, with the right conditions, warrant development. On the other hand, a site that is flat but has small undulations in slope across the developable area would require the site to be graded, increasing project costs. Similarly, a site with a steady 5% slope with a northern aspect would be less favorable than a southern facing slope of 10%. Additionally, the type of PV arrays used have different slope tolerances. Fixed axis arrays can be built on undulating land, while a single axis tracker requires a site with much less undulation. This problem is being addressed by manufactures such as Nevados Engineering who are developing what they have coined as “all terrain trackers” (Nevados, 2020). Due to the complexity of evaluating slope on a project by project basis, slope of any aspect above 10% was removed from the parcel geometry. This seems to be the most popularly held threshold, despite not being universal (cite).

3.1.5. Parcels

Property data, in the form of parcel geometry, was used as the basis for creating utility scale PV sites. Because potential sites must adhere to real world boundaries, the parcels themselves are used to create the developable area. Parcel geometry datasets can generally be acquired from the county accessor. Weakley County, TN, where the study area is situated, only provides parcel geometry as .pdf maps. As a result, this parcel geometry was sourced from Digital Map Products (DMP). DMP assembles proprietary parcel datasets and provides them as a feature class with over 300 attributes to choose from. For the purposes of this research, all that was required was the parcel geometry and calculated acreage.

3.1.6. Satellite Imagery

The crux of this research is the satellite imagery. As previously discussed in Chapter 2, VHR imagery was required for the success of this project. This is because this research hinges on the ability to accurately identify site impediments on a scale beyond what is achieved through traditional methods. The accuracy of the segmentation process is partially determined by the spatial resolution of the imagery used. Because the costs of VHR imagery can be prohibitive, imagery was provided by Hexagon Geospatial under an academic license. The academic license provided one image, no larger than 60 km^2 , free of charge, with the only stipulation that it could not be used for commercial purposes. Two images were provided, an RGB and a CIR for use. The images have a spatial resolution of 30cm, and are provided as GeoTIFFs with an NAD83 projection.

3.2. Software

Two software platforms were required for this research. Esri's ArcMap 10.6 was used to remove undevelopable land from the parcel geometry, calculate acreage, identify potential sites, and create the mask then used in the OBIA. Harris Geospatial's ENVI FX was used for the segmentation and classification process. ArcMap was provided by USC's Spatial Science Institute while ENVI FX was accessed using an academic license from Cloudeo.

3.2.1. Cloudeo

Cloudeo is a third party provider of Software as a Service (SaaS) and Data as a Service (DaaS). Cloudeo was used to access ENVI FX, rather than acquiring it directly from Harris Geospatial; this was a result of cost and license terms. Harris Geospatial only offers lifetime and yearly license for access to ENVI, with the Feature extraction module being an additional cost. It was estimated that it would take approximately 1 month to complete the work in ENVI making a perpetual or yearly license was both cost prohibitive and unnecessary. Cloudeo provides 1 month academic licenses for ENVI FX accessed through a remote desktop. This option provided this project with ENVI FX at fraction of the costs of Harris Geospatial terms and the ability to extend the license on a month to month basis if it was required. Table (X) below details the costs associated with each license.

3.3. Methodology and Workflow

This section will discuss and describe in detail the methodology and steps taken to complete the project. The workflow consists of two primary steps- data preparation and OBIA. Data preparation was completed in ArcMap 10.6 and OBIA in ENVI FX 5.5.3.

3.3.1. Data Preparation

Data preparation consists of identifying potential sites using a traditional site selection processes. Once the sites are identified, a mask is created so only areas of interest were included during the OBIA process. Hard criteria included in the masking are discussed in sections x and y; this creates a reduction in processing time and resource consumption when going through the OBIA process.

3.3.1.1. Mask Creation

Mask creation was an important component to this workflow because it excludes unwanted areas inclusion in the segmentation process resulting in faster processing times. The process of creating the mask began in ArcMap, where wetlands, floodplains, and slope greater than 10% were removed from a parcels geometry by using the erase tool. The output of this process was a shapefile including only the developable area within the potential sites. The order in which the constraints were removed does not affect the final remaining area, but does determine the total acres lost in each category. Because of overlap in the constraints, areas that are excluded because of wetlands will not be included in the number of acres for areas lost in the different categories and vice versa. This research found that erasing wetlands first, followed by floodplains, and lastly slope provided the quickest processing times. This process is outlined in Figure 4.

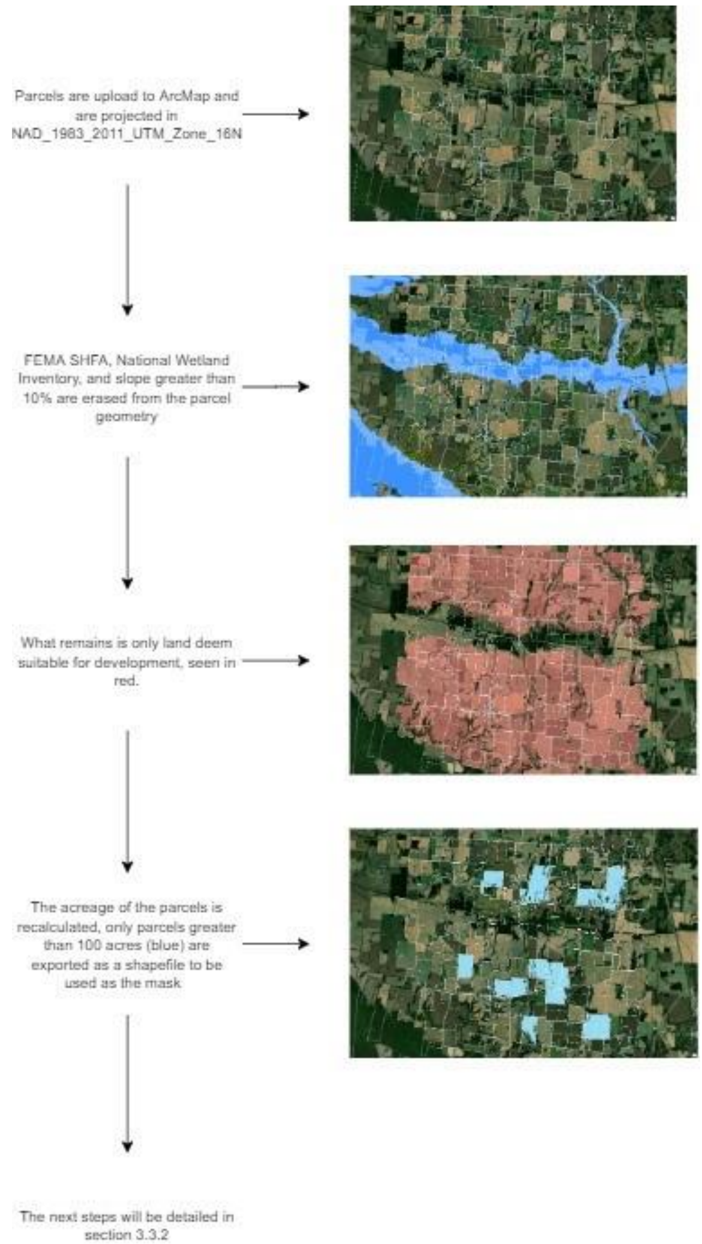

Figure 4: Site identification and mask creation process.

The masking process was able to eliminate a combined 3010.25 acres of the study areas 13955.14 acres, or 21.57%. Of this 881.45 acres of wetlands, 1549.22 acres of floodplains, and 533.58 acres of slope were excluded leaving 10944.88 acres of developable land. This was further reduced by only selecting sites with 100 or more developable acres remaining, leaving only 1520.08 acres, or 10.76% of total study area. This results in reduced processing time during segmentation and classification.

While a user can create a mask in ENVI, this workflow takes advantage of the fact that the mask created is a byproduct of the site selection process itself. By using the parcel geometry as the basis of the exclusion process, the sites remaining after removing all undevelopable land can be exported as a shapfile and used as the mask in ENVI. This eliminates the need to repeat this process in ENVI.

3.3.2. Segmentation

The process of OBIA is comprised of object identification and feature extraction. Object identification beings with segmenting the image; the segmentation process defines the objects and computes their spatial, spectral, and textural attributes. ENVI FX employs an edge-based segmentation algorithm that, based on scale level, suppresses weak edges (Visual Information Solutions, 2007). This is done by grouping pixels of like values into objects, which are defined by their spectral attributes.. The boundaries of these objects are formed by the edges where there are abrupt changes in the spectral gradient (Segmentation Algorithms background, n.d). The scale level selected ran from 0-100, and determined the accuracy of the segmentation process. A high scale level will result in less segmentation, conversely, a low scale level will result in increased segmentation. Included in segmentation is the optional step of merging.

While merging is optional, it was used, with trial and error showing it yields better segmentation results than without. Merging works by aggregating small segments that fall within larger segments to account for over segmentation. Highly textured objects such as clouds and trees are a cause of over segmentation.

Texture, in this context, is defined as the spatial variation of grayscale levels as a function of scale (Texture Metrics Background, n.d.). The level is representative of pixel size of the box used to compute the statistics. Thus, a scale level of 3 would equate to a 3 x 3 pixel box. The kernel texture box creates the attribute information used in rules based classification. A box too small will not capture enough variation among pixels for an accurate calculation. A box too large will cause overlap leading to blending of texture across objects making creating rules based on textural attributes unreliable.

The process began by uploading the image and mask to ENVI. The feature extraction module will automaticity convert the shapefile into a single band raster to be used as the mask, this can be seen in figure 5.

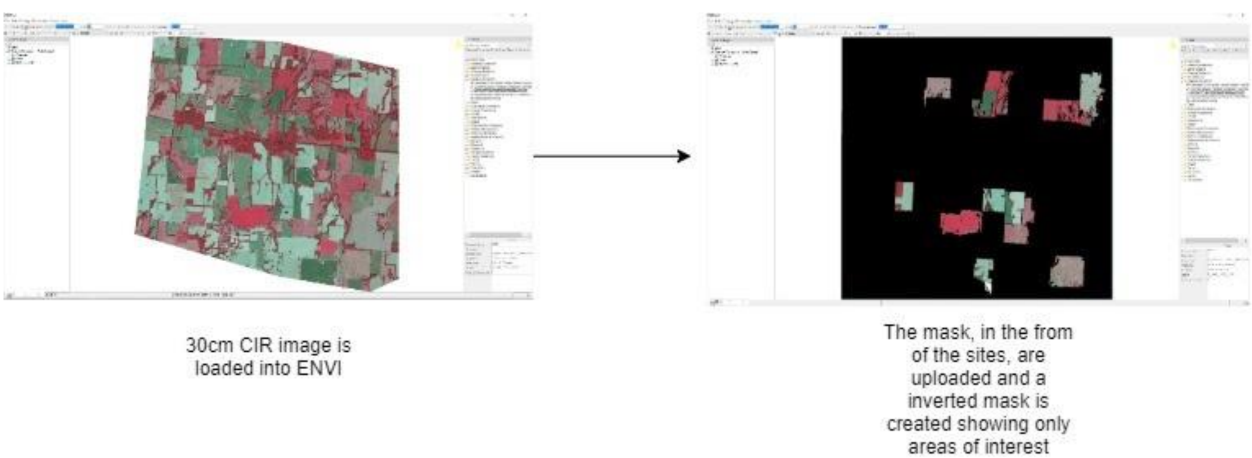

Figure 5: Mask utilization in ENVI

With the mask created, the scale and merge levels were set. Choosing the correct scale and merge levels is an iterative process to identify ideal levels. This process was guided by comparing each result to the previous iteration's segmentation output. ENVI offers small preview of the segmentation output based on the levels chosen prior to running the full segmentation process. The parameters were developed by first starting with the default scale level of 50, merge level of 0, and texture kernel size of 3. On the suggestion of the ENVI FX tutorial the levels were adjusted, first in increments of 10, followed by increments of 1, and lastly increments of 0.1 (Visual Information Solutions, 2007). This process was iterated through numerous times, each time adjusting the parameters based on the previous iterations results until the desired outcome was achieved. This example used a scale level of 60 and merge level of 80 and a kernel size of 3. These attributes were used to create the rules for the classification process.

3.3.3. Classification

Rule based classification was used as it allows increased control over the classification process. Rules are created based on the attribute information calculated in the segmentation process using AND / OR logic. AND is used to combine multiple attributes within rule, and the OR operator is used to combine multiple rules within one class. This process was rejected in favor or using class and rules scores. The class score is a function of the rule score and is defined as Class Score = ∑(Rule Score x Rule Weight). The rule score is defined as Rule Score = ∑(Attribute Score x Attribute Weight), where attribute score is the likelihood of an object meets the conditions of an attribute. Attribute and Rule weights are defined by the user and must sum to 1 (Rule Classification Background, n.d). The rule created for this example used the spectral mean of band 3 with a class threshold of .5 to identify tree stands. The classification process creates a temporary .dat file containing the identified objects. This is converted a shapefile that is fed back into ArcMap to account for the now identified impediments previously missed. This can be seen in figure 6 below.

Figure 6: Object identification and export

3.3.4. Process Iteration

The methodology outlined in this section is just one example of multiple iterations completed in the course of this research. The iteration process is time consuming, but necessary, as it can takes a considerable amount of trial and error to identify the combination that provides the most accurate results (Campbel and Wynne 2012, 372). Each iteration uses unique rules in an attempt to identify those that yielded the most accurate results. The creation of the rules followed a similar process to the development of the segmentation parameters. The rules were developed, by first experimenting with the various attributes to identify those unique to trees. Using research into the spectral returns of trees it was determined that spectral and textural attributes have shown to be successful in identifying trees (Lin et al, 2013). Similarly to the preview window provided in the segmentation process, ENVI also has a preview window that can be used to display a rule confidence image while adjusting the rule parameters. The rule confidence image demonstrates the relative confidence of an object belonging to a feature, the brighter the color the greater the confidence, and vice versa (Visual Information Systems, 2007). As the rule parameters were adjusted, the preview window was used to visualize the results of each subtle change, allowing for on the fly adjustments and not having the run the entire classification process to glean insight into the results.

Chapter 4 Results

The intent of this research was to discern if OBIA and rule-based classification could accurately replicate and/or improve upon a manual utility scale solar site suitability prescreen workflow. To achieve this, multiple iterations of the process were run, with adjustments made to the segmentation parameters and/or the rules, in an effort to identify the most accurate combination to identify tree stands within the study area. This chapter will discuss the results of each iteration, the rules employed, and the justification for sampling technique and size.

4.1. Segmentation

As previously discussed, the accuracy of the classification process is largely influenced by the accuracy of the segmentation process. For the purposes of identifying tree stands, the scale level, set between 0-100, should be set at a level low enough to properly delineate trees without causing over segmentation. To identify the correct scale and merge levels, 47 segmentation iterations were run, beginning with a scale level of 50 and a merge level of 0. A general rule of thumb is, as the scale level decreases, the merge level should conversely increase (ENVI, 2008). This process was assisted by ENVI's segmentation preview window which allows the user to view a subset of the results prior to initiating the segmentation process. As previously noted, the selection of ENVI for this research was partially related to this specific feature. After multiple iterations, the combination that most accurately delineated the trees from their surroundings was iteration 7; with a scale level of 37, merge level of 97.5, and texture kernel size of 3. The 7 iterations to be discussed can be found in Table 3 below. Once the segmentation process was providing accurate results, only small adjustments of the input values were required to alter the segmentation output. The resulting outputs required adjustments to the classification rules to account for changes in the spectral, textural, and spatial attributes of the segmentation image. The results of each segmentation can be found in the appendix.

Table 3: Segmentation Parameters

Iteration	Scale Level	Merge Level	Texture Kernel Size
1	23	98	5
2	23	98	3
3	23	95	3
4	28.5	95	3
5	38	95	3
6	38	97	3
7	37	97.5	3

4.2. Rules

Similar to the segmentation process, the rules created for rule based classification were a result of an iterative process guided biophysical characteristics of trees found within the study area. A review of the attribute information generated during the segmentation process found that the spectral and textural attributes of the trees were the most homogenous across the class. A review of the spatial attributes found that there was too large of a range between the spatial attributes of a single or small group, or trees to that of a large tree stand. As such, spatial attributes were not used in the creation of the classification rules.

4.2.1. Rule Development Process

The development of the rules began by first identifying the biophysical characteristics that make trees unique from their surroundings. The rules must be able to discern green grass from green trees, or dark shadows from dark tree canopies, which can share similar spectral returns for example. To achieve this, the rules were developed using an iterative process that relied on the previous results to inform the changes required to further refine the rules. Take for example, the rule used in the seventh iteration, seen below in table 4.

Table 4: Rule 7

RULE 7	Min	Max	Band
Texture Entropy	-0.59416	-0.53717	2
Spectral Max	66.71148	112.14201	3
Spectral Mean	22.21387	89	1
Class Threshold	0.75		

Rule 7 uses 3 separate attributes in combination to define a tree. In this example, texture entropy is being used to help differentiate between green, but otherwise smooth, grass from a green, but highly textured tree canopy. When ran in combination, the results, seen in figure 7, show how the rule was able to correctly classify trees while minimizing the misclassification of grass as trees.

Figure 7: Results of Rule 7

When rule 7 is ran again, this time removing the texture entropy constraint the results are vastly different with large swathes of not only grass, but also barren land misclassified as trees. This can be seen in figure 8 below.

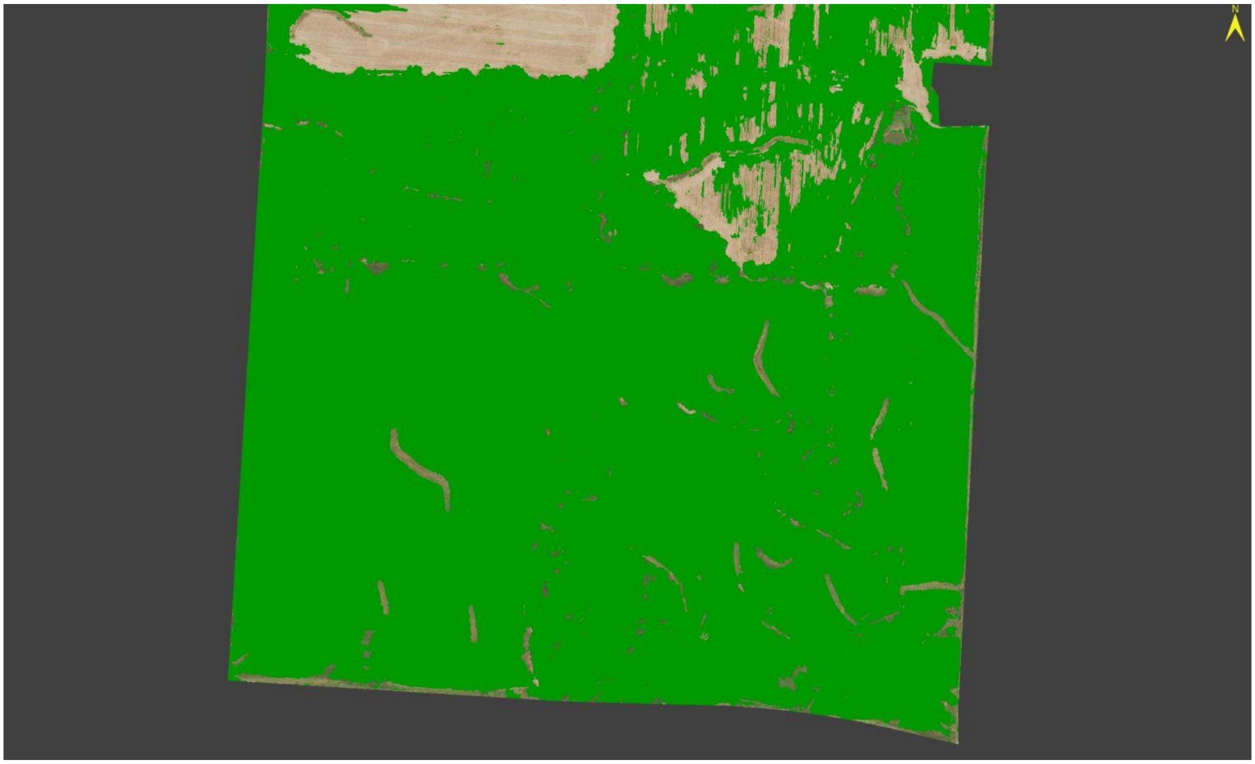

Figure 8: Rule 7 Modification Results

This process also demonstrates how important a single constraint can be in a rule, as well as inform the creator of the rule what constraints were eliciting the changes made when ran in combination.

4.3. Accuracy Assessment

To assess the accuracy of each iteration, 545 randomly sampled ground truth points were generated and manually classified as either 1 for trees or 0 for unclassified. This was done using the same 30cm VHR image employed in the segmentation and classification process to eliminate errors of registration (Campbell and Wynne, 2012, 416). The ground truth points were used to generate error matrixes, also known as confusion matrixes, for each iteration by comparing the reference, or ground truth data, to the classification results.

The accuracy of the results is the determining factor in judging this exercise to be a success or not, as such the accuracy assessment employed was based on the framework created by Alan Hay. While the confusion matrix provides the overall accuracy, this value alone does not provide the context required to understand the results. To determine the accuracy, Hay proposes using the error matrix to answer the following questions (Hay, 1979.)

1. What proportion of all the sample predictions proved to be correct?
2. What proportion of the sample predictions of a single category proved to correct?
3. What proportion of land, within a category, is correctly predicted?
4. Is the net effect, of numbers 2 and 3 above, for predictions to overestimate or underestimate a given category?
5. If error occurs in either of the ways 2 and 3, is there any bias in these errors towards specific categories?

4.3.1. Process Iteration

The need to run multiple iterations of both the segmentation and classification process to identify the ones that yield the most accurate results is a common theme found the related works. The ideal OBIA workflow put forth by Blaschke et al incorporates the iterative nature of the process into the workflow demonstrating the need to iterate the process to refine the results. Figure 7 outlines this workflow and shows that both the segmentation and classification steps within the workflow are iterated through.

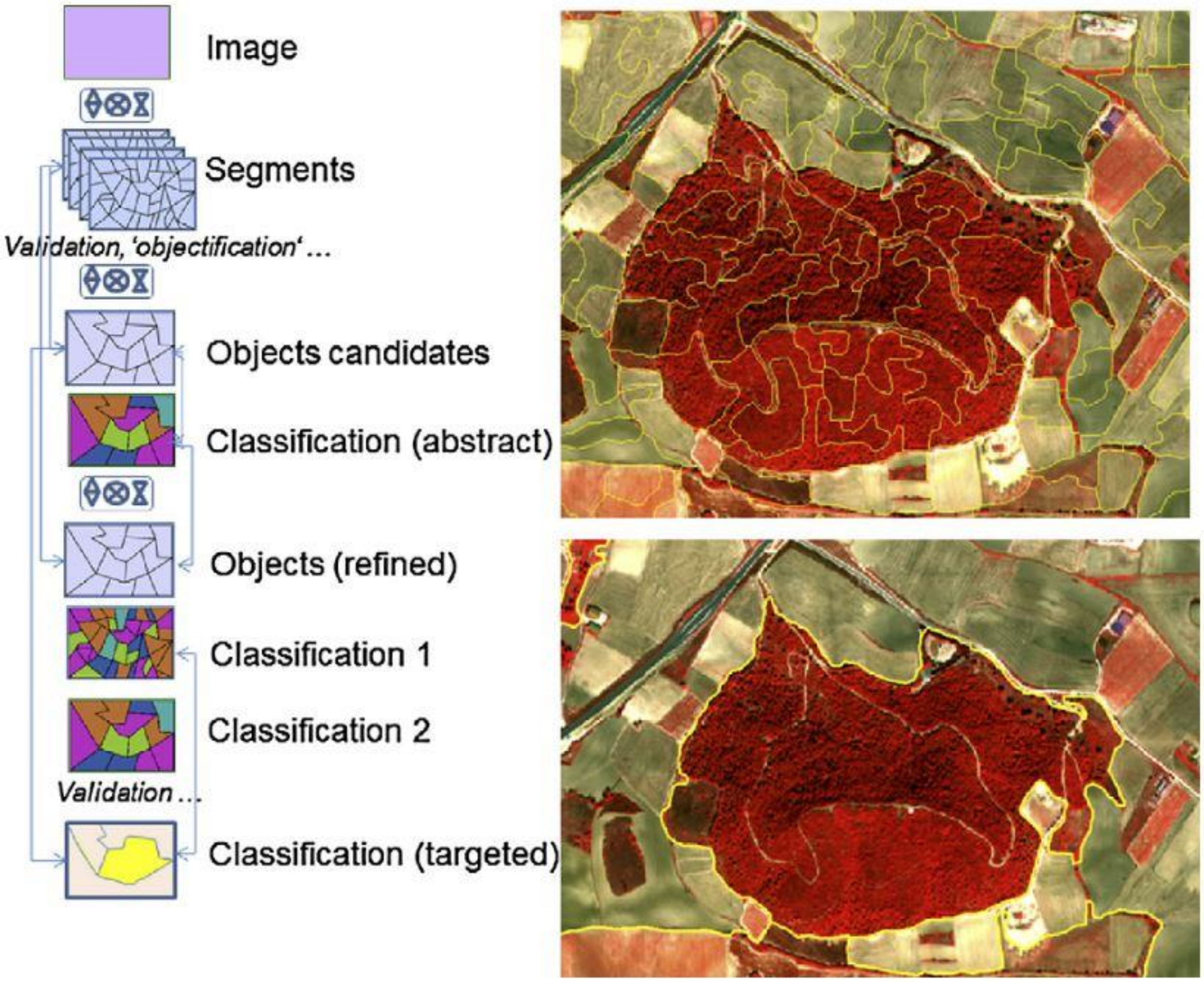

Figure 9: Example of the iterative nature of the idealized OBIA workflow (Blaschke et al 2012, 186)

The benefit of iterating though each step is it refines the outputs, the theory being that each iteration will guide the GIS technician towards the most accurate results based on their interpretations. A drawback of this process is that it requires iteration, and it cannot be assumed that accurate results are achieved without it. This coupled with the differences in spectral, textural, and spatial properties across VHR images makes it unfeasible to establish segmentation parameters and classification rule sets that can be applied across different image sets. This limitation and its effects on the ability to replicate the work presented in this chapter is discussed in detail in Chapter 5.

4.3.2. First Iteration

The first iteration in this sequence was the result of multiple trial and error efforts to identify an acceptable baseline to attempt to improve upon. Table 4 provides the segmentation parameters, rule, and confusion matrix for the first iteration. The rule created to classify trees relied on the spectral mean and textural range of band 3.

Table 5: First Iteration

Iteration	Scale Level	Merge Level	Texture Kernel Size		
1	23	98	5		
RULE 1	**Min**	**Max**	**Band**		
Spectral Mean	33.68989	60	3		
Texture Range	32	58.67765	3		
Class Threshold	0.75				
Class Name	**Unclassified**	**Trees**	**Total**	**U_Accuracy**	**Kappa**
Unclassified	376	52	428	0.8785	0
Trees	2	115	117	0.9829	0
Total	378	167	545	0	0
P_Accuracy	0.9947	0.6886	0	0.9009	0
Kappa	0	0	0	0	0.7456

The first iteration provided an overall accuracy of 0.9009, but only had a producer's accuracy (P_Accuracy) (also known as errors of omission) of 0.6886. In other words, trees were only properly identified 68.86% of the time. This is not an acceptable level of accuracy if this is to be used for actionable decision making. Additionally, the Kappa value of 0.7456 demonstrates that the results of this iteration would achieve an accuracy that is 75.56% better than what would be expected from a chance assignment of ground truth points to categories (Campbell and Wynne, 2012, 420). A subset of the classification results can be seen below in Figure 8.

Figure 10: Classification results of the first iteration, the green represents areas classified as trees, the grey represents masked areas.

4.3.3. Second Iteration

In an attempt to create more granular textural attributes, the second iteration reduced the texture kernel size to 3, with all other segmentation parameters remaining the same (Table 5). To account for the changes in the segmentation attribute, the range of the spectral mean was decreased to 38.43266 – 59.7500. This did not achieve the desired results with the overall accuracy reduced to 0.8092, the producer accuracy to 0.5389, and the kappa value to 0.5101. The results of this change can be seen in figure 9; note the misclassified grasses adjacent to trees as well as less trees being correctly classified.

Figure 11: Second iteration classification results, green represents areas classified as trees, green represents masked areas.

Table 6: Second Iteration

Iteration	Scale Level	Merge Level	Texture Kernel Size		
2	23	98	3		
RULE 2	**Min**	**Max**	**Band**		
Spectral Mean	38.43266	59.75	3		
Texture Range	32	58.67765	3		
Class Threshold	0.75				
Class Name	**Unclassified**	**Trees**	**Total**	**U_Accuracy**	**Kappa**
Unclassified	351	77	428	0.8201	0
Trees	27	90	117	0.7692	0
Total	378	167	545	0	0
P_Accuracy	0.9286	0.5389	0	0.8092	0
Kappa	0	0	0	0	0.5101

4.3.4. Third Iteration

For the third iteration, the merge level was lowered to 95 with all other segmentation parameters remaining the same. In an attempt to increase the accuracy of Rule 2, the texture range was for band 2 was set to > 32.28139 as seen in table 6. This was done to attempt to exclude grassy areas, which had similar spectral properties, but a lower textural range. This change again reduced the overall accuracy, the producer accuracy, and the kappa value.

Table 7: Third Iteration

Iteration	Scale Level	Merge	Texture Kernel Size		
3	23	95	3		
RULE 3	**Min**	**Max**	**Band**		
Spectral Mean	38.43266	59.75	3		
Texture Range	>32.28139		2		
Class Threshold	0.75				
Class Name	**Unclassified**	**Trees**	**Total**	**U_Accuracy**	**Kappa**
Unclassified	378	114	492	0.7683	0
Trees	0	53	53	1	0
Total	378	167	545	0	0
P_Accuracy	1	0.3174	0	0.7908	0
Kappa	0	0	0	0	0.3921

4.3.5. Fourth Iteration

For the fourth iteration, the scale level was increased to 28.5 with all other segmentation parameters remaining the same. For this iteration, a new rule was created to focus on the textural entropy of band 2 and the spectral max of band 3 (Table 7). These changes were implemented as previous iterations were becoming less accurate when the rule parameters were adjusted. This change in direction was added via the ENVI preview window, which allowed for "on the fly" viewing of the classification results. This change increased accuracy over the previous iteration, but was still less accurate than the baseline set in the first iteration.

Table 8: Fourth Iteration

Iteration	Scale Level	Merge Leve	Texture Kernel Size		
4	28.5	95	3		
RULE 4	Min	Max	Band		
Texture Entropy	-0.59416	-0.53717	2		
Spectral Max	65.13619	101.27068	3		
Class Threshold	0.75				
Class Name	**Unclassified**	**Trees**	**Total**	**U_Accuracy**	**Kappa**
Unclassified	377	83	460	0.8196	0
Trees	1	84	85	0.9882	0
Total	378	167	545	0	0
P_Accuracy	0.9974	0.5030	0	0.8459	0
Kappa	0	0	0	0	0.5798

4.3.6. Fith Iteration

After seeing a positive correlation between the changes made in the fourth iteration and accuracy levels, the scale level was again increased, this time to 38, with all other segmentation parameters remaining the same (Table 8). Further review of the classification results of the fourth iteration identified that the RULE 4, in an attempt to exclude shadows, also excluded dark trees. RULE 5 accounts for this by including the new attribute of Band 1 Spectral Mean < 74.75175. With this change, the spectral max of band 3 was similarly adjusted, increasing the minimum to 66.71148 and the maximum to 112.14201. This change increased the overall accuracy to 0.8826, the producer accuracy to 0.7126, and the kappa value to 0.7081, which improves upon the fourth iteration.

Table 9: Fifth Iteration

Iteration	Scale Level	Merge Level	Texture Kernel Size		
5	38	95	3		
RULE 5	**Min**	**Max**	**Band**		
Texture Entropy	-0.59416	-0.53717	2		
Spectral Max	66.71148	112.14201	3		
Spectral Mean	< 74.75175		1		
Class Threshold	0.75				
Class Name	**Unclassified**	**Trees**	**Total**	**U_Accuracy**	**Kappa**
Unclassified	362	48	410	0.8829	0
Trees	16	119	135	0.8815	0
Total	378	167	545	0	0
P_Accuracy	0.9577	0.7126	0	0.8826	0
Kappa	0	0	0	0	0.7081

4.3.7. Sixth Iteration

In the sixth iteration, the merge level was increased to 97 with all other segmentation parameters remaining the same. Similarly to the results of the fifth iteration, the sixth iteration again excluded to many dark trees in an effort to exclude shadows. To manage this, the spectral mean was increased to < 88.23574. This change had the most significant positive change to the accuracy of the classification. Overall accuracy was increased to 0.9174, producer accuracy to 0.8862, and kappa value to 0.8080 (Table 9).

Table 10: Sixth Iteration

Iteration	**Scale Level**	**Merge Leve**	**Texture Kernel Size**		
6	38	97	3		
RULE 6	**Min**	**Max**	**Band**		
Texture Entropy	-0.59416	-0.53717	2		
Spectral Max	66.71148	112.14201	3		
Spectral Mean	<88.23574		1		
Class Threshold	0.75				
Class Name	**Unclassified**	**Trees**	**Total**	**U_Accuracy**	**Kappa**
Unclassified	352	19	371	0.9488	0
Trees	26	148	174	0.8506	0
Total	378	167	545	0	0
P_Accuracy	0.9312	0.8862	0	0.9174	0
Kappa	0	0	0	0	0.8080

4.3.8. Seventh Iteration

For the seventh iteration, the merge level was increased to 97.5 with all other segmentation parameter remaining the same. Upon inspection of the results of the sixth iteration, it was found that shadows were again being included and classified as trees. In an attempt to mitigate this, the spectral mean of band 1 was changed from < 88.23574 to 22.21387 – 89.00, as seen in Table 10. This was surprising because there was no change in the confusion matrix and thus no change in accuracy.

Table 11: Seventh Iteration

Iteration	Scale Level	Merge Level	Texture Kernel Size		
7	38	97.5	3		
RULE 7	**Min**	**Max**	**Band**		
Texture Entropy	-0.59416	-0.53717	2		
Spectral Max	66.71148	112.14201	3		
Spectral Mean	22.21387	89	1		
Class Threshold	0.75				
Class Name	**Unclassified**	**Trees**	**Total**	**Comission**	**Kappa**
Unclassified	352	19	371	0.9488	0
Trees	26	148	174	0.8506	0
Total	378	167	545	0	0
Omission	0.9312	0.8862	0	0.9174	0
Kappa	0	0	0	0	0.8080

4.4. Conclusions

The hypothesis underlying this research was that OBIA can be used to accurately replicate a manual USSE site review workflow. While each real world use case brings with it its own unique environmental properties, the results of this research shows the potential for the use of OBIA in USSE site suability analyses. A key finding is that the measurement of accuracy must be put in the context of the desired outcome, namely with respect to what is determined to be an acceptable error rate. For the purposes of using the classification outputs to make actionable decisions a 90% accuracy rate would be desired. While an overall accuracy of 91.74% was achieved, no more than 88.62% of the trees were correctly classified, resulting in a kappa value of 0.8080. With more experience and iterations, it is assumed that the accuracy of a classification technique such as this can be increased, but the measurement of the accuracy will always be subjective as it is up to the end user to determine their confidence in the results.

Chapter 5 Discussion and Conclusions

Chapter 5 discusses the results of the OBIA process, limitations of the study, and recommends areas of further research. This project set out to investigate the use of OBIA to augment or replace the time consuming process of visually inspecting each potential USSE site for construction impediments. The results of this research demonstrated that OBIA using VHR imagery can identify trees with 88.62% accuracy within the study area. This number was achieved by running multiple iterations of OBIA, each time adjusting either the segmentation parameters or class rules based on the previous iteration to increase accuracy.

5.1. Findings

The goal of this research was to identify if OBIA can be used to accurately identify construction impediments on potential USSE sites, and if so, if a workflow could be developed to achieve similar outcomes as if the sites were visually reviewed by a GIS technician. OBIA was selected because it has the ability to apply logic that mimics some of the higher order logic employed by GIS technicians (Campbell and Wynn, 2012). Success in this case is determined by two factors; the accuracy of the OBIA results and the ability to use OBIA, at scale, to replicate the site suitability analysis currently completed using human intervention.

The level of accuracy required to confidently make actionable decisions on is subjective and determined by the needs and requirements of the end user. For this project, the desire was to achieve a classification accuracy of greater than or equal to 90%. While an overall accuracy of 91.74% was achieved, the greatest accuracy achieved in identifying trees was 88.62%, which, in this case, would be below the required threshold. With further iterations and development of classification rules, it would be assumed that accuracy could be increased. This research has further demonstrated that, when accurate rules are developed, OBIA can be applied to homogenous areas to screen sites for unfavorable conditions and features. While there is considerable upfront investment in time to develop the rules for classification, once they are established they can be reused in future land acquisition campaigns within the same territory to generate similar returns.

5.2. Applications and Benefits

The guiding idea behind the use of OBIA in USSE was that it had the capacity to improve upon existing approaches to site selection, which are not scalable, time consuming, and prone to human error. To assess the real world applications of this research requires complex cost benefit analysis to determine if there is a favorable return on investment. This must be conducted at the level of an individual organization to consider their ability to fund the acquisition costs associated with VHR images and the specialized software required for OBIA. As each organization has a different approach to quantifying and justifying their investments in GIS, this research focused on the overall types of benefits that can come from the application of this technology (Croswell, 2009). To evaluate the potential benefits of using OBIA in USSE site selection a list of categories and descriptions created by Peter L Croswell to assess the impact of GIS was used.

Table 12: Potential benefits gained from the use of OBIA in USSE site selection (Croswell, 2009).

Category	Description	OBIA Benefits
Operational Efficiency Gains	Expected Gains in current personnel efficiency and productivity allowing work to be accomplished in less time.	• Using OBIA to assist in the site selection process works as a force multiplier allowing more sites to be reviewed in less time and with less personnel.
Cost Savings	Reduction in current expenses such as contract costs and salaries.	• Unknown and calculated per organization.
Cost Avoidance	Reducing or eliminating costs that would be incurred without the use of GIS technology, when new programs, regulatory requirements, or other new demands are placed on an organization.	• Using OBIA to asses, at scale, site conditions in the early phases of development results in more accurate cost estimations. • Early identification of possible construction impediments can disqualify a potential site before more labor hours are invested in its development.
Revenue Enhancement	Use of GIS technology and data in a manner that results in increased revenue from existing or new sources.	• Enhancement of unrealized future operating revenue by decreasing capital expenditures for site construction by favorable altering expected return on investment.
Non-Monetary Quantitative Benefits	Potential benefits that can be measured quantitatively but do not translate precisely into monetary terms.	• Unknown and realized on a per organization level.
Difficult to Predict Benefits	Benefits that are driven by external events and thus are not easily predictable or routine in nature and that are not easily reflected in a return on investment analysis.	• Unknown and realized on a per organization level.
Qualitative Benefits	Benefits that are not easily quantified yet have a positive impact on operations, decision making, quality of service, social conditions, or economic or environmental health.	• Quantified outputs of the OBIA process creates data that is relevant to the organization and can be shared to assist with decision making.

As seen in table 11, the benefits that can be realized by using OBIA to assist in the site selection process manifest in different ways. OBIA can contribute to operational efficiency gains, cost avoidance, revenue enhancement, and qualitative benefits. Cost savings, Non-Monetary quantitative benefits, and difficult to predict benefits are can only be calculated by the organization itself, as there are too many unknowns to make accurate predictions in these categories. Any organization that intends to implement OBIA into their current operations should conduct a thorough cost benefit analysis beforehand to accurately assess the impact it may have on their operations.

This research's intent was to validate the application of OBIA to assist in USSE site selection processes, and provide a conceptual framework which an organization can use to identify if OBIA has the potential to improve the site selection process. Due to OBIA being highly influenced by the specific inputs used, it will be difficult to exactly replicate the results of this research without identical inputs. While this can be done, it would be more advantageous for an organization to first asses their current, if any, RS data to identify if it can be used for OBIA or if VHR imagery must be acquired. By then following the framework provided in this research, an organization can assess if they can achieve their desired accuracy, and if the investment of capital required to extract value from OBIA is warranted.

5.3. Limitations

This project identified numerous limitations in the use of OBIA for the purposes of identifying construction impediments. Some of the limitations of OBIA, such as the need for VHR imagery, were expected and factored into the initial workflow. Unexpected limitations of OBIA became evident during the classification process.

5.3.1. Temporal

OBIA relies on VHR imagery as its primary input, and the temporal relevance of the image is extremely important to achieving accurate results. Rules written to classify trees during the summer months would struggle to classify the same trees in fall or winter. The seasonal transformation that many types of vegetation go through changes their physical appearance which for the purposes of OBIA would require that rules are specific to seasonal changes. For example, a deciduous tree loses it leaves in winter, resulting in a change in the spectral returns because of the lack of green leaves. These changes also effect, in a similar fashion, the textural and spatial attributes of an object. Additional seasonal changes, such as snow or drought, will also affect classification rules by altering the physical landscape. For example if the image being used is captured in winter, there can be snow on the ground and vegetation has gone dormant, this changes the physical characteristics of vegetation and as result their spectral returns.

5.3.2. Regional

Similar to seasonal changes, region is also a factor. Changes in the physical environment across a large utility territory would need to be accounted for in rule development. A service territory such as the Electric Reliability Council of Texas (ERCOT) that spans the entire state of Texas presents vastly different environments depending on the location of the state. Rules developed for classification in the south east of the state, where there are vast wetlands and rivers, would not necessarily apply to the arid lands of the Permian basin. This limitation constrains the rules to the region they were designed for, making it difficult to create a ruleset that would generate accurate results across a large area. This limitation can be mitigated, but only by breaking down large regions into more homogeneous subregions. This would require additional labor, but presumably would only need to be conducted once.

5.3.3. Complexity

OBIA's ability to classify multiple objects of different origin in one pass is a result of a complex process that means investigating the spectral, textural, and spatial attributes of an object of interest. The development of the rules requires an understanding of remote sensing and working with VHR imagery. The primary investigator required 3 months of studying, practicing, and trial and error until they had a confident understanding of how the process worked, and how to the adjust segmentation process and the rules to elicit the desired results. Even after spending considerable time working with ENVI FX and studying OBIA and rule based classification there is still much more to be learned to fully understand the process and underlying science. Because of the complexity of OBIA, it would require an employee with knowledge of the process to develop and implement the workflow, which is not a skill inherent in all GIS technicians.

The complexity of OBIA leads to another limitation imposed by the process, which is the upfront labor required to develop the rules. As discussed, OBIA is an iterative process and requires trial and error when identifying the correct scale and merge levels, and developing the rules. This research focused on one impediment, trees, and spent 3 months researching to create the simple rules employed in this project. To be completed at scale and capture the totality of a site's conditions, vastly more complex rules would need to be developed to identify a multitude of different features each with their own unique attributes. This would require considerable upfront capital expenditures and labor to achieve, something not always on hand.

5.3.4. Labor Investments

One noted limitation of this process is how labor intensive it is to set up. The requirement to understand the biophysical characteristic of the target area local environment is necessary to accurately segment and classify an image. This is further compounded by the limitations listed previously, which dictate that this process must be redone for each region of interest. The total man hours required to begin to achieve accurate results would, in this case, negate any time savings incurred by using OBIA in the screening process. One key benefit that arises from investing the time to develop rules is that they can be reused in the future should an area be revisited.

5.4. Areas of Further Research

This project intended to classify a multitude of features such as trees, roads, wetlands, and buildings. In the initial stages of the research it was determined that this would be difficult to achieve in the time required for this project. As such, a focus was placed on developing rules for only one class as a proof of concept. As such, there is still much research to be done to fully develop the ideas presented in this paper. This section discusses the ways in which this can be improved upon and further developed.

5.4.1. Objects

The first area that warrants further research is developing rules for the numerous site conditions that can be encountered. While this paper only focused on a handful of features and developed rules for only one, for OBIA to be truly effective in assisting site suability analysis workflows it must be able to identify all features or conditions that create impediments to construction. For this to be achieved properly, the individual developing the rules must understand the prevailing site conditions in the region and the features that are expected to be encountered. This process requires an upfront investment in time to study an area prior to developing the rules. Without this upfront investment, the process described here is unlikely to be successful.

5.4.2. Scalability

For OBIA to be successful it must be scalable. This relates to both area of interest and computational resources. The study area selected for this study was limited to 60 km^2 as a condition of the vendor who provided the VHR images for this project. For context, the Tennessee Valley Authority is approximately 207199 km^2, meaning only approximately .0002% of the service territory was included for analysis. To scale this workflow to cover a whole service territory would require an immense amount of capital to acquire VHR images for full area coverage. Working with a dataset of this size would require immense computational resources to process. These two factors would make this endeavor cost-prohibitive for many users.

5.5. Conclusion

There is a growing consensus that clean, renewable sources of energy are necessary to address global energy needs and address climate change. Solar energy provides passive clean energy generation but not without costs. Utility scale solar requires large areas of land, can displace local flora and fauna, encounters push-back from communities and environmental groups, and requires large capital expenditures. This makes it all the more important to find new ways to identify suitable locations for solar development.

This research explored the use of OBIA to assist in site suitability identification with a desire to eventually scale the process to be used on a large scale. While OBIA provided promising results, it also presented a number of obstacles that makes its use, at scale, a difficult but worthwhile endeavor. This research lays a framework that can be built upon by anyone willing to invest the time and resources, and identifies the opportunities and challenged in doing so.

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Appendix A

Figure 12: First Iteration Segmentation Image

Figure 13: Second Iteration Segmentation Image

Figure 14: Fourth Iteration Segmentation Image

Figure 15: Fifth Iteration Segmentation Image

Figure 16: Sixth Iteration Segmentation Image

Figure 17: Seventh Iteration Segmentation Results