An evaluation of high-resolution land cover and land use classification accuracy by thematic, spatial, and algorithm parameters

by

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Author’s Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Statement of Contributions

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Abstract

High resolution land cover and land use classifications have applications in many fields of study such as land use and cover change, carbon storage measurements and environmental impact assessments. The wide range of available imagery at different spatial resolutions, potential thematic classes, and classification methods introduces the problem of understanding how each aspect affects accuracy. This study investigates how these three aspects affect the results of land cover classification. Results show that the maximum likelihood classifier was able to produce the most consistent results with the highest average accuracy (82.9%). Classifiers were able to identify a spatial resolution for each thematic resolution that achieved a distinctly higher overall accuracy. In addition, the effects of different land cover classifications as input to an object-based classification of land use at the parcel scale were evaluated. Results showed that land use classification requires higher resolution imagery to obtain satisfactory results than what is required for land cover classification. Also, the highest accuracy land cover classification did not produce the highest accuracy for land use, where a higher number of thematic classes performs better than fewer thematic classes. The highest accuracy LC classification by MLC with 8 classes occurred at 640 cm and achieved an overall accuracy of 83.3%. The highest accuracy LU classification was produced by the 80 cm LC with 8 classes and achieved an overall accuracy of 88.0%. Aside from the produced land cover and land use classifications, this study produces a lookup table in the form of multiple graphs for future research to reference when selecting imagery and determining thematic classes and classification methods.

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List of Abbreviations

Abbreviation	Term
LC	Land Cover
LU	Land Use
LUCC	Land Use and Cover Change
OBIA	Object-Based Image Analysis
ISODATA	Iterative Self-Organizing Data Analysis Technique
MLC	Maximum Likelihood Classifier
SVM	Support Vector Machine
SAM	Spectral Angle Mapper
SWOOP	Southwestern Ontario Orthoimagery Project
ABM	Agent-Based Model
RAM	Random Access Memory
RDIMM	Registered Dual Inline Memory Module

1. Chapter 1: Land Cover and Land Use Classification

1.1 Introduction

Land cover (LC) is the biophysical characteristics of the land surface, which includes both natural and anthropogenic features (Brown, Robinson, French, & Reed, 2013). Land use (LU) can be defined as the human use of the biophysical assets of the land (Cihlar & Jansen, 2001). The composition of LC typically varies by land use (Robinson et al. 2013) and the composition and configuration of LC can be used as predictors of LU when classifying using remote sensing.

Depending on the typology of LU classes, multiple LU classes may have similar LC compositions and a single LU class can have large variation in the composition of LC found within. The presence and amount of each LC class in a LU class will be typically more similar within a local region (e.g. Verburg et al. 2000) and may vary among regions. This can be observed when comparing a residential subdivision on the periphery of Toronto, Canada, to a residential subdivision on the periphery of Shanghai, China, since local governments may have different restrictions on building regulations, or social differences which may influence a land owner's decision to change his/her land cover, such as building a pool (He et al. 2013). LC composition within a LU may also vary over time due to many factors including vegetation growth and human modifications (Huang et al. 2014). The spatial and temporal change in LU and LC is referred to as land use and cover change (LUCC).

To model and determine LUCC for purposes such as carbon budgeting or land-use planning, both LC and LU data need to be acquired. Although LC and LU data are primarily created from the classification of readily available remote sensing data, there is a chronic lack of usable LC and LU data for reasons such as costly production and little high resolution imagery with large extents (Verburg et al., 2011). LC and LU data needs to be temporally, spatially, and thematically consistent for effective LUCC analysis (Verburg et al., 2011) and can be classified by many different methods. Class definitions of LC and LU can be inconsistent across individuals and organizations (Cihlar & Jansen, 2001). LC class definition is difficult mainly due to the constant variation over space and the presence of multiple LC classes in the same pixel such as trees overhanging a road or the edge of a roof passing through a pixel. LC can also be difficult to classify due to fuzzy borders between non-anthropogenic classes, such as the transition area between two different forest types.

Three dimensions of LC and LU classification are investigated in this study. The first is the spatial resolution of the imagery and data products. This is defined in this study by the pixel size of the data, or the size of the polygons if considering vector data. The second dimension is the thematic resolution of the classes being used to define the landscape. A higher thematic resolution, similar to higher spatial resolution, has more classes describing the same landscape while a low thematic resolution has fewer classes. The last dimension being investigated is the method used for classification. This can be divided into unsupervised and supervised classifiers, and pixel-based and object-based classifiers as defined later in this paper. Although there are more dimensions of LC and LU classification such as spectral and temporal resolutions, only the three listed are being investigated.

1.2 Literature Review

An investigation into 70 articles published within the International Journal of Remote Sensing was conducted on studies performing LU classification and identifying the comparisons of three identified dimensions (i.e., spatial, thematic, classification method). Articles were selected by first using the search term: "land use classification" and then the first 70 articles (see Appendix A), sorted (by the journal's website) in order of relevancy on October 6th 2016, and were reviewed. Of the reviewed articles, none compared classification results with different thematic resolutions, 21 used at least two different classification methodologies and seven included the results of classifications that had a minimum of two spatial resolutions. None of the articles studied more than one of the three identified dimensions. The International Journal of Remote Sensing was selected because of its focus on how the imagery is processed instead of journals such as Remote Sensing which seemed to focus more on the topic of the study using remote sensing. The total of 70 articles was selected because there were too many articles to review all of them. After approximately 50 articles there was a noticeable decrease in the relevancy of each new article due to the studies simply using LU classification data instead of creating LU classifications.

1.2.1 Thematic Inconsistency in Land Use Classifications

A common problem among the 70 articles was the mix of LC and LU classes. In many classification schemes, there were LU classes in a LC classification and LC classes in a LU classification (Table 1). Thematic consistency across datasets is an important issue for global change studies (Verburg et al., 2011) and remote sensing specialists often consider LC and LU interchangeable (Barnsley, Møller-Jansen, & Barr, 2001). However, the mixing of LC into LU classifications not only causes confusion when using LU data, but also creates datasets that may have difficulty integrating with other projects due to the improper classes. If a class is labeled "water" or similar, it is considered LU as there is often no LU class which better describes a waterbody. For example, in a project by Man (2015) classifying urban LU, 5 of the 15 classes are actually LC classes, with one of the LU classes being water (Table 1). These data may not be usable in a model which requires LU input unless prior modifications are done. Additionally, this mixing of LC and LU may prevent the data from being usable in projects such as LU change or carbon flux estimates.

Table 1: Land use classifications with land cover classes included used by the first 25 papers found in the search. Papers omitted from the 25 papers either stated the classification was a mix or did not have any land cover classes.

Paper	# of LC classes	# of LU classes
(Horgan, Glasbey, Soria, & Gozalo, 1992)	3	3
(Schneider, Buhk, & Ammer, 1999)	7	5
(El-Magd & Tanton, 2003)	5	6
(Broek, Smith, Toet, Smith, & Land, 2004)	3	2
(Özkan & Erbek, 2005)	7	5
(Frey, Rigo, & Parlow, 2007)	4	7
(Ashish, Mcclendon, & Hoogenboom, 2009)	6	1
(Man, Dong, & Guo, 2015)	5	10

The mixing of LC into a LU classification can have benefits and disadvantages. The main benefit is to assist in describing low resolution imagery when the resolution is too coarse to accurately determine the true land use (e.g. Özkan & Erbek 2005). Özkan uses several LC classes in a LU classification on the relatively coarse resolution imagery obtained from Landsat. Assigning a LC class may not represent the LU as desired, it may add information that can be used to assume LU in future models and calculations.

Mixing LC into LU classifications also creates problems when using the data in future applications such as carbon stock analysis. Don et al (2011) uses LU to determine changes in soil organic carbon between different natural and agricultural LU types. Having LU and not LC is important in their calculations because similar LC may occur in many different LU classes. For example, two of their classes are “cropland” and “grassland”. Both of these classes may have similar LC classes at certain times of the year. If the LC class “grass” was used in their dataset instead of “cropland” and “grassland” the use would not be known at certain times of the year and therefore the amount of soil organic carbon may not be accurately measurable.

Modelling LU change is also effected by thematic consistency. Many studies which use models or simulations to predict LU change use datasets with purely LU classifications (e.g., Hamers & Piek, 2012; Kelley & Evans, 2011; Martinuzzi et al., 2015). This is needed to show the change from one LU class to another. If a LC class was used in the datasets their model would not be able to predict its change without altering the model to accommodate for LC classes. Studies like these that model LU exclusively need thematic consistency within their LU datasets as pointed out by Verburg et al (2011).

To address this issue in consistency the Anderson (1976) classification was created to standardize LU and LC classes across classifications made from a variety of imagery and data sources. A lingering problem with Anderson’s classification scheme is that it is a mix of LC and LU. Anderson’s first two levels of classification were designed for coarser resolution imagery with Landsat being used for the first level and scales of 1:80,000 or less being used for the second level. The third and fourth levels are designed for finer resolution imagery with scales of 1:80,000 and finer, which is similar to the imagery used in this study. At these finer levels the classification represents detailed LU more exclusively and no longer have LC classes. For example, instead of “urban or built-up land” in level I, there are classes such as “residential” in level II, and “single family units” in level III.

1.2.2 Land Cover Classification

LC can be classified from satellite and aerial images (Table 2) by a variety of different methods (Table 3). These methods can be described by the type of classification (i.e., per-pixel or object based, although manual digitization is also possible) and the amount of user input (e.g., training data, manual classification, and class descriptions).

Table 2: Data Used in Land Cover and Land Use Classification by a Selection of Reviewed Papers

		Land Cover												Land Use	
	Paper	(Imani & Ghassemian, 2014)	(Jiang et al., 2012)	(Li et al. 2014)	(Lu et al., 2004)	(Memarian et al., 2013)	(Van Niel et al., 2005)	(Park & Stenstrom, 2008)	(Reddy & Reddy, 1996)	(Ren et al., 2011)	(Satyanarayana et al., 2011)	(Shao & Lunetta, 2012)	(Wentz et al., 2008)	(Lackner & Conway, 2008)	(Hu and Wang 2013)
Resolution	Low (e.g. MODIS)	X	-	-	-	-	X	-	-	-	-	X	-	-	-
	Medium (e.g. Landsat)	-	X	X	X	-	-	X	X	-	-	-	X	-	-
	High (e.g. Quickbird)	-	-	-	-	X	-	-	-	X	X	-	-	X	-
	Very High (e.g. Aerial Imagery)	-	-	-	-	-	-	-	-	-	-	-	-	-	X
Additional Data	Road Network	-	-	-	-	-	-	-	-	-	-	-	-	X	-
	Ownership Parcels	-	-	-	-	-	-	-	-	-	-	-	-	X	X
	Lidar	-	-	-	-	-	-	-	-	-	-	-	-	-	X

Note: “X” = Present “ - ” = Not Present

Unsupervised classifiers do not require the user to define what comprises a class (Imani et al. 2014; Jiang et al. 2012) or the number of classes to be identified (Li et al. 2014). Unsupervised classifiers are generally not used as they do not achieve high accuracy in most scenarios (Li et al. 2014). Unsupervised classifiers excel when classifying LC classes which have drastic differences in spectral signature (Li et al., 2014; Singh et al., 2013) for example, water and impervious surfaces. When a large spectral difference is present, no training is needed for the classifier, which greatly reduces the processing time. To determine what each identified class represents, the user needs to compare the classes to the original image and assign a name (Li et al. 2014). An example of an effective unsupervised classification may be to automatically classify impervious surfaces in a landscape for urbanization monitoring due to the large spectral difference between vegetation and impervious surfaces such as concrete.

In contrast to unsupervised classifiers, supervised classifiers require more human input to create class definitions for an image. Supervised classifiers use manually defined training samples to classify an image (Jiang et al., 2012; Shao & Lunetta, 2012). A commonly used supervised classifier is the Maximum Likelihood Classifier (MLC) (Table 3). MLC uses training samples to create probability curves in multidimensional space which contains the likelihood of a pixel belonging to each of the included classes. When a pixel is being classified, it is compared to its location in the multidimensional space and is assigned to the class which has the highest likelihood of being true. In general, the MLC performs consistently well across imaging platforms (e.g., Landsat, SPOT-5, aerial) and spatial resolutions, although it is not guaranteed to be the most accurate supervised classifier under all conditions (Li et al. 2014). Performing well at large spatial extents results in requiring fewer sets of training samples due to the fewer classifications performed. Some advantages to MLC is that it is easy to use, well defined, and has been accessible to researchers for many years (e.g. Reddy and Reddy 1996; Memarian et al. 2013). The high accessibility of MLC gives a benefit of being well known by many researchers and used in many studies, allowing new results of MLC to be compared against many studies. MLC is common in many software packages such as ArcGIS, ENVI, and PCI Geomatica, and requires little user training to use. A disadvantage to MLC is the assumption that the data is normally distributed while the class definitions may not be normally distributed. For example, if the class of "trees" is being used, and includes both deciduous and coniferous trees in the spring, the data will have two peaks in the distribution and will not be normal. Other available classifiers include the Support Vector Machine classifier (SVM) (Marconcini et al. 2014) and the Spectral Angle Mapper (SAM). While these two have the potential to outperform MLC, it has been shown that they perform poorly when classifying multiple urban LU classes (Li et al. 2014).

Table 3: Classification Methods Used by Selected Papers

Classification Method	Land Cover													Land Use	
	(Hu & Wang, 2013)	(Imani & Ghassemian, 2014)	(Jiang et al., 2012)	(Li et al. 2014)	(Lu et al., 2004)	(Memarian et al., 2013)	(Van Niel et al., 2005)	(Park & Stenstrom, 2008)	(Reddy & Reddy, 1996)	(Ren et al., 2011)	(Satyanarayana et al., 2011)	(Shao & Lunetta, 2012)	(Wentz et al., 2008)	(Hu & Wang, 2013)	(Lackner & Conway, 2008)
MLC	X	-	-	X	X	X	X	-	X	-	X	-	-	-	-
OBIA/Feature Extraction	-	X	-	X	-	X	-	-	-	-	-	-	-	-	X
Decision Tree	-	-	-	X	-	-	-	-	-	-	-	X	-	X	-
Spectral Mixture Analysis	-	-	-	-	X	-	-	-	-	-	-	-	-	-	-
Support Vector Machine	-	-	-	X	-	-	-	-	-	-	-	X	-	-	-
Neural Network	-	-	-	X	-	-	-	-	-	-	-	X	-	-	-
K-Means	-	-	-	X	-	-	-	-	-	-	-	-	-	-	-
ISODATA	-	-	-	X	-	-	-	-	-	-	-	-	-	-	-
Radial Basis	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Hybrid Expert System	-	-	-	-	-	-	-	-	-	-	-	-	X	-	-
Bayesian Network	-	-	-	-	-	-	-	X	-	-	-	-	-	-	-
Minimum Distance	-	-	X	-	-	-	-	-	-	-	-	-	-	-	-
Regression Models	-	-	-	-	-	-	-	-	-	X	-	-	-	-	-

One factor which limits the accuracy of all supervised image classifiers is the quality of training samples (Van Niel et al. 2005). If too few samples are taken, the accuracy can be poor (Li et al. 2014). The general rule for the recommended number of training samples is between 10n and 30n for each class, where n represents the number of image bands used in the classification (Van Niel et al. 2005; Park and Stenstrom 2008). However, it has been shown that only 2n to 4n training samples may be required to achieve 95% of the accuracy obtained using the recommended number of training samples (Van Niel et al. 2005). Other research confirms similar results, with some saying a maximum of 10n training samples is needed for MLC (Piper 1992). These findings show that the accuracy only marginally improves when the number of training samples increases from 10n towards 30n (Piper 1992).

One issue with relying on only a pixel's value to classify LC is the presence of mixed pixels (Lu et al., 2004). Mixed pixels contain multiple LC classes within the single pixel, which results in the pixel value not fully representing any of the desired classes (Lu et al., 2004; Shao & Lunetta, 2012). Increasing the resolution of the image can reduce the number and impact of mixed pixels on an image, (Lu et al., 2004) but it may also increase pixel value variation within classes.

Object-based image analysis (OBIA) can be used as an alternative to per-pixel classifiers to account for the increased variation within classes (Memarian et al., 2013). An OBIA approach is partially insulated from the effects of mixed pixels as it uses groups of pixels, called objects, to perform the classification. Homogenous areas are extracted from the imagery by the OBIA to form the objects. These objects are classified based on spatial attributes such as shape and size, and the distribution of spectral signatures within the object (Lu et al., 2004; Memarian et al., 2013). The use of objects reduces the impact of mixed pixels as they represent a small proportion of the group of pixels of which they comprise and therefore have very little impact on the object's attributes. Once a number of objects have been identified, a number of classification techniques, often similar to the per-pixel techniques (e.g., MLC and SVM) can be used to assign classes to objects.

1.2.3 Land Use Classification

Remote sensing is only capable of capturing the matter which physically resides on the surface of the earth (i.e., LC) and cannot measure LU directly. Although there is no simple one-to-one mapping between LC and LU, a prediction of LU can be derived from the patterns found in LC. Since multiple LU types can be found in the same location (i.e., a forest being protected for conservation can also be a recreational area) ancillary data is required in addition to the imagery. These data can be combined and classified with OBIA into homogeneous regions of LU (Lackner & Conway, 2008). The homogeneous regions of LU can be determined through analyzing the imagery through OBIA, but this usually requires expensive software and hardware with large amounts of processing power and time (Lackner & Conway, 2008). A much simpler and faster source of obtaining homogenous regions of LU is using ownership parcels, which will typically only contain one LU (Hu and Wang 2013; Lackner & Conway, 2008).

Two of the object-based classifiers within eCognition are decision tree and random forest (Trimble, 2015). The decision tree and random forest classifiers are similar. The decision tree analyzes the sample data for threshold values within a single variable to create subgroups of objects that are more similar to each other than to objects in other subgroups (Tehrany et al. 2013; Trimble

2015). This is done again for each of the subgroups using any of the available variables to further segment the data until only subgroups of homogenous LU classes are created, or there are no more identifiable thresholds. When displayed in a logic diagram, the sets of decisions for each threshold resembles a tree (Figure 1). The tree is then applied to the entire dataset to classify every object.

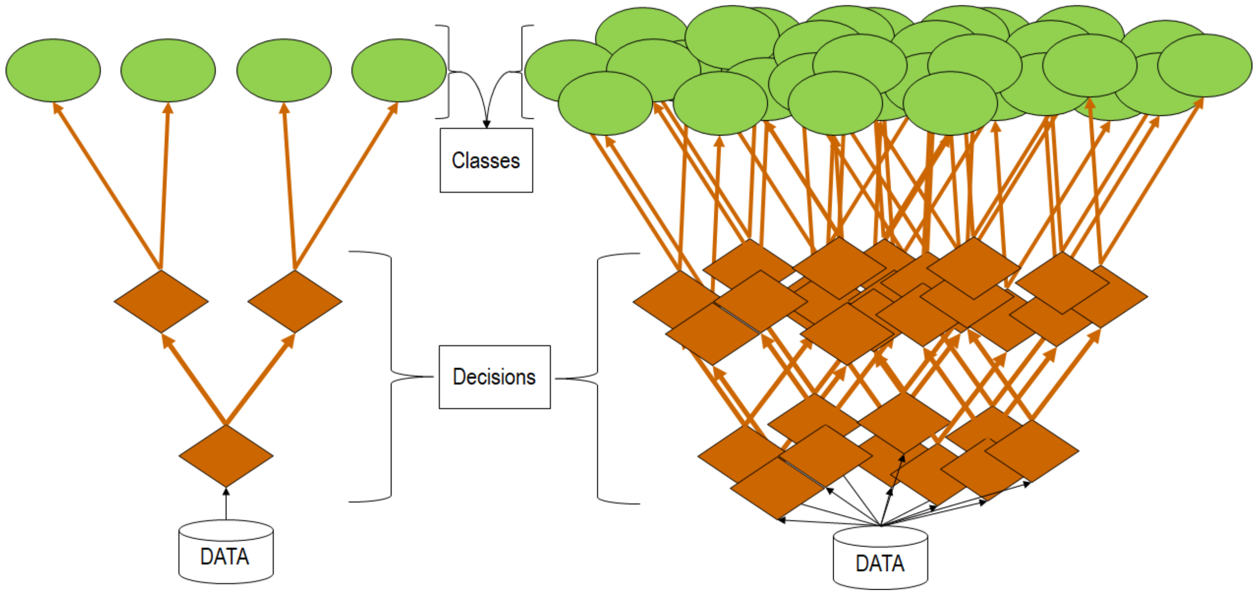

Figure 1: Left: Decision Tree; Right: Random Forest

The random forest classifier uses a similar process to the decision-tree classifier, however, a random forest classifier creates multiple decision trees using random subsets of the sample data (C. Li et al., 2014; Trimble, 2015). The collection of trees created represents the forest referred to in the name "random forest" (Figure 1). Each object is then analyzed by each tree in the forest the most common LU class determined by the collection of trees in the forest is assigned to the parcel. The decision trees can analyze any variable which can be represented in an attribute table, such as the composition of LC classes within the object or shape characteristics (eg. Hu & Wang, 2013).

LU can also be automatically classified directly from imagery, but often results in a lower thematic resolution than OBIA. Per-pixel classifiers, such as the MLC, are reported to produce low resolution LU classifications due to relying solely on pixel reflectance values (Memarian et al., 2013). The imagery used for direct LU classification often has a low-to-medium resolution of 15 m to 30 m, and includes at least the visible and near-infrared bands (e.g. Wentz et al. 2008). It is possible to increase the accuracy by manually classifying difficult classes such as public institutions, mines and golf courses (Wentz et al., 2008). An example of automatic LU classification directly from imagery is a study conducted in the Amazon using Landsat TM images (Lu et al., 2004). This study claimed to achieve a highly accurate classification (86.6%), although many spectrally similar classes were merged to avoid classification confusion. An example is the "bare land" class, which included urban areas, roads and bare soil, which can be difficult to distinguish apart, yet are significantly different in use.

The three core concepts identified during litterature review which affect image classification for LC and LU are the thematic resolution, spatial resolution and classifier used. Thematic resolution defines what features in the images will be classified while spatial resolution defines the scale at which the features will be classified. The classification method determines the algorithms used to both train the classifier and to apply the classification to the image. In this study these three concepts are compared against each other to determine their affects on the accuracy of the resulting classifcation. To compare each of these concepts a combinatorial study was completed which classified imagery into LC with multiple thematic and spatial resolutions for multiple classifiers. These LC classifications for the best classifier were then used to classify LU at the parcel scale. The results are compared in terms of overall accuracy, and the type of confusion between classes and its amplitude for all combinations.

1.3 Overview of Thesis and Methods

This thesis aims to answer two research questions: "what combination of spatial, thematic, and classification methods produce the highest LC and LU accuracy?" and "what is the relationship between LC and LU?" The objective of completing this research is to better understand the relationship between spatial resolution, thematic resolution, and classification method and LC and LU classification accuracy. This will be achieved through three goals: 1) determine the optimal combination of spatial resolution, thematic resolution, and classification method for the classification of LC and LU; 2) examine the effect of spatial resolution, thematic resolution and classification method on the accuracy of LC classification; and 3) examine the effect of spatial resolution, thematic resolution and classification method of LC classification on the accuracy of object-based LU classification when LC is used as an input with property parcel data.

The general structure of the methods follows the diagram in Figure 2. The diagram is repeated for each LC classifier. First, the imagery is resampled into eight different pixel sizes. Then each pixel size is classified into four different sets of LC classes, or Thematic Typology, by the current classifier. The resulting 32 LC classifications then have their accuracy assessed by the four sets of samples created for this step, one for each Thematic Typology. Parallel to this, 20 of the 32 LC classifications which fall into the spatial resolution limits are classified for LU by the OBIA classifier. The reason behind these limits are explained in section 2.3.4 in Chapter 2. Similar to LC, the 20 LU classifications are assessed for accuracy using the LU samples created for this step. This is then repeated for all remaining LC classifiers.

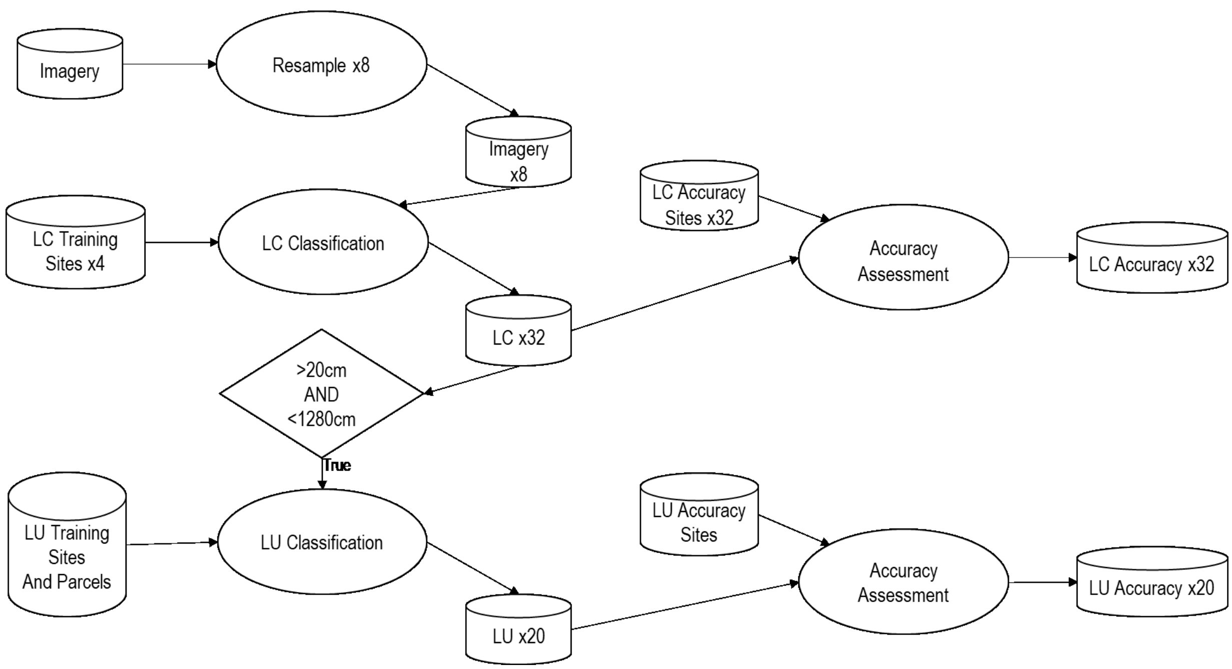

Figure 2: Process flow diagram of the methods used in this thesis for each LC classifier

The four pixel based LC classifiers being used are ISODATA, MLC, SVM, and SAM, although ISODATA did not provide usable results. ISODATA is the only usupervised classifier of the four, while the rest are supervised. It assess the pixel values in the imagery to find distinct groups of pixel values which should represent unique classes. Each pixel is assigned to the most similar group of pixel values. MLC used training samples to determine the probability of each combination of pixel values belonging to each defined class. During classification, each pixel is assigned the most likely class for its combination of band values. SVM creates a hyperplane through the data which best divides two classes based off training data. During classification each pixel is assigned to a class based off which section of the space it is in. For more than two classes a pairwise classification is performed by the classifier. SAM uses the spectral angles between the training data and the unclassified data to assign the class which with the lowest spectral angle.

These four classifiers were chosen to represent several general types of classifiers. ISODATA was selected to represent the unsupervised classifiers, SVM was selected to represent the machine learning classifiers, SAM was selected to represent the hyperspectral classifiers and MLC was selected as it was the most common classifier in the reviewed literature. Although many classifiers exist in many categories, these four were readily available and the author believe they represent a large portion of per-pixel classifiers.

2. Chapter 2: Quantifying the Effects of Thematic Resolution, Spatial Resolution, and Classification Methods on Land Cover and Land Use Classification Accuracy

2.1 Introduction

Land use and cover change (LUCC) is the second greatest source of anthropogenic greenhouse gases, accounting for 12% to 20% of annual emissions (Don et al. 2011), and historically ~30% of all emissions (Sundquist, 1993). The impacts of LUCC can be identified from the global environment down to local regions (Don et al., 2011). These changes are visible in many areas such as protected areas where it may impact the available habitat (Martinuzzi et al., 2015) or alter the carbon storage of the region, both of which contribute to global greenhouse gases. Because of the impacts of LUCC, it is important to monitor and model land cover (LC) and land use (LU) patterns to estimate greenhouse gas emissions and for the protection of the natural environment from anthropogenic damages such as pollution (Jiang et al., 2012).

Driven partly by increasing global population, LUCC occurs to meet increasing resource requirements (Ren et al., 2011) such as food, building materials, and building space. For example, as urbanization occurs and cities need to accommodate higher populations they tend to expand. The expansion may be vertical through the building of apartments or condominiums, horizontally, through the creation of residential suburban landscapes, or by decreasing living space which increases population density. Horizontal expansion of cities commonly transforms agricultural and forested lands to urban lands (Hamers & Piek, 2012). A decrease in agricultural land may then force other non-agricultural and natural lands to be converted into agricultural land if agriculture yield density does not increase (Pearson & Brown, 2013).

Due to the heterogeneity of economic, environmental and social drivers of LUCC acting over space and time, the outcome of LUCC may also vary. For example, the amount of change in agricultural area and urban area in one region differ from other regions (Haas et al. 2015). This difference may be caused by many different drivers such as different rates of population growth, agricultural practices or government influences. Due in part to these differences, specific case studies and models are often created to accurately measure, monitor, predict or use LUCC (e.g., Luus, Robinson, & Deadman, 2011; Derek T. Robinson et al., 2013). If a general LUCC model or method is used it may miss drivers of LUCC which are specific to the system under study and may produce inaccurate results.

Typically, LUCC is measured and monitored using data acquired through remotely sensed imagery obtained from satellite or airborne platforms. While research using LC and LU classification has occurred for decades with great success, there has been relatively few comparative analyses that evaluate the effects of spatial resolution, thematic resolution, and classification method in combination on classification accuracy. Instead where comparisons have been made they have focused on classification method comparison at specific spatial and thematic resolutions. (e.g., Gong & Howarth, 1992; Man et al., 2015; Novack, Kux, Feitosa, & Costa, 2014). The comparison of spatial resolution or thematic resolution are less common and are secondary to the research problem (e.g., Banzhaf, Grescho, & Kindler, 2009; Royer, Charbonneau, & Bonn, 1988). To the best of the authors knowledge, no research has combined at least two of these three attributes of LU classification to determine the optimal combination. The optimal combination is being determined because determining the ideal combination would require many more combinations to be compared to find the best possible combination. Knowing the predicted optimal combination of these attributes will allow a researcher to pick spatial and thematic resolutions and classification method which will produce an expected outcome within the project requirements.

Satellite and aerial images show LC through picture element (i.e., pixel) values representing the spectral reflectance of the surface of the Earth within the area represented by the pixel. Several different image classifiers can be used to determine which user specified LC class represents each pixel. Multiple factors affect which LC classes can be used, such as the physical location represented in the image and the spatial resolution. Different areas such as urban or rural will require different LC classes to accurately describe what is observed in the image. Also, as the pixel size increases, the LC classes must become more general as they will begin to represent groups of features since the features themselves are smaller than the pixel (creating a one-to-many relationship). For example, the creation of a class for residential buildings comprising a sloped, shingled roof, may be appropriate with a pixel size of 20 cm but the building may not be observable with a pixel size of 30 m, where "low density impervious surfaces" or "high density impervious surfaces" may be more appropriate LC classes.

Complementing what physically resides on the surface of the earth (i.e., LC) are the activities of humans at a given location (i.e., LU). Unlike LC classification, classifying LU directly from a remotely sensed image is difficult. Instead LC is typically used as an input in the classification of LU (Lackner & Conway, 2008). Classifying LU is typically more difficult than classifying LC because standard classes are not as well defined in literature compared to LC classes (Lackner & Conway, 2008) and contributes to multiple LU types potentially describing the same area. Boundaries to represent LU can be determined by several methods of segmentation.

Imagery can be manually segmented by interpreting the imagery to estimate the borders of each LU. Automatically segmenting the imagery can be done using parcel (property boundary) information to avoid some of the difficulties of manually determining these boundaries (Lackner & Conway, 2008). There are several challenges of determining LU boundaries which manual segmentation or parcel segmentation does not address. Neither method fully eliminates the problem of multiple LU types occurring simultaneously, although this issue will be reduced.

Another challenge is finding LU boundaries where no visible boundaries exist. Parcel segmentation solves more of this issue than manual segmentation but neither fully solve the problem. If there is no fence, road, hedgerow, or other visible boundary an estimation must be made. The lack of a visible boundary also suggests that there may be a transition zone where LU from either side of the boundary may be applicable. Multiple LU may also appear identical, or near to identical, such as protected forests and forests for lumber or recreation.

The LC composition within parcels can be used to predict which LU class is most representative (Hu and Wang, 2013). The parcel size and LC composition are two of the many variables available for LU classification, but many other parcel spatial properties can be calculated and used within software packages (e.g. Trimble 2015). Ideally urban parcels will have one LU as the owners will be regulated through zoning and by-laws. This restriction forces parcels to be similar to other parcels of the same LU. For example, two parcels used for residential purposes should appear more similar to each other than to a parcel used for commercial purposes. This is because of the amounts of the composing LC classes will be similar. Residential parcels will have a house and likely also have a front and/or back yard and a parking area such as a driveway. Although urban core properties may lose their yards or parking spaces, they will always have a house.

Commercial properties also share similarities in that they all comprise a building to conduct business and typically a parking area. Similar to residential properties, commercial properties may lose their parking areas if located in an urban centre as visitors will either park underground, in public lots, use public transportation, or arrive on foot or bicycle. Patterns in LC such as the examples provided along with the aforementioned spatial properties of a parcel can be used together to determine which LU type to classify the entire parcel.

Some LU classes have similar LC compositions, such as commercial and industrial, and can be more difficult to differentiate (Lackner & Conway, 2008; Park & Stenstrom, 2008). Similar LU classes may be easy to distinguish by human, but computers have a difficult time and need to use optical patterns (i.e., imagery) and ancillary data to determine the LU class. Using parcels, or other methods of segmentation to determine LU boundaries, allows for more information to be used in the classification than simply assigning LC classes to LU classes (Jiao et al. 2012) or using LC patterns alone. Although similar LU classes may be easier to classify with the incorporation of additional data into the classification process, they typically have a lower accuracy than spectrally and LC-pattern distinct classes.

The presented research uses a systematic approach to LC and LU classification to evaluate "what combination of spatial, thematic, and classification methods produce the highest LC and LU accuracy?" and "what is the relationship between LC and LU?" By answering these questions, the presented research 1) contributes to the literature by defining a relationship between LC and LU accuracy and spatial and thematic resolution, and classification methods; 2) creates a methodology to determine optimal combination of resolutions to produce the highest accuracy LU; and 3) produces a novel data set for a region lacking detailed LC and LU data.

2.2 Methods

2.2.1 Data

Airborne remotely-sensed imagery was acquired from the Southwestern Ontario Orthoimagery Project (SWOOP) for 2010. The imagery has a resolution of 20 cm and has three visible bands and one near-infrared band. The SWOOP imagery covers Southwestern Ontario during April and May, which is the leaf-off period of the year for this region. The leaf-off period is prior to bud break and leaf growth and after snow melt. Grasses for lawns, winter crops, and coniferous trees or shrubs are the only sources of green vegetation in the imagery. The SWOOP imagery was selected for multiple reasons. The imagery contains no cloud cover which guarantees complete coverage of the study area. The small pixel size also allows for resampling to larger pixel sizes without using alternative sensors such as Landsat or Sentinel. The SWOOP imagery also was calibrated before distribution, decreasing the amount of preprocessing required. Together these two reasons help to ensure that the results can be duplicated for other study areas within the SWOOP extent for multiple years.

Parcel boundary data for 2010 was acquired from Teranet to define regions of homogeneous LU. Due to privacy issues and the proprietary nature (cost and sharing agreements) of the data, acquired parcel data are void of attribute information such as ownership or land use zoning information. Although zoning information could be collected from alternate sources, using only parcel boundary data increases the replicability of this study.

Although some LC and LU products do exist for Southwestern Ontario, they either have low resolution or classification inconsistencies and inaccuracies. Three available datasets for Southwestern Ontario include two Agriculture and Agri-Food Canada (AAFC) datasets mapping LC and a product from DMTI Spatial Inc. (DMTI) mapping LU. The first AAFC LC classification was created for 1990, 2000 and 2010 with low spatial (30 m) and thematic resolutions (e.g. only two urban LC classes representing roads and urban). A second AAFC dataset created in 2011 for Ontario, has only one class which represents both urban areas and roads, 48 classes for natural features such as water, trees and crop types, and a 30 m spatial resolution.

The company DMTI created a dataset for Southwestern Ontario which classifies parcels for LU in 2002 and 2007. Although the spatial resolution of this dataset is sufficient to accurately display urban areas, the thematic resolution could be improved. The classification only includes one residential class and does not have a class to solely represent roads. The road class in the DMTI dataset is a separate classification which overlaps with the main classification. The DMTI data are not consistent over time and use different classification methods. Furthermore, there exists parcel omissions from the LU classification where they are classed as “not mapped”. Issues similar to those found in both the AAFC and DMTI datasets are also found in other datasets for Southwestern Ontario to various degrees. There exists a need for a standard and justified methodology to classify LC and LU to make a series of datasets which can be used for LUCC studies.

2.2.2 Training and Accuracy Sample Selection

For classifier training and accuracy assessment of LC, multiple sets of sample data are required. A per-pixel classification of LC requires two sample datasets (one for training and one for accuracy assessment) with the number of sample sites being at least ten times the number of image bands used (Park & Stenstrom, 2008; Piper, 1992; Van Niel et al., 2005), with each sample incorporating as many pixels as possible. All sample sites are located in the middle of homogenous segments of known LC classes to avoid mixed pixels with larger pixel sizes.

The classes used consist of four Thematic Typologies where each one is an aggregated version of the previous, finer resolution, Thematic Typology. Aggregation is used to define more coarse typologies instead of collecting new samples to avoid bias due to training sample selection. Another set of training data are created the LU classification. The LU sample sites have only one Thematic Typology and use property parcels as the LU boundaries with approximately the same number of samples per class as the LC sample sites. Some LC and LU classes were not able to achieve the desired number of sample sites. This is due to these classes not having acceptable sample sites occurring at a high enough frequency to collect more without sampling the entire population. These classes become apparent during the collection of training sites when it becomes difficult to find new suitable sites and the existing site appear to represent the population rather than a sample. A suitable site can be described as large enough that it will still be visible at coarser resolutions. Additionally, it is far enough from the edges that there will be as few mixed pixels as possible at the coarser resolutions. Some LU classes have more samples because they represent large portions of the landscape and require more samples to account for their increased representation.

To reduce error, spatially diverse training and accuracy sites are selected within the region. Samples for each class are selected from a variety of areas to attempt to prevent any neighborhood of specific building age or household income level from being neither under represented nor over represented. This process was done by finishing one class before moving to the next, and finishing all of the training samples before selecting the accuracy samples. Completing the whole class at once was done to ensure there was no accidential overlap to prevent a neighborhood or subdivison from being over represented. Finishing the training sample creation before starting the creation of accuracy samples was done to separate the same classes within each sample to further prevent selection bias. The samples being used for accuracy assessment of LC and LU classifications were completed before the classification was conducted to avoid any bias.

Two other methods of sample selection were considered. Using randomly placed points (e.g. Hu et al., 2013) was initially considered but not used because several classes in both LC and LU would have a very high chance of being missed. For example, two of the LC classes “water” and “shadow” and two of the LU classes “low density residential” and “under development” would need special attention to ensure samples were collected. Another method which was considered was to use transects across the study area (Tenenbaum, Yang, & Zhou, 2011) and classify all LC or LU touching these lines. This method was attempted but implementation required an exended amount of time and it was difficult to identify an unbiased approach that captures the desired classification classes.

2.2.3 Study Area

The Region of Waterloo was chosen as a study area to determine the optimal methods which can be applied to the entire area of Southwestern Ontario (Figure 3) in the future. The Region of Waterloo has been chosen because the region contains a variety of LC and LU which is found throughout Southwestern Ontario. Kitchener, Waterloo and Cambridge are the only three cities within the region, and contain almost all the urban LC and LU classes which are found in Southwestern Ontario. Each city contains a downtown core with multiple types of residential (e.g. high and medium density) and commercial (e.g. single store and malls) properties, as well as suburban sprawl. The surrounding rural areas contain similar LC and LU to most of Southwestern Ontario, including many different types of agriculture and contain several lakes and conservation areas.

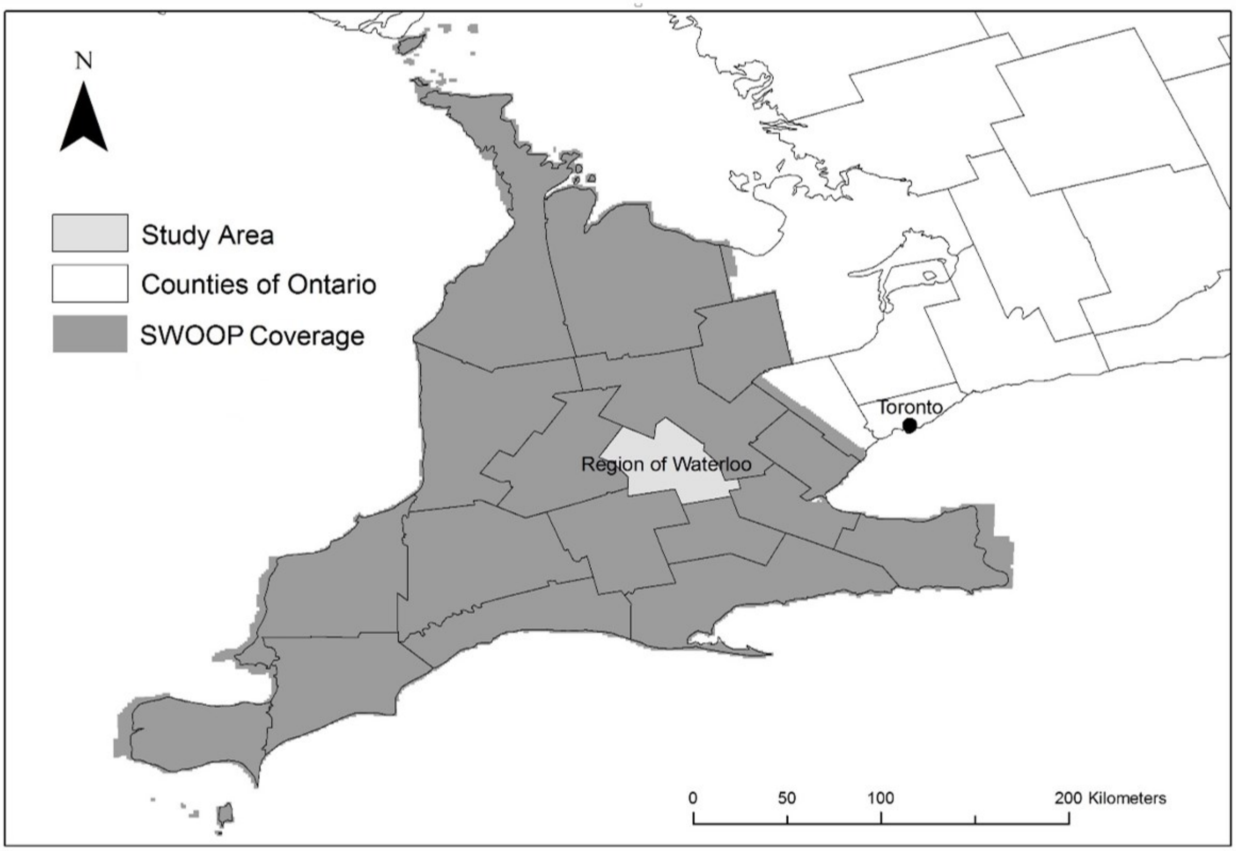

Figure 3: Study Area in Southwestern Ontario, Canada

2.2.4 Land Cover Classification

Classification of LC was performed using SWOOP imagery and manually collected training samples. Several classification attributes were modified and tested in the study area to determine the optimal settings for the specific datasets. These attributes include image resolution, classification techniques, and class resolution. Conducting these tests identify the trade-offs among the attributes and inform the choice of a final classification approach. This classification approach can be used in the future to classify the entire dataset to obtain the LC for all of Southwestern Ontario.

Four pixel-based classification techniques were applied, which included one unsupervised classifier (Iterative Self-Organizing Data Analysis Technique, ISODATA) and three supervised (Maximum Likelihood Classifier, MLC; Support Vector Machine, SVM; Spectral Angle Mapper, SAM, classifiers. The best of these classifiers was then chosen to be compared against an object-based image analysis classification using a random forest classifier.

The classifiers for LC were partially processed in ArcMap using plugins from the software called ENVI. The ISODATA classifier was run with various settings in an attempt to create an accurate result. None of the results were usable and accuracy was not able to be confidently assessed. MLC was used with no thresholding to guarantee all pixels receive a value. SAM was also used without any thresholding for the same reasons. The results from SVM were processed by ArcMap's built-in classifiers and the recommended default settings were used.

Each of the four pixel-based classifiers was used to create 32 LC classifications by classifying the data at eight spatial resolutions and four thematic resolutions (Table 4). The first spatial resolution is the original imagery resolution of 20 cm, with coarser resolutions derived by degrading the original resolution by a factor of two, up to 25.6 m (i.e., 20, 40, 80, 160, 320, 640, 1280, and 2560 cm). The spatial resolutions were created by aggregating pixels and assigning a value based on cubic resampling prior to classification. Using a factor of two ensured four whole cells from the previous resolution were used and to reduce the amount of images needed to reach 2560 cm. The upper limit of 2560 cm was chosen, to coincide with the freely available Landsat imagery for comparison by other project team members. To reduce the misclassifications caused by noise or static in the imagery, a majority filter is applied after classification. The majority filter takes each pixel with the eight surrounding pixels and reclassifies the original pixel to the most common value of the nine pixels.

In addition to testing the spatial resolution on land-cover and land-use classification, the thematic resolution was investigated by altering the number of LC classes. Four typologies of LC classes were tested with each subsequent typology becoming more general through aggregating previous similar classes (Table 4). Each set of LC thematic typologies and spatial resolutions was used to classify LU to determine the optimal combination of thematic and spatial resolution of LC classification to use as input to the LU classification. Due to the imagery available and the automatic classification of the imagery, Anderson's classification is being used as a template to guide the selection of classes in this thesis (see Appendix B). This will allow the classification to be compared to other studies which also use Anderson's classification as guide for their classes.

Table 4: LC Thematic Typologies and Hierarchy

<table>
<tr><th>Typology #</th><th>1</th><th>2</th><th>3</th><th>4</th></tr>
<tr><td rowspan="8">Classes</td><td>Water</td><td>Water</td><td>Water</td><td>Water</td></tr>
<tr><td>Shadow</td><td>Shadow</td><td>Shadow</td><td>Shadow</td></tr>
<tr><td>Grassland/Pasture/ Maintained Lawn</td><td rowspan="2">Green Vegetation</td><td rowspan="2">Green Vegetation</td><td rowspan="4">Pervious Surfaces</td></tr>
<tr><td>Coniferous</td></tr>
<tr><td>Deciduous</td><td rowspan="2">Brown Vegetation and Soil</td><td rowspan="2">Brown Vegetation and Soil</td></tr>
<tr><td>Cropland and Bare Soil</td></tr>
<tr><td>Pitched Roofs</td><td>Pitched Roofs</td><td rowspan="2">Impervious Surfaces</td><td rowspan="2">Impervious Surfaces</td></tr>
<tr><td>Pavement/ Flat Roofs</td><td>Pavement/Flat Roofs</td></tr>
<tr><td># of Classes</td><td>8</td><td>6</td><td>5</td><td>4</td></tr>
</table>

In addition to testing the spatial resolution on land-cover and land-use classification, the thematic resolution was investigated by altering the number of LC classes. Four typologies of LC classes were tested with each subsequent typology becoming more general through aggregating previous similar classes (Table 4). Each set of LC thematic typologies and spatial resolutions was used to classify LU to determine the optimal combination of thematic and spatial resolution of LC classification to use as input to the LU classification. Due to the imagery available and the automatic classification of the imagery, Anderson's classification is being used as a template to guide the selection of classes in this thesis (see Appendix B). This will allow the classification to be compared to other studies which also use Anderson's classification as guide for their classes.

In addition to the per-pixel classification of LC, object-based image analysis (OBIA) was also used to classify LC by objects. Objects are groups of pixels which attempt to represent feature visible in imagery such as a patch of grass, a roof, or a tree. In large features several objects may be required for complete coverage. Software is needed to determine which pixels belong to the same object through a process called segmentation. Each object is then assigned to a class by a trained classifier. This was done using OBIA software (eCognition) on SWOOP imagery resampled to 80 cm with the highest thematic resolution. Higher resolutions were not possible due to not being able to process the larger file size. This can be attributed to both the hardware and the software. If four times the RAM was available the process could possibly be completed in a reasonable amount of time (less than a two weeks). It would be possible however with the current hardware, except it would take an unreasonable amount of time. Classification of the 40 cm imagery was attempted but after a three week processing time it crashed. During this time it did not pass the first step, which is the segmentation process and it is estimated that it would have taken another 3 weeks or more to finish. When the 20 cm imagery was attempted it gave an error explaining there was not enough available disk space for temporary files, which would have reached an estimated minimum of 2 TB or more on a single drive when the computer had approximately 0.5 TB of free space on the required drive. Although the image could be divided into tiles, the creation and use of tiles presents two isses. First, the division creates edge effects at the borders which could cause reduced accuracy through misclassification errors. Second, the training data for each class were created to be distributed around the entire study area to not under or over represent any one area. With a set of image tiles, large portions of training data will be absent from individual tiles and they will not be comparable to the rest of the study area.

While images with a coarser spatial resolution could be classified, each new spatial resolution used in an OBIA process requires an entirely new set of segmentation and classification rules to be created. This would introduce more variability between the classifications and differences could not be solely explained by the change in spatial resolution. The same requirement for rule generation occurs with a change in thematic resolution. Therefore, for consistency, the same training and accuracy samples were retained and used for both pixel-based and object-based classifiers. The training sample data was applied by classifying all objects which interesected the training samples to form the training objects. These training objects were then used as the sample data to train the classifier. The training objects were then overwritten when the classifier was applied. The overwrite allows for the correction of objects which represent other classes but were erroneously included in the training data due to a small intersection with the training samples.

Major misclassification were reduced using the object relationships derived by eCognition. Relationships were used instead of pixel values or textures when creating the process to increase the probability that it will work in other areas with different imagery with little to no modification to the process. If an object belonging to specific classes was completely surrounded by only one other class it was treated as a misclassification and reclassified (Table 5). Three classes, “residential roof”, “pavement/flat roof” and “shadow” were manually selected to have this fix applied. These classes were chosen to avoid reclassifying as many correct classifications as possible. Houses in the study area should not fall within the reclassification for several reasons. First, houses have a driveway or sidewalk represented by “pavement/flat roof” which is next to the building and would break any of the conditions above. Houses also cast shadows which could also break the conditions above. A similar concept can be applied to "pavement/flat roof". This LC class is found on surfaces such as roads, sidewalks, driveways, parking lots, apartment buildings and stores. In all of these cases they are either connected to more paved area or follow the same principles as houses. In addition, "shadow" was only reclassified as "water" to account for deep pits in rivers and streams which appeared dark. These deep pits are dark mostly because they have a shadow, but the surface of the water was considered more important. There are very few cases where this process would have negative effects. A small shed represented by only one object of a few pixels in the middle of a homogenous area with no path leading to it and does not cast a visible shadow may be reclassified. Alternatively a paved surface in a field such as a helipad may be misclassified if only represented by a single obeject. Neither of these cases were found in the study area, although it is noted that they may be possible.

Table 5: OBIA Land Cover Reclassifications

Original Land Cover Class	Surrounding Land Cover Classes
"residential roof"	All except "pavement/flat roof" and "shadow"
"pavement/flat roof"	"deciduous", "coniferous", or "bare ground and soil"
"shadow"	"water"

2.2.5 Land Use Classification

LU was classified by using the LC classification and parcel data in an OBIA. OBIA was used instead of per-pixel techniques since a single LU can be composed of many different LC classes. For example, a residential property will contain a house, yards and a driveway. This requires a group of pixels to be used in the classification to include these components. The parcels will be used as the objects instead of identifying objects separately within the LC classification.

While it is possible, depending on the typology used, to identify multiple LU types for a given location or property parcel, each parcel often represents a single LU and provides a minimum resolution for classifying LU (Lackner & Conway, 2008). Many LU and LC decisions are made at the parcel resolution (Robinson, 2012), either by the parcel owners changing what the parcel is used for as a whole or by the local government setting restrictions on what a parcel or group of parcels can be used for. It is possible for there to be multiple LU types within a single parcel such as a building with a store on the ground level and residential apartments on the upper floors. The LU classification method used was a random forest classifier, which is built into and applied using the eCognition OBIA software package (Trimble, 2015).

Table 6: LU Classes and Definitions

LU Class	Definition
Low Density Residential	Single family housing on large properties (>2000 m^2) which are typically on the fringe of urban areas, or beside natural areas such as rivers and lakes. Easily identifiable by the presence of side yards in many cases.
Medium Density Residential	Typically, a single family in a detached house, although it includes townhouses where units are not stacked vertically.
High Density Residential	Parcels where residential units are stacked vertically such as apartment or condo buildings.
Commercial	Parcels with a primary use of conducting business including small stores, shopping malls, and offices. With the exception of garden and landscaping stores, no outdoor storage facilities are present.
Industrial	Parcels used to manufacture products and contains an outdoor storage facility.
Institutional	Parcels which contain schools and hospitals, manually classified.
Transportation	Roads, railways, along with the boulevards, sidewalks and other surrounding features included in the right of way.
Protected Areas and Recreation	Parks and natural areas which can be either forested or grassy.
Agriculture	Parcels used primarily for cropland and pastures used to produce food for humans and animals. May contain a farm house and barns.
Water	Parcels where water features occupy a large percentage of the area, such as a recreation area focused around a lake, or a river. Small water features may be superseded by other land uses if they are not large enough.
Under Development	Areas of land where construction is underway at the time of the image. These parcels may become any land use found in urban areas including protected areas and recreation in the case of a suburban park.

* for a detailed description of LU classes see Appendix C

2.2.6 Analysis

Three forms of accuracy were used to assess the results of the classifications and are depicted through confusion matrices. The confusion matrix was chosen as it contains all the forms of accuracy reporting noticed in the reviewed literature. For every classification result a confusion matrix was made which shows the overall accuracy, user's accuracies and producer's accuracies. The confusion matrix was chosen as it shows how much confusion occurs among the classes. To relate all of the matrices, many with different numbers of classes, overall accuracy is used. Overall accuracy allows this study to be compared to other studies. The user's and producer's accuracies are included to help condense the information within confusion matrices to understand the accuracy of each class.

2.3 Results

2.3.1 Overview of LC Results

In total 129 LC classifications were created spanning multiple spatial and thematic resolutions and multiple classifiers. Four example classifications, one for each Thematic Typology, have been extracted and shown in Figure 4 for the MLC classifier at 20cm for an urban neighborhood near downtown Kitchener, Ontario. In all typologies, both "water" and "shadow" appear and all shadows and the pool on the right side of the image remain somewhat consistent throughout each reduction of thematic resolution.

In Thematic Typology 1 and 2, the combination of "grass" and "coniferous" into "green vegetation" can be observed when looking into the backyards of the block in the centre of Figure 3. In Thematic Typology 1 these two classes show the variation of vegetation in the backyards which is currently green, as opposed to Thematic Typology 2 which generalizes them into one class. Between these two typologies "cropland and soil" and "deciduous" are merged together into "brown vegetation and soil". The largest differences between these are that Thematic Typology 1 shows many deciduous trees growing on the properties and dust and dirt on the road is classified separately. In Thematic Typology 2 the trees and dirt covered road appear the same, making it difficult to determine if the road is dirty or simply has overhanging trees.

The transition to Thematic Typology 3 from 2 merges the classes “pitched roofs” and “pavement/flat roofs” into “impervious surfaces”. This reduces the ability to distinguish houses from their driveways, sidewalks, patios and roads, as well as buildings with flat roofs. This is important when trying to determine the size or type of building on a property and will have a greater effect during the classification of LU.

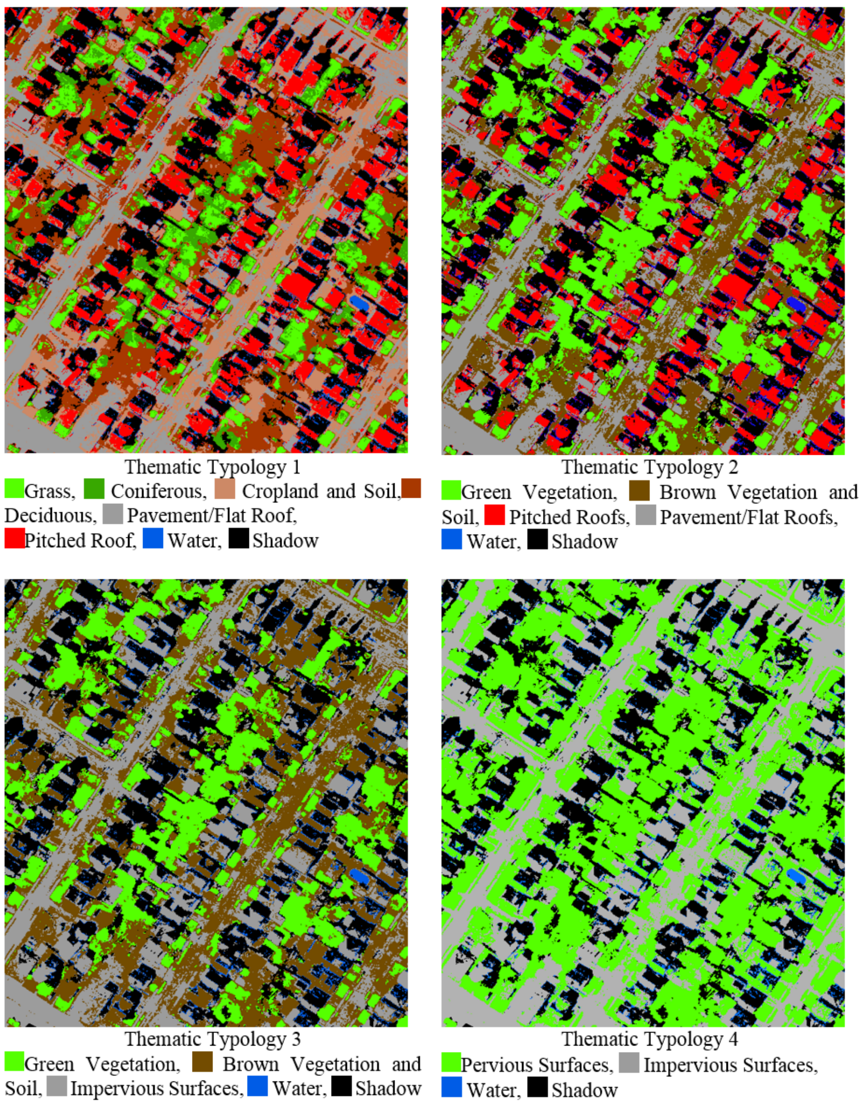

Figure 4: Samples of the four thematic typologies for the 2010 imagery at 20cm

Moving to Thematic Typology 4 merges “green vegetation” and “brown vegetation” from Thematic Typology 3 into “pervious surfaces”. These two classes represent the only classes which have the ability to absorb precipitation without the use of constructed drainage systems such as storm drains used to drain water from impervious surfaces. All the vegetation and bare ground is merged into this class which removes all detail from the natural features of the images.

2.3.2 Pixel-Based LC Accuracy

Overall, MLC provided the highest average accuracy of all classifications evaluated, average accuracy of each thematic resolution and average accuracy of each spatial resolution (see Appendix D). On average, MLC achieved an average classification accuracy of 82.9% across all classifications while SVM and SAM achieved average accuracies of 76.6% and 63.8% respectively. For six of the eight spatial resolutions and all the thematic resolutions MLC recorded the highest average accuracy. SVM only had a higher average accuracy at 640 and 2560 cm, beating MLC by 0.9% and 0.5% respectively. In seven of the eight spatial resolutions MLC also achieved the highest maximum classification accuracy (maximum overall accuracy achieved by any of the classifications at each resolution by the classifier). In all classifications with a pixel size of 640 cm or smaller, MLC achieved at least 80% accuracy, while none of the other classifiers were able to do this.

Behind MLC was SVM, recording the highest maximum classification accuracy for Thematic Typologies 1, 2, and 3, with 85.4%, 88.2%, and 88.7% (all at 640 cm). This beat MLC's maximum classification accuracies of 83.3% (640 cm), 87.7% (640 cm), and 87.2% (320 cm) for Thematic Typologies 1, 2, and 3 respectively. In Thematic Typology 4 MLC achieved the highest maximum accuracy by 5.6% with 91.6% (320 cm) versus SVM's 86.0% (160 cm). Achieving the lowest accuracy in every category was SAM, which had its highest classification accuracy in Thematic Typology 3 at 160 cm, achieving 77.6%.

The two spatial resolutions where SVM was able to achieve a higher average accuracy than MLC were both past the point in which the features being classified can be observed. The average accuracy for MLC had already begun to decease before 640 cm while SVM had 640 as its highest average accuracy. Although SVM had the highest average accuracy for 640 cm with 86.7%, it was still not higher than the average accuracy MLC achieved at 320 cm with 87.2%. The other spatial resolution that MLC was lower than SVM was at 2560 cm, however both classifiers were dramatically decreasing in accuracy and both classifiers were below 70% average accuracy (MLC: 67.7%, SVM: 68.2%).

Since MLC on average performed best overall, it was used for all future steps in this study. Several trends were observed in the single classification accuracies of MLC. As spatial resolution becomes coarser accuracy increases until it's peak is reached and then accuracy decreases (Figure 5). The decrease in accuracy found in the presented study occurs approximately when the pixels become as large as houses and trees, and the pixels begin to become extremely mixed with the surroundings (see Appendix E). Of 30 houses samples, one from each neighborhood identified, the average size was 122 square meters. While trees were difficult to measure due to the blurry edges with other trees and their shadows, they were usually smaller than the houses. A 640 cm pixel has an area of 40.96 square meters while a 1280 cm pixel has an area of 163.84 square meters. Between 640 cm and 1280 cm is where the decrease in accuracy begins. Four of the eight classes in Thematic Typology 1 represent features the size of houses and trees ("residential roofs", "coniferous", "deciduous" and "shadow") and an additional two classes represent features which when in an urban setting are either similar in size to houses or have a similar width ("pavement/flat roof" and "grass"). Since a majority of the image features are classified as these six classes the overall accuracy drops when they are mixed with other land cover classes.

In the first five spatial resolutions, the classification accuracy is inversely related to thematic resolution as it is increasing as the thematic resolution decreases (Figure 5). After these spatial resolutions, the pattern becomes weaker as the classification struggles with the large pixels sizes. This pattern in thematic resolution is caused by the generalization of the classes. As the spectrally similar classes are merged to form fewer classes and confusion between them has fewer chances to occur and is more difficult as the classes are more spectrally distinct.

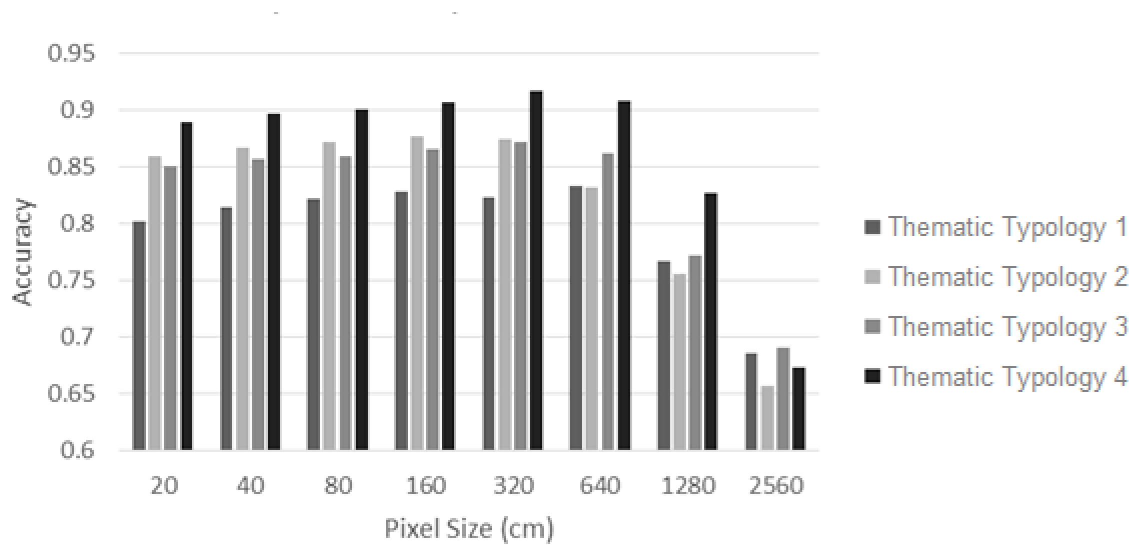

Figure 5: Accuracy of LC for the 2010 imagery

The confusion between the classes can show how the accuracy varies for each class. In Thematic Typology 1 at 20 cm “grass” and “coniferous” are often confused, with “grass” being misclassified as “coniferous” 37.7% of the time and “coniferous” being misclassified as “grass” 20.7% of the time (Table 7). These two classes were merged in Thematic Typology 2 due to this foreseen confusion, which increased both the producer’s and user’s accuracies (see Appendix F). Although “deciduous” and “bare ground and soil” were not highly confused, they were also merged as they both appear brown in the imagery. These classes were merged before the results were known and it was predicted that they would have higher levels of confusion. These four classes are also thematically similar as they both represent pervious LC classes.

Two of the highest confused classes were also merged between Typology 2 and 3 (see Appendix F). The two classes “pitched roof” and “pavement/flat roof” were merged as they are the only two impervious surfaces in the classification except for “shadow” which could be hiding both impervious and pervious surfaces. This merge is what also causes the drop in overall accuracy between Thematic Typology 2 and 3. The confusion matrices show that in Thematic Typology 2 both classes are also confused with “brown vegetation and soil”. This confusion exists because many roofs are brown and appear similar to dirt or deciduous trees, and dirty pavement can appear similar to dry soil. In Thematic Typology 2 at 20 cm “pitched roof” and “pavement/flat roof” have a combined misclassification of 11.0% with “brown vegetation and soil” while “impervious surfaces” in Thematic Typology 3 at 20cm has a misclassification of 27.5% with “brown vegetation and soil”. This misclassification in Thematic Typology 3 at 20 cm accounts for more than half of the total confusion for this combination of spatial and thematic resolution. Which a similar pattern exists for all the other spatial resolutions for Thematic Typology 3, only 20 cm has this misclassification accounting for over half the total confusion.

One class remained consistently highly accurate, which was “water” (see Appendix F). It had a producer’s accuracy of at or near 100% and a user’s accuracy over 99% in all combinations of spatial and thematic resolutions. Water is one of the only blue features in the image, and although it is often cloudy with suspended sediment, it is still spectrally different than any other class, especially in the near-infrared band. When only considering the red, green, and blue bands “water” and “shadow” often appear dark due to light penetrating the water or reflecting in a different direction than the sensor, and shadows not receiving much light by definition. In the infrared band water in the image appears much darker than the shadows.

Table 7: Confusion matrix for 2010 LC Thematic Typology 1 at 20cm, MLC

	Sample Data Classes (m^2)									
Classified Result Classes	C. 1	C. 2	C. 3	C. 4	C. 5	C. 6	C. 7	C. 8	Total	User’s (%)
C. 1	12472	0	0	0	24	4138	0	0	16634	75.0
C. 2	0	13994	2448	0	70	0	554	200	17266	81.0
C. 3	0	1606	14918	0	893	0	1513	5	18936	78.8
C. 4	0	43	0	20001	1	0	0	14	20059	99.7
C. 5	8	780	65	0	18004	36	337	184	19414	92.7
C. 6	7563	0	0	0	186	15824	0	1289	24863	63.6
C. 7	0	2210	2580	0	666	0	17632	0	23087	76.4
C. 8	0	1393	6	2	161	16	0	4310	5887	73.2
Total	20044	20025	20017	20004	20006	20014	20036	6006		
Producer’s (%)	62.2	69.9	74.5	~100.0	90.0	79.1	88.0	71.8	Overall:	80.2%

Legend

C. 1	Grass	C. 2	Pitched Roof
C. 3	Pavement/Flat Roof	C. 4	Water
C. 5	Deciduous	C. 6	Coniferous
C. 7	Bare Ground and Soil	C. 8	Shadow

2.3.3 Object-Based LC accuracy

Using an 80 cm spatial resolution, the object-based classification of LC achieved an overall accuracy of 96.7% (Figure 6, Table 8). All classes achieved a producer’s accuracy of over 90%

with the exception of "residential roofs". Similarly, with the exception of "deciduous", all classes achieve a user's accuracy of over 90%. The biggest misclassification from 9.7% (1949 m^2) of the "residential roof" pixels being classified as "deciduous".

Both "residential roof" and "deciduous" are often confused partially because they are often located beside each other. In the urban areas, it was noticed that most vegetation is either grass or deciduous trees and bushes. In many cases there were trees overhanging part of a roof, which may hide the edge of the roof. When the roof is a brown shingled roof the object may expand into the tree as it does not see the edge of the roof, and potentially onto the lawn (Figure 6). The segmentation process requires a form of hard edge to determine the edge of the image features. Without this hard edge, the objects will grow until they reach their maximum size, covering multiple LC classes. When this happens, the object can be classified as "pitched roof", "deciduous", or in some rarer cases "grass" and one part of the object is guaranteed to be classified incorrectly.

Figure 6: Example of an object covering a roof, tree, and lawn at 80 cm

Additionally, it was noticed that the measured accuracy, using the same sample data as the other classification methods, may be higher than the absolute accuracy. Misclassified objects, mainly as “pitched roof”, were noticed in transition areas which were not included in the sample data due to belonging to multiple classes (Figure 7). These transition areas often were not between “pitched roof” and another class, meaning the “pitched roof” class could not be correct. This also occurred most often in transition areas including deciduous trees and bare agricultural fields as both are brown, similar to brown shingles on a residential roof.

Table 8: Confusion matrix for 2010 LC, Thematic Typology 1 at 80 cm, classified by OBIA

		Sample Data Classes (m^2)									
		C. 1	C. 2	C. 3	C. 4	C. 5	C. 6	C. 7	C. 8	Total	User’s (%)
Classified Result	C. 1	20032	34	0	0	26	96	0	0	20188	99.2
	C. 2	0	16484	86	0	38	3	0	0	16612	99.2
	C. 3	0	291	19755	0	0	0	333	8	20187	96.9
	C. 4	0	90	0	20006	0	0	0	0	20097	99.6
	C. 5	0	1949	135	0	19952	0	420	0	22456	88.8
	C. 6	0	75	0	0	0	19862	0	0	19937	99.6
	C. 7	0	560	0	0	0	0	19276	0	19836	97.2
	C. 8	0	548	0	0	4	66	0	5997	6616	90.6
Total		20032	20031	19976	20006	20021	20027	20030	6005		
Producer’s (%)		100.0	82.3	98.9	100.0	99.7	99.2	96.2	99.9	Overall:	96.7%

Legend

C. 1	Grass	C. 2	Pitched Roof
C. 3	Pavement/Flat Roof	C. 4	Water
C. 5	Deciduous	C. 6	Coniferous
C. 7	Bare Ground and Soil	C. 8	Shadow

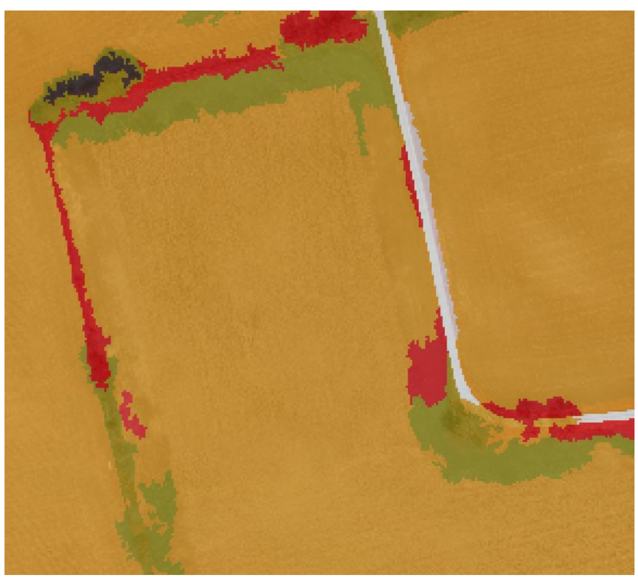

Figure 7: Example of “pitched roof” (red) occurring along a hedge row of a deciduous hedge (green) in a field (orange) and along the driveway (grey) of the farm house

2.3.4 Object-Based LU accuracy – pixel-based input

The LU classification with the highest overall accuracy (88%) came from the random forest classifier using the LC Thematic Typology 1 at an 80 cm spatial resolution (e.g., Figure 8, Figure 9, and Table 9). The classifications with 80 cm and 160 cm pixel size also achieved the highest average accuracy with a tie at 85.9%. The classifications which used Thematic Typology 1 as the input also achieved the highest average accuracy with 87.0% with Thematic Typology 2 a close second at 86.5%. Overall the object-based LU classification accuracy was similar across all classifications with the highest classification of 88% at 80 cm with Thematic Typology 1 only 10.2% higher than the lowest classification of 77.8% at 640 cm with Thematic Typology 4.

Figure 8: Example of LU Classification, 80 cm input with Thematic Typology 1

The 20 cm resolution LC data was omitted due to the large number of pixels not being able to be segmented due to hardware and software restrictions. The two coarsest resolutions were omitted due to pixel sizes becoming too large for the parcels. For example, 71% (out of 120397) of medium density residential parcels in the study area were smaller in area than four 1280 cm pixels or one 2560 cm pixel. In addition, eCognition first aligns the parcel boundaries to match the image resolution and the parcel boundaries differ substantially from the original parcels (Figure 10). The effects of parcel rasterization can be observed at resolutions finer than the 1280 cm pixel size. After their maximum accuracy occurring at 80cm Thematic Typologies 1, 2, and 4 all experience a downwards trends in accuracy as the pixels become larger.

The general trends of the LU accuracy show that decreasing the thematic resolution of the input LC decreases classification accuracy (Figure 9). This trend becomes exaggerated at coarser spatial resolutions as the difference between the highest and lowest classification accuracy increases from 3.9% at 40 cm to 7.4% at 640 cm. This increase in difference is mainly caused by the larger decrease in accuracy of Thematic Typology 4 where it was 5.6% lower than its maximum accuracy. In comparison, at 640 cm Thematic Typology 1 is only 2.8% lower than its highest accuracy.

“Commercial” and “industrial” are the two classes with the most confusion, whereby 20 of the 100 “commercial” parcels are classified as “industrial” and 21 out of 100 “industrial” parcels are incorrectly classified as “commercial”. “Water” is also confused with protected areas and recreation, although the opposite confusion does not occur frequently. This may be due to the amount of shoreline or other land included in “water” parcels. An example of the LU classification can be seen in Figure 8.

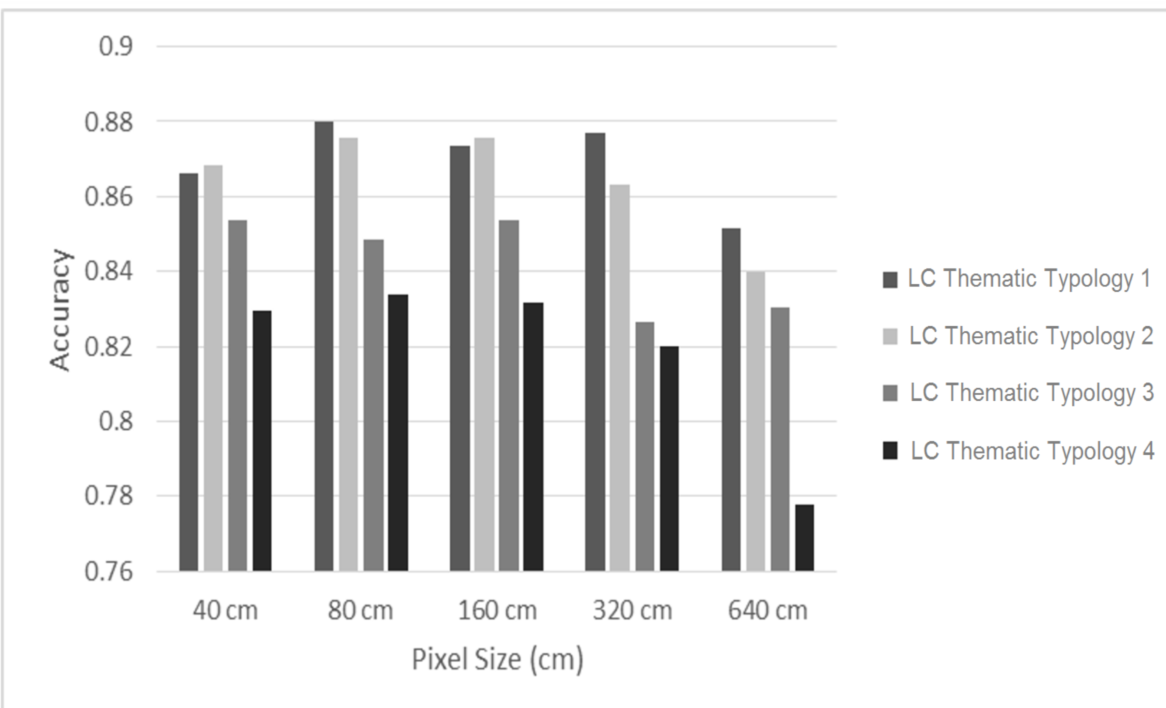

Figure 9: Accuracy of LU classification for the 2010 imagery

Table 9: Confusion Matrix for 2010 LU, 80cm, Thematic Typology 1

Classified Result Classes	Sample Data Classes (# of parcels)											
	C. 1	C. 2	C. 3	C. 4	C. 5	C. 7	C. 8	C. 9	C. 10	C. 11	Total	User's (%)
C. 1	92	0	3	0	5	0	8	0	0	0	108	85.2
C. 2	0	100	0	0	0	0	0	0	0	0	100	100.0
C. 3	7	0	77	3	5	1	1	0	0	0	97	79.4
C. 4	0	0	10	72	20	0	0	0	0	0	102	70.6
C. 5	0	0	9	21	68	0	0	0	0	0	98	69.4
C. 7	0	0	1	0	0	99	0	0	0	0	100	99.0
C. 8	1	0	0	0	0	0	141	5	7	0	154	91.6
C. 9	0	0	0	1	2	0	0	120	1	0	124	96.8
C. 10	0	0	0	0	0	0	0	0	17	0	17	100.0
C. 11	0	0	0	0	0	0	0	0	0	50	50	100.0
Total	100	100	100	100	100	100	150	125	25	50		
Producer's (%)	92.0	100.0	77.0	72.0	68.0	99.0	94.0	96.0	68.0	100.0	Overall:	88.0%

Legend

C. 1	Low Density Residential	C. 2	Medium Density Residential
C. 3	High Density Residential	C. 4	Commercial
C. 5	Industrial	C. 6	Institution – manually classified, omitted from matrix
C. 7	Transportation	C. 8	Protected Areas and Recreation
C. 9	Agriculture	C. 10	Water
C. 11	Under Development		

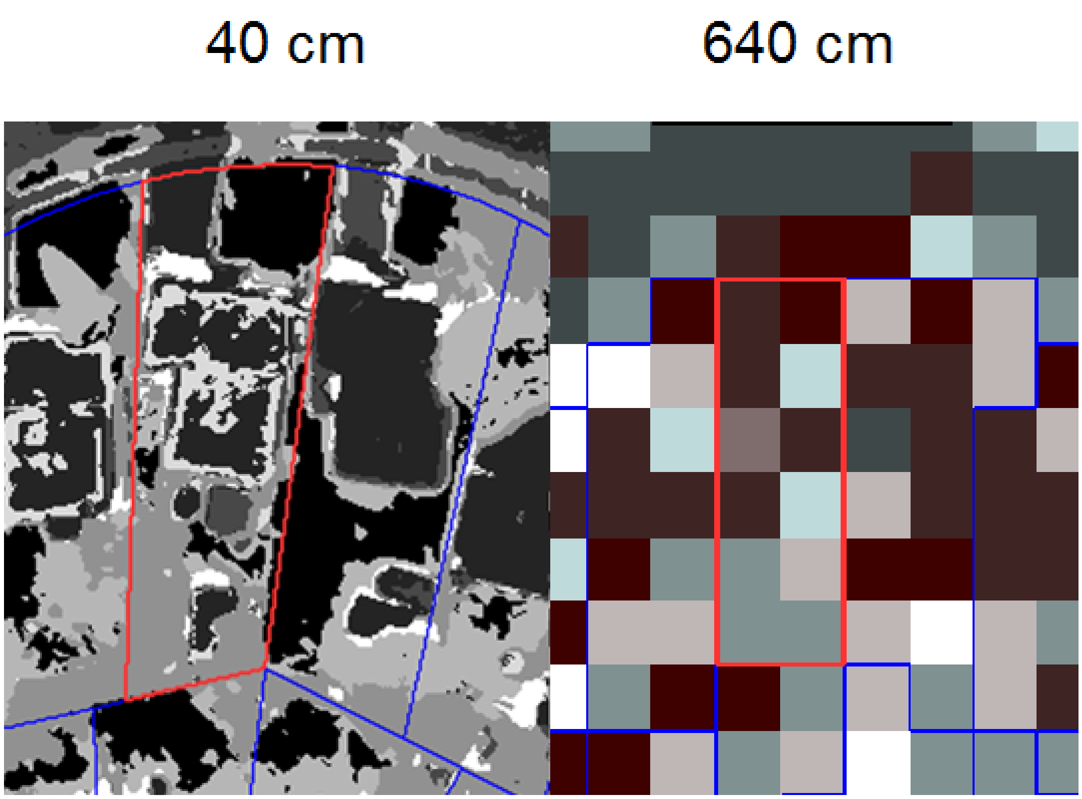

Figure 10: Example showing parcel rasterization at 40 cm and 640 cm

2.3.5 Object-Based LU accuracy – object-based input

The overall accuracy of LU classified from the LC created by OBIA through eCognition achieved an accuracy of 82% (Table 10). Similar patterns are found in the confusion matrix when compared to the LU classified from the pixel-based LC but with an increase in error. The most notable increase in error is "protected forest and recreation" being misclassified as "low density residential" in 25 of the sample parcels. The classification accuracy when object-based LC is used is lower than all but two of the classifications when pixel-based LC input is used. It is also 6% lower than the maximum overall accuracy when pixel-based LC input is used. Several of the common misclassifications are expected, including the confusion "commercial" and "industrial". These two classes both have similar traits such as a large building with a flat roof and potentially large parking lots. The main difference is the outdoor storage areas found on "industrial" properties. Not all "industrial" properties will have a significant outdoor storage area. Some "commercial" properties will have an area that appears similar to a storage area when classified, such as an area of bare ground or sparse trees.

The "water" class was also not able to achieve a very high producer's accuracy, which was not expected. This was because it was rare for a parcel to only be water, and usually included some sort of recreation area or housing area. In many cases, classifying "water" as "protected areas and recreation" is not a large error. Many recreational areas include a water feature such as a pond or a stream. In many "water" parcels which are not limited to the river banks or lake shores they can be considered recreation depending on the user's point of view, making this misclassification have a smaller effect than it appears to have.

Many of the classes in this LU classification have very little confusion. For example, "medium density residential" received an almost perfect 100% in both producer's and user's accuracies. The only misclassification was one "under development" parcel which will be a "medium density residential" property when construction has finished. Another class, "agriculture" also performed very well. This class has one of the largest observed parcel sizes with only "protected areas and recreation" having a similar size. When these two are similar it is a simple distinction as one is covered in trees and the other is either bare ground or grass.

Table 10: Confusion Matrix for 80cm LU, Thematic Typology 1, OBIA LC Input

	Sample Data Classes (# of parcels)											
Classified Result Classes	C. 1	C. 2	C. 3	C. 4	C. 5	C. 7	C. 8	C. 9	C. 10	C. 11	Total	User's (%)
C. 1	84	0	8	2	14	0	25	0	1	0	134	62.7
C. 2	0	100	0	0	0	0	0	0	0	1	101	99.0
C. 3	5	0	71	4	9	0	1	0	0	0	90	78.9
C. 4	3	0	11	67	20	1	0	0	0	0	102	65.7
C. 5	2	0	6	25	55	0	0	0	1	1	90	61.1
C. 7	0	0	2	0	0	98	0	0	1	0	101	97.0
C. 8	5	0	2	0	0	1	121	4	8	0	141	85.8
C. 9	0	0	0	1	2	0	1	121	0	0	125	96.8
C. 10	1	0	0	1	0	0	2	0	14	0	18	77.8
C. 11	0	0	0	0	0	0	0	0	0	48	48	100.0
Total	100	100	100	100	100	100	150	125	25	50		
Producer's (%)	84.0	100.0	71.0	67.0	55.0	98.0	80.7	96.8	56.0	96.0	Overall:	82.0%

Legend

C. 1	Low Density Residential	C. 2	Medium Density Residential
C. 3	High Density Residential	C. 4	Commercial
C. 5	Industrial	C. 6	Institution – manually classified, omitted from matrix
C. 7	Transportation	C. 8	Protected Areas and Recreation
C. 9	Agriculture	C. 10	Water
C. 11	Under Development		

2.4 Discussion

2.4.1 Pixel-Based Land Cover Classification

LC accuracy attained in the presented research exhibited expected outcomes along the evaluated spatial and thematic resolution gradients tested. As the spatial resolution increased, accuracy also increased. This can be attributed to the reduction of noise and other abnormalities through the generalization of pixel values. However, the reported LC accuracy declines in the fine spatial resolutions. This was determined to be caused by the size of the structures being classified. The first decrease in accuracy occurs at 640 cm, which is the resolution which houses cannot be identified (see Appendix E). This decrease in accuracy is amplified at the lower resolutions as the pixel size becomes larger than features such as roads and commercial buildings. As predicted, decreasing thematic resolution also increases accuracy due to the generalization and merging of LC classes. As LC classes, such as "grass" and "coniferous" merge, any pixels previously confused between the two classes are now correct. The more general class definition also increases the likelihood that a previously uncertain pixel will now belong to the correct class by giving less strict limits to accepted values.

Common LC class confusion in the first Thematic Typology occurs between “grass” and “coniferous”, “pitched roof” and “bare ground and soil”, and “shadow” and “coniferous”. “Grass” and “coniferous” are confused with each other because they both are green vegetation at the time of imagery aquisition. “Pitched roof” and “bare ground and soil” also appear similar in the imagery as roofs in the region are generally made of shingles which are covered in crushed rock. “Shadow” is often confused as “coniferous”, however the opposite confusion is not as common. Due to the cone shaped trees, there are many small shadows in coniferous forests in the area, and therefore become part of the “coniferous” class. The more general thematic typologies show similar confusions for the classes, with the exception of “green vegetation” which combines “grass” and “coniferous”.

Knowing and understanding the range and pattern of classification accuracy for LC is important for many fields such as global carbon modelling and LUCC analysis. In areas where very high resolution aerial imagery is not available, medium resolution satellite imagery may be used. The resolution of the imagery can be used to determine the thematic resolution which performs best. For example, if a satellite provides a resolution closest to 640 cm, Thematic Typology 2 should be avoided because Thematic Typology 1 has a higher accuracy and a finer thematic resolution. The decision between Thematic Typologies 1, 3, and 4 would depend on the required accuracy and thematic resolution thresholds. Alternatively, if funding partners or project requirements demand an overall accuracy above 85% for Thematic Typology 2, and assuming higher resolution imagery is more expensive, it would be possible to pick the cheapest imagery which has a high chance of meeting the demands. In this example, it could be predicted that 320 cm is the coarsest imagery which can achieve the goal (Figure 5), reducing the funding needed if the 80 cm imagery was used instead.

2.4.2 Object-Based Land Cover Classification

The results of the object-based LC classification were more accurate than Lackner and Conway (2008) who used a PAN sharpened IKONOS image with a spatial resolution of 1 m and 17 thematic classes and achieved 73% accuracy. Lackner has a similar resolution to the 80 cm used in this study but has more than twice the classes. Lackner's classification also used ancillary road network data in the classification of the image. Lackner's study area was predominantly urban, with very little rural area (10 fields which may potentially be agricultural) although more urban thematic classes were used. This focus on urban areas means that their study is not applicable at the regional scale. They reported that their accuracy increases to 77% when the building classes are combined. After examining the examples of their results, they seem to have a large amount of noise, potentially from using smaller objects. Lackner and Conway may also not have used any tools to clean up the data such as searching for objects representing noise and reclassifying them to their proper class.

The LC classified by eCognition using OBIA had a higher accuracy than any of the pixel-based classifications in this study. For the same spatial and thematic resolution, OBIA produced a higher accuracy by 14.4% (from 82.3% to 96.7%). Two notable differences exist between the confusion matricies for these two classifications. Using OBIA reduces the misclassification of "grass" as "coniferous " to zero, while in the pixel-based classifier misclassified 39% of the "grass". The opposite misclassification of "coniferous" classified as "grass" was also reduced to 0.4% from 13.5%. This improvement is caused by the additional attributes available to the classifier by using objects. Areas such as lawns or fields will have relatively compact objects which can be distinguised from the less compact objects found in forests or single trees. In the forests and single trees, the objects have a larger number of edges caused by shadows and different types of trees which may define the object boundaries. This will also cause the objects to be smaller which makes the classification easier.

The second major difference in the classifications is the misclassification of "shadow" as "coniferous ". OBIA had very few "shadow" samples classified as "coniferous " while pixel-based had 22% of the sample pixels classified as "coniferous". Although there was an increase in opposite misclassification, it is still very low with pixel-based only having 0.04% misclassification and OBIA having 0.3% misclassification. In the coniferous forests found in the study area, the cone shaped trees cast shadows on the lower parts of the trees behind them. This creates random patches of "shadow" and "coniferous" when observed from above, such as in the imagery. Objects are able to follow the boundaries between trees and shadows in coniferous forests (e.g. Hernando, Tiede, Albrecht, & Lang, 2012) and each object can be classified seperately. In comparison, the pixel-based classifier only considers the pixel value, making the borders difficult to classify when neither class is fully represented. When using OBIA, the difficult borders are divided into different objects which gives them the same class as the whole object. This reduces the uncertainty of these border pixels and reduces the misclassification.

2.4.3 Object-Based Land Use Classification

The relationship between LU classification accuracy and input resolution shows a similar trend to the one identified in LC. As the resolution decreases, in this case, the input LC data to the OBIA LU classifier, the accuracy initially increases and then decreases. This is due to the number of pixels which occupy a single parcel and the segmentation process. Although the parcels are used as the guide for segmentation, the final objects must follow the edges of the pixels. At the finer resolutions, this does not pose a problem, as it simply makes the borders of the parcels slightly rough due to the large number of pixels, similar to a straight line being represented on a television. At the lower resolutions, the parcel objects resemble the actual parcel less, which distorts many of the spatial patterns available to be used in the classification (Figure 10). These lower resolutions also provide fewer pixels for the classifier to use to determine the LU class. Resolutions with pixel sizes greater than 640cm were excluded due to the identified loss of accuracy in the input LC. Also, at these resolutions, many parcels were occupied by only a segment of a single pixel of LC and could not be represented in the software.

The native resolution of 20 cm was omitted due to computer random access memory (RAM) limitations. For the entire imagery to be processed at once at the native resolution, an estimated 256 GB of RAM may be able to work, but 512 GB would be ideal. Obtaining the required motherboard, processor and RAM registered dual-inline memory modules (RDIMMs) to make this possible in a desktop computer would be cost prohibitive. These highly speciallized computers were not used as it would make this study very difficult to reproduce. It is also unknown if eCognition would be able to process such a large amount of data.

The relationship between number of classes and the accuracy of LU is the reverse of the relationship for LC. As the number of LC classes in the input data decreases, the accuracy also decreases. This is due to the decreased amount of information available in fewer classes. As fewer

LC classes are used to represent the region, there are fewer classes available for LU classification. This reduces the possibility for patterns in LC to emerge and aid in the prediction of LU.

Although all the classifications had an overall accuracy within a range of only 10.2% there are still patterns which can be observed which are helpful to future studies of LUCC. The results show that although a high spatial resolution is needed to classify at the parcel scale, the very high resolution imagery does not perform as well as the slightly lower resolution imagery. Even if the 20 cm imagery is available, it should be resampled to approximately 80 cm to achieve the best results. This range of accuracy values can also be used to reinforce the need of high resolution imagery. If the only imagery available for a study is 640 cm, it can be observed that obtaining higher resolution imagery would be beneficial to the project, and would not be a waste of resources. Alternatively, the accuracy ranges in this study could be used to justify the current imagery is acceptable as the high resolution imagery will not increase accuracy enough to spend resources aquiring new imagery.

2.4.4 Object-Based Land Use Classification with Object-Based Land Cover as Input

Using the same methods, training samples and accuracy samples to classify and assess LU from LC created from OBIA produced lower accuracy results than the pixel based LC. This decrease in accuracy may be due to the generalization of the LC by the objects. This generalization may reduce the amount of information available to the classifier to make decisions on class membership. The LC objects will merge very small features into larger ones during segmentation. This creates a clean classifcation with many of the small patches overlooked. Although this works well for LC, these small objects will add a lot of information which can be used in the classification of LU. These small objects may be classified differently in the pixel-based classification than they would be in the object-based classification. For example, a small patch of dry grass in a agricultural area may be classified as “bare ground” in the pixel-based classifier but is merged into the surrounding “grass” object in the object-based classification. Similarly a patch of very green grass on a manicured lawn in a residential area may be classified as “coniferous” in the pixel-base classification but “grass” in the object-based classification. This increased variation in the pixel-based classification may lower the LC classification accuracy but provide more information to the LU classification, increasing the classification accuracy.

The patterns in the confusion matrix for the LU classified from pixel-based and object-based LC data are very similar. In both scenarios, “commercial” and “industrial” are the two most confused classes, “protected forest and recreation” is misclassified with “low density residential” and “commercial” is misclassified with “low density residential”. It is hypothesized that the common patterns is due to the high accuracy in both input datasets. With both input datasets having high accuracy, many of the same patterns will be visible because they naturally occuring in the landscape. The difference may then be caused by the misclassifications corrected by the generalization of objects as previously mentioned.

For the purposes of LC classification, OBIA is a worthy expenditure, as it drastically increases accuracy. If LU is the desired product, OBIA should be skipped for LC classification as it produces lower accuracy than using the pixel-based LC classification. To achieve higher accuracy using OBIA for both LC and LU to match the other methods in this study, a greater investment of time and computing resources would be needed. This is needed to tailor the LU classification methods to the OBIA input data. The use of OBIA for both LC and LU also decreases capability to expand the same methods to new datsets and regions by requiring more human involvment in creating rulesets for each new dataset and region. In the current state with pixel-based LC classification and object-based LU classification, only sample data need to be produced to use the methods with new datasets or in new regions.

The combination of thematic and spatial resolution of LC classification which produced the highest accuracy LU classification is Thematic Typology 1 at a spatial resolution of 80 cm. At this point, the spatial resolution is matching the size of some features in the image while still having a large number of pixels within each parcel. The large number of pixels, with all the LC classes present, allows for more information to be used in the classification of LU. This large amount of information is important as the spatial and thematic resolutions in this combination do not produce the highest accuracy of LC. To achieve the highest accuracy LC without changing thematic resolution, spatial resolution would need to be decreased to a pixel size of 160 cm, although this reduces LU accuracy.

Finding this combination of resolutions is an important step. In many studies, the native spatial resolution of the image is used with an arbitrary number of thematic classes without questioning if the data could be resampled, or thematic classes modified to produce a higher classification accuracy in the next product.

2.5 Conclusions

Spatial and thematic resolution is a property of all image classifications. Understanding this core part of image classification is important to maximize the accuracy of classification that may be performed and to assess and evaluate the trade-off in accuracy among different data and classification approaches. While a study may be restricted by funding, available imagery, requested classes and minimum accuracy levels, this study can assist in determining the exact methods and data to use. The results presented demonstrate how different classifiers, spatial resolutions and thematic resolutions effect the overall accuracy of a classified image. When a decision is needed to pick from two available imagery sources, this lookup table can be used to ensure the proper source is selected. When LC or LU classes are being determined before conducting field sampling, this lookup table can be referenced.

This study can also be used as a benchmark for image classification. If a similar study is being conducted and the accuracy is different than what was achieved here, the reseachers can investigate the reasons behind the difference. This does not mean this study definitively achieved the highest accuracy possible for each combination, simply that it has consolidated the results of 96 LC and 32 LU classification results into one location for the purposes of comparison.

This study has allowed for the future comparison of Southwestern Ontario with regions which have had similar studies conducted such as Michigan (Huang et al. 2014; Robinson 2012), Indiana (Kelley & Evans, 2011). This available comparison is important to analyze how LUCC is different across various regions and climates.

3. Chapter 3: Context and Future Direction

3.1 Implications

This study has produced three beneficial products which were not previously available for the Region of Waterloo, and can be expanded to Southwestern Ontario. The first product is the relationships between LC and LU for the Region of Waterloo and Southwestern Ontario in general. This is important for a variety of reasons such as understanding the preferences of homeowners and land developers in terms of how properties are developed. It can also be used for understanding carbon storage and emissions by LU class. The second benefit produced by this study is the ability for future studies to use the data. For example, the LC can be used for research in areas such as urban planning (Memarian et al., 2013) and the LU can also be used for urban planning, carbon storage calculations (Park & Stenstrom, 2008) and market and populations growth and dynamics (He et al., 2013). The third products are the LC and LU datasets. These data are unique to the region and allow for the future studies and applications to be done.

3.2 Challenges and Opportunities

There are many challenges which can decrease the usefulness or accuracy of image classifications and models. Poor data quantity and quality limits the accuracy of many studies. In this study, the 2010 SWOOP imagery was used as it includes an infrared band. An earlier SWOOP product which was acquired in 2006 however does not contain the infrared band. This imagery was classified alongside this thesis and did not achieve an accuracy as high as the 2010 imagery with the infrared band. The use of parcels in OBIA can increase the accuracy between LC and LU as can be seen for the 80 cm image with Thematic Typology 1. Applied to the 2006 imagery this could account for much of the lost information from not having an infrared band and produce a high quality LU product.

The focus on the specific study area reduces the usability of identical methods and identical parameters on other areas, such as Asia or Europe. This is due to the change in the effect of LU predictors and LUCC drivers over space. The framework of this study allows the research to be replicated for alternate regions and the results from this study would provide a comparison for the new region. In some cases new classes may be needed for potentially both LC and LU. For example, a mountainous region may need the added classes of “bare rock” or “snow” for LC and “uninhabited mountainous” for LU to accommodate for the difference in landscapes.

There is a possibility that increasing the number of LC classes could increase the accuracy more in this study. Because the most accurate combination included the Thematic Typology with the most classes, it is not possible to definitively conclude that number of classes in Thematic Typology 1 is optimal. Including more classes introduces another issue as there are few LC classes not included in Thematic Typology 1, and new classes would have large thematic and spectral overlap with the existing classes. When determining which classes to use, the landscape was studied through the imagery to determine all the possible LC classes. This list of LC classes was used as Thematic Typology 1. If more classes were to be added, they would be very difficult to train into the classifier. New classes would need to be formed through the division of previous classes. Different types of roofing materials or different types of trees could be identified but would likely not produce significantly better results.

The use of parcels representing sets of pixels also introduces the modifiable areal unit problem (MAUP). For example, if a farmer has forest covering half the property, the forest may be lost in the classification. If several neighboring farms all have a portion of the same forest, the forested area could be larger than any one of the farm’s agricultural area, although it will be ignored. Although census dissemination areas could be used, the same issue would be present as it is the same concept except with large polygons. Using the LC dataset in combination with the LU dataset can avoid some of this problem by being able to represent sub-parcel compositions of LC. The distribution of the LC within the LU would not be distributed throughout the parcel, but could simply be represented in table form. These values can either be calculated from the LC map if it is the original LU, or from regional averages for similar LU types and parcel sizes. Using this method would allow for general assessments of the region to be conducted on the final results of the model.

The previous example is also a case for mixed use parcels. Similar to mixed pixels, mixed parcels are parcels which are being used for two or more LU types. An additional example is found in the urban core where it is very common to have business located on the bottom floor of buildings with residential apartments above. This could create inaccurate reports of residences or business in an area, depending on which class they are labelled as. To avoid this issue, a LU class could be used to represent these areas which would mitigate some of the effect.

3.3 Future Directions

3.3.1 Land Cover Analysis within Parcels

The results and methods from this study can be applied to the analysis of LC within parcels. This type of analysis can compare LC composition across the different parcel sizes (e.g., Robinson, 2012) and over time (e.g., Huang et al., 2014). Combined with their physical properties and relationships with other parcels, these LC patterns can be used to determine many environmental processes and attributes such as carbon storage (e.g., Huang et al., 2014). Since these studies are analyzing LC composition within parcels, the LC data must be of a high enough spatial resolution that it can show variation among parcels. If the spatial resolution is too coarse, parcels may only be represented by a few pixels and will not be able to have accurate patterns calculated.

The widely available LC data tends to be derived from freely available satellite imagery such as Landsat. The moderate-to-coarse spatial resolution of Landsat, MODIS, and other satellite platforms allows those satellites to cover a larger area in the same time as finer resolution platforms. Parcel LC composition requires finer spatial resolution than platforms such as Landsat due to a vast majority of the residential parcels being approximately the same size as a single pixel. As the spatial resolution becomes finer the imagery will generally become less widely available either due to platform coverage or cost. As this happens the LC classifications will become more specific to the project. This reduces the standardization in thematic resolution across LC classifications. Although this allows the LC classes to be tailored to the project, it reduces the comparability with other similar projects. If LC composition projects can be compared against each other, they can be used to determine how patterns change over space and time to better understand the environmental factors being investigated.

In addition, the parcel data required to perform an analysis of LC composition is required. Wealthy countries can produce parcel data fairly easily while some poorer nations, or nations with less urban structure, may lack the resources to produce parcel data. Although methods could be produced to automatically create parcel data through image interpretation, they would be estimations of the parcels and would not represent the actual ownership of the land. This produced data may be usable for measuring the occurrence of LU change, but since it has been created from patterns in the imagery and LC, it would not be suitable to study LC composition. Parcels could be created by manually digitizing imagery, however this could be a long process and may be difficult in poor areas such as urban slums.

Assuming parcel data is available, two solutions can be done to increase the comparability of projects. The first solution is to increase the availability of high resolution imagery. Although this is not a realistic solution, it would allow for large regions to have LC and LU classified from the same image platform from around the same time period. This study could be used to help make this solution a reality in two ways. The first would be to inform the government or organization funding the new platforms select the appropriate spatial resolution. The maximum pixel size can be determined through the LU classification accuracy report. For example, if at least 86% overall accuracy is required, 320 cm would be the largest the pixels can be from the selected spatial resolutions. This would just be the maximum pixel size and other factors may reduce this size. The second way would be to inform the researchers conducting their projects on which spatial resolution to choose. Either way would increase the comparability of projects by increasing their similarity in spatial resolution.

The second solution is to increase the standardization in thematic resolution. Increasing the standardization will make studies more comparable through describing the same types of patterns. This study can help this solution by showing what accuracy each Thematic Typology reaches for the available spatial resolutions. Although the exact classes used in this study may not be used, the approximate resolution can be used to create a new Thematic Typology standard. The Thematic Typologies in this study could also be used to compare accuracies of projects. For example, if project one uses Thematic Typology 1, and project two uses Thematic Typology 2, their accuracies could still be compared. This study could show that for the specific spatial resolution of the projects, the accuracy of project one is equivalent to that of project two if they had both used the same Thematic Typology. Increasing the standardization of thematic resolution or introducing a method to compare accuracies would both increase the overall comparability of LC composition studies.

3.3.2 Agent-Based Modelling

Another field which may benefit from this study is agent-based modelling (ABM), specifically for LUCC. In an ABM, the agents are pieces of programming which act independently of each other to make changes to the data it is given, following a set of rules. The agents can be viewed as characters in a role playing video game (Barnaud, Le Page, Dumrongrojwatthana, & Trébuil, 2013), each within a general class (e.g. a knight or archer in a fantasy video game) which defines the set of attributes which will influence the agent's actions. Each agent in the ABM must belong to one of the agent classes. The class defines what role the agent has in the model, and subsequently, the actions available to it (Murray-Rust, Robinson, Guillem, Karali, & Rounsevell, 2014). For example, in a LUCC ABM, one agent may be in a land developer class. A land developer may have an action which changes the LU to one with a higher level of anthropogenic disturbance, such as forest to agriculture, or agriculture to residential. The land developer class may be part of a group of anthropogenic classes which contains agent types which simulate human interactions with the environment. These roles and actions are defined by the ABM developer (Brown & Xie, 2006; Li, Colson, Lejeune, Speybroeck, & Vanwambeke, 2015), and are influenced by the observed patterns of historical change.

Although an ABM could be designed to work at any scale, an ABM which simulates LUCC in a single city or region typically operates at a fine resolution. This applies mainly to spatial resolution of LC and LU, while thematic resolution relies more on the desired product of the model. Coarse spatial resolution LC and LU data will not be able to represent a single household or city block which can be represented by finer resolutions, although the specific resolution used by an ABM will depend on the available data, the requirements of the topic being modelled, and the desired computational performance of the model. A model performing the same computations on coarse data, in theory, will be faster for the same spatial extent than if fine data were used. An ABM could theoretically be developed that modelled both regional and local LUCC. This would need both coarse data and fine data to be available for the entire study area.

There are very few ABMs which have been specifically designed to model LUCC in Canada. Although generic models may be capable of this, they have not been designed for drivers which may be different in Canada than in other regions of the world. Searches for “ABM land use “Canada”” in both Scopus and Google Scholar result in very few relevant papers or books. Scopus only gives one result, a book on ecosystem services, focusing on Europe. Google Scholar produced 9870 results and only one of the first 100 developed an ABM for use in an area of Canada (e.g. Jjumba & Dragićević, 2012). Many of the results of the search that developed an ABM of any kind focused on a small region or city. This requires fine resolution input data from either fine resolution imagery classified for LC or LU, or from city parcel data.

This study provides the necessary LC and LU classifications to develop LUCC models for the Region of Waterloo. This study also provides a methodology to create similar LC and LU classifications from existing data for Southwestern Ontario, including a few extra counties collected in SWOOP. In addition to the 2010 data used in this study, data is also available for 2006 and 2015. For both these years the LC and LU for the Region of Waterloo has been classified. These three years of data can be used in calibration and validation of a LUCC ABM. With another dataset expected to be collected by SWOOP in the upcoming years, this methodology can be applied in the future to the data. This will allow a model created today to predict the future and have it validated within the lifetime of the project.

This study also provides many resolutions of data, both spatial and thematic. This will allow for a multi-resolution ABM to be created. A multi-resolution ABM will be able to predict regional scale change across Southwestern Ontario which can then be used in the local scale change predictions. For example, if the model shows that at the regional scale a town or city should grow by X number of people, it can then determine how the town or city will grow by adding X number of people to the local scale predictions. The multiple resolutions of the LC and LU data will also allow for multiple LUCC ABMs to be created to examine the effect of resolution on the performance and accuracy of the models.

3.3.3 Global Land Cover and Land Use Datasets

There are many LC and LU datasets which have global or regional extents. These datasets have been derived from global satellite imagery such as Landsat, Moderate Resolution Imaging

Spectroradiometer (MODIS), or Advanced Very High Resolution Radiometer (AVHRR). Landsat has the highest spatial resolution of 30 m (USGS, 2016), MODIS has spatial resolutions of 500 m and 1000 m (Nishihama, Wolfe, Solomon, & Patt, 1997), and AVHRR has a spatial resolution of 1.09 km (NOAA/NESDIS, 2014). The low spatial resolution of these products limits their use for LC and LU classification within small regions. Landsat's spatial resolution of 30 m is similar to the highest pixel size in this study (25.6 m). This shows that this data would not produce accurate LC classifications and would not be usable for LU classifications given the methods in this study. If a regional municipality was conducting a LC or LU analysis of their region, they would not be able to use any of the global data products simply due to the spatial resolution.

The thematic resolution of LC products derived from these platforms can be similar to what was used in Thematic Typology 1 of this study. For example, the LC dataset provided by MODIS contains 17 classes of which the three anthropogenic classes are urban and built-up, croplands, and cropland/natural vegetation mosaic and the rest are natural classes (Friedl et al., 2010). The classification contains more classes than Thematic Typology 1 due to the spatial extent of the data containing more LC classes. The one exception to this is that the dataset uses types of forests instead of types of trees like in Thematic Typology 1. This is necessary due to the large pixel size combining many trees into one pixel. The one class which is not represented in some way in the MODIS dataset is "shadow". This is to be expected as the shadows cast by buildings and trees are much smaller than the pixels and the features casting the shadows will me a majority of the pixel. The "shadow" class was only necessary in this study due to the fine resolution imagery having pixels small enough to accurately depict the shadows.

3.4 Conclusions

Through answering the first research question "what combination of spatial, thematic, and classification methods produce the highest LC and LU accuracy?", it has been determined that out of the parameters examined, MLC is on average the best classifier to use to classify LC. The best combinations of spatial and thematic resolution within MLC are 160 cm and 640 cm for Thematic Typology 1, 160 cm for Thematic Typology 2, 320 cm for Thematic Typology 3, and 320 cm for Thematic Typology 4. The results showed that a mid-range spatial resolution outperformed the very fine and very coarse resolutions and that coarser thematic resolutions increase accuracy. These relationships are useful to understand as it allows a researcher to select the appropriate imagery for their study. Not only can this increase the accuracy of the generated products, but it can also save time and resources spent on imagery which may not improve the results. The results also showed that the optimal resolution of LC classification to use as input to the LU classification was Thematic Typology 1 with 80 cm pixels. While this combination did not perform highly in the LC classification, it outperformed all other combinations.

Answering the second research question "what is the relationship between LC and LU?" shows that a finer pixel size than that of the optimal LC classification is needed for the LU classification. Also, the finer the LC thematic resolution the higher the LU classification accuracy. This study shows that an intermediate LC product requires higher spatial and thematic resolution than a final LC product. The accuracy of the intermediate LC classification is lower than the accuracy achieved when the LC classification is the final product desired. This is important as it means that both accuracy and resolution need to be considered together when creating or selecting an intermediate product. Neither one can be the only attribute used in determining the product to use. This also means that when a commercial LC classification is acquired for LU classification, it will likely underperform compared to a custom LC classification from the same imagery.

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Appendices

Appendix A

List of papers found in the International Journal of Remote Sensing in order of relevancy when the search term “land use classification” is used

#	Paper reference
1	Bryan, M. L. (1983). Urban land use classification using synthetic aperture radar. *International Journal of Remote Sensing*, *4*(2), 215–233. https://doi.org/10.1080/01431168308948542
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Appendix B

Comparison of Land Cover Classes to the National Land Cover Database 2011 (Based off Anderson's 1976 Classification)

NLCD2011	This Study	Reasoning
Open Water	Water	Perfect Match
Perennial ice and snow	None	Does not exist in study area
Developed, open space	Grass	Parks and fields in developed areas
Developed Low Intensity Developed Medium Intensity Developed High Intensity	Residential Roof Flat Roofs and Paved Surfaces Grass Deciduous Coniferous Water Shadow	NLCD2011 was created for a much lower resolution and therefore needed to be split into the components
Barren land	Bare ground	Barren land is land without vegetation
Deciduous forest	Deciduous	Good match, modified for higher resolution
Evergreen Forest	Coniferous	Good match, modified for higher resolution
Mixed forest	None	The high resolution of this study makes this class obsolete
Dwarf Scrub	None	Only found in northern latitudes
Shrub/scrub	None	Does not exist in study area
Grassland/herbaceous	Grass	Completely fits within this class
Sedge/Herbaceous	None	Only found in northern latitudes
Litchens	None	Only found in northern latitudes
Moss	None	Only found in northern latitudes

Pasture/Hay	Grass Bare Ground	Fields are either bare or have light crop cover at the time of the imagery
Cultivated Crops	Grass Bare Ground	Fields are either bare or have light crop cover at the time of the imagery
Woody Wetlands	Water Deciduous Coniferous	At high resolution the distinct parts can be identified
Emergent Herbaceous Wetlands	Water Deciduous Coniferous	At high resolution the distinct parts can be identified

Appendix C

Manual Land Use Classification of Parcels in the Region of Waterloo

#	Name	Classification description based on perceived uses and services
1	Low Density Residential	Parcels which appear to contain a single dwelling for a single family on a large property. These parcels typically appear outside the urban core in suburbs or rural areas. While houses tend to be larger than medium density residential, it is not a requirement for the classification.
2	Medium Density Residential	Average sized parcels containing a single dwelling for a single family, which may or may not be attached to adjacent dwellings. This class contains the majority of residential parcels within subdivisions and the urban core. In most parcels, the house and driveway cover most or all of the width of the parcels, with yards in the front and back.
3	High Density Residential	Parcels containing buildings with multiple dwellings or units, and therefore multiple families within the parcel. Typically in two forms, apartment or condo buildings, and townhouses where one parcel contains multiple units. Parcels may contain green space and parking lots in addition to the buildings.
4	Commercial	Parcels containing business where customers visit to obtain products and services, or office buildings which may not receive customers. Larger parcels, such as malls or box stores, will contain large parking lots for customers. These parcels do not contain large outdoor storage areas, although garden and home improvement stores may have some outdoor storage.
5	Industrial	Parcels which contain a business with an outdoor storage area such as a factory or a car scrapyard. These business typically do not receive customers although there may be parking lots for employees and areas for incoming materials and outgoing products.
6	Institutional	Manually classified parcels for schools (private and public) and hospitals. Schools and hospitals can appear as a variety of classes but provide different services from these misclassifications (e.g. Commercial or Protected Areas and Recreation). Manually classifying these parcels allows for them to be included in the landscape without large amounts of misclassification.
7	Transportation	Parcels which represent roads and railways. These parcels often include the boulevard and sidewalks. Highway interchange parcels include all the land which is owned and managed by the managing government.
8	Protected Areas and Recreation	Areas which have a primary purpose of recreation, such as parks, or protected areas such as forests. Commercial forests and private forests are included in this class as they appear very similar, or even identical to the natural forests.
9	Agriculture	Parcels which are primarily used for raw food production. This includes fields for crops and pastures. Some parcels will have barns and/or a farm house, while others may have neither. Parcels may also include a portion which is forested, sometimes referred to as “the back forty”.
10	Water	Parcels which have a main purpose of outlining waterbodies such as rivers. Lakes are included when the lake occupies a majority of the parcel. The rest of the parcel

		may include sections which would otherwise be classified as Protected Areas and Recreation.
11	Under Development	Properties where construction has not been completed and no residents or business has moved in. These parcels may become many different classes when complete, but the class cannot be guaranteed at the time of the imagery. Depending on the progress of a development project, residential areas and big box stores or shopping complexes may appear similar as the area is represented by only a single parcel.

Clarifications Between Similar Land Use Classes

First Class	Second Class	Problem	Solution
Low Density Residential	Medium Density Residential	Parcel size is a continuous variable and it is difficult to define the exact separation between the two classes.	In many cases where there is confusion, the house is the same size as the surrounding properties which are either low or medium density and is a similar distance from the road. The parcel in question will usually have its additional size added through its backyard. If the backyard visually occupies two thirds of the property, it can be easily called low density, if less, medium density. If the parcel has a backyard smaller than two thirds, but the front yard and house are large, then it can also be classified as low density. If an absolute value of size is needed, $2000m^2$ should be used as the minimum size for Low Density Residential.
Low Density Residential	Protected Areas and Recreation	Household in a large parcel is surrounded forest or green land with no appearance of backyard/garden.	If size of the house and the maintained portion of the property is very small compared to the area of the forest, the parcel should be classified as Protected Areas and Recreation. If the house and the maintained portion of the property is a significant portion of the parcel, it should be classified as Low Density Residential.
Medium Density Residential	Under Development	A house is visible in the parcel that is under development	If there is a completed house with grass on the property it should be considered complete and classified as Medium Density Residential. If the house does not appear complete or there is no grass where there should be, it should be classified as Under Development.

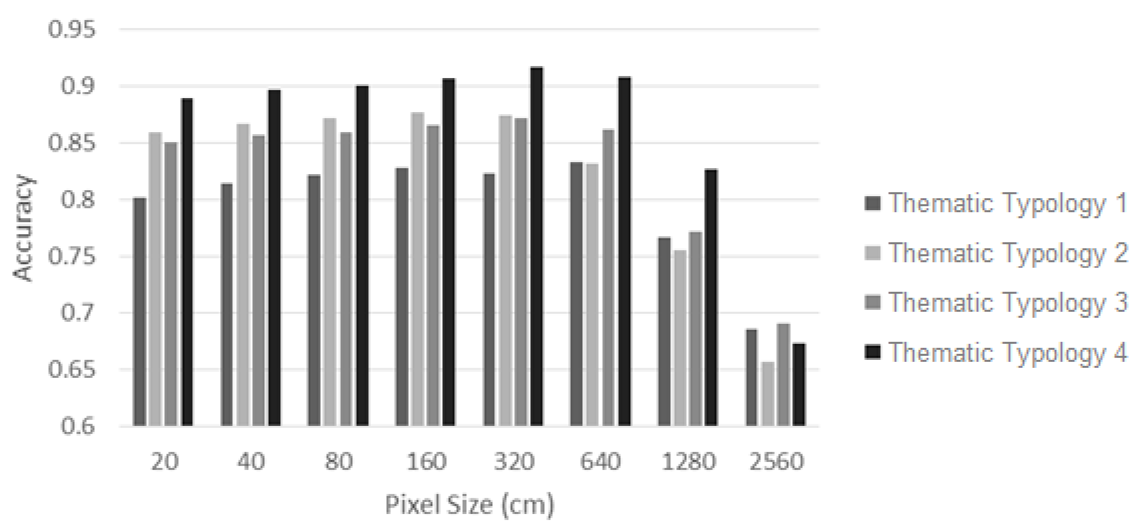
Exemptions and Special Cases in Land Use Classification

Example	Class	Reasoning
Airport	Commercial	Airports provide services similar to Commercial parcels, where people are constantly visiting the parcel. Visually they are similar as they both include large paved areas such as parking lots and a large building.
Fire stations	Commercial	Although functionally different from Commercial parcels, they are very similar in the imagery.
Graveyard	Protected Areas and Recreation	Graveyards and cemeteries are visually similar to parks, where there are paths for people to walk and grass fields. The only visual difference is that there are pieces of stone (headstones) scattered across the fields and there is no sports equipment.
Water Tower	Protected Areas and Recreation	Water towers can be visually similar to parks as they can have large grassy areas surrounding the tower. If the water tower is in a parcel without much grassed area, it may be classified as Commercial instead.
Commercial Forest – Post-Harvest	Various	If the harvested forest appears to be converted into agriculture, classify as Agriculture. If it shows signs of urban development, it should be classified as Under Development. If it appears to be replanted and is still being used as a commercial forest, classify as Protected Areas and Recreation.
Catwalk	Transportation	The paths between houses, or catwalks, are similar to roads, although a little smaller. A path through a park or green space would not be considered transportation.
Walking paths	Protected Areas and Recreation	Walking paths in the area can often be found under large electrical transmission lines. The transmission lines and towers account for a small portion of the parcel, and therefore simply appear as grassy corridors through subdivisions, similar to parks.
Church	Commercial	Churches are visibly similar to Commercial parcels because they are a building which has a parking lot and some property. Functionally they are also similar as people will visit a church for a relatively short period of time, similar to a business.
Artifacts	N/A	The parcel data is not perfect and has artifacts from either previous versions, or mistakes during creation. Some artifacts have little impact on the data, while others have large impacts. The most frequent example is a single parcel being divided into multiple parcels by the artifacts.
Artifacts – Splits	N/A	When a parcel is divided by artifacts all segments should be classified as the original type if suitable. If a segment can clearly be classified as another land use type it should be done. For example, if a Low Density Residential parcel is divided into three pieces, two covering the house and one covering a forest at the back of the property, the two on the house should be Low Density Residential and the one on the forest should be Protected Areas and Recreation.

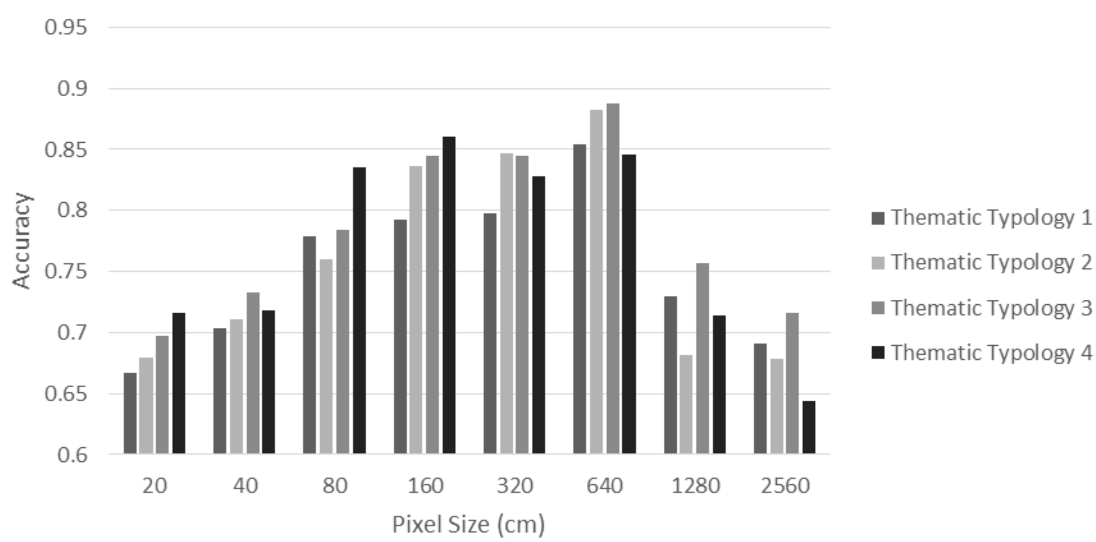
Artifacts - Slivers	N/A	Another form of artifact is a sliver. These sliver parcels are very thin and long. Examples can be a few centimeters wide but almost a kilometer long. Sliver parcels should be ignored and not classified if noticed.
Mixed Parcels	N/A	Occasionally parcels will contain multiple land use types other than the previously mentioned scenarios. For example a parcel may contain a house and land on one half and part of a waterbody on the other half. In these scenarios where there is no clear majority of land use type the following order of priority should be used: Medium Density Residential > High Density Residential > Low Density Residential > Commercial > Industrial > Institution > Transportation > Under Development > Agriculture > Protected Areas and Recreation > Water
Future Development	N/A	In the scenarios where parcels have been created but no development has begun, classify the parcel based on the currently present land use type. If the imagery shows evidence of development, then classify as Under Development.

Appendix D

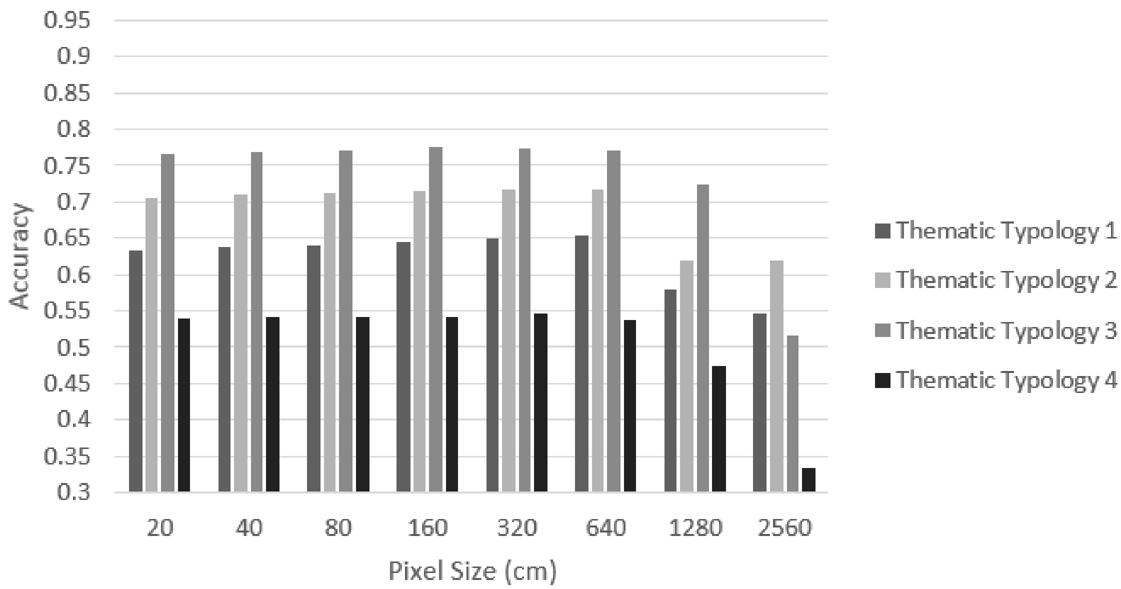
Land cover classification accuracy for all spatial and thematic resolutions are displayed in the graphs following graphs for the different classification algorithms. The ISODATA unsupervised classifier is not shown as reliable results were not attainable as many of the automatically created classes could not be merged into any one of the existing classes.



Accuracy of LC for the 2010 imagery - MLC

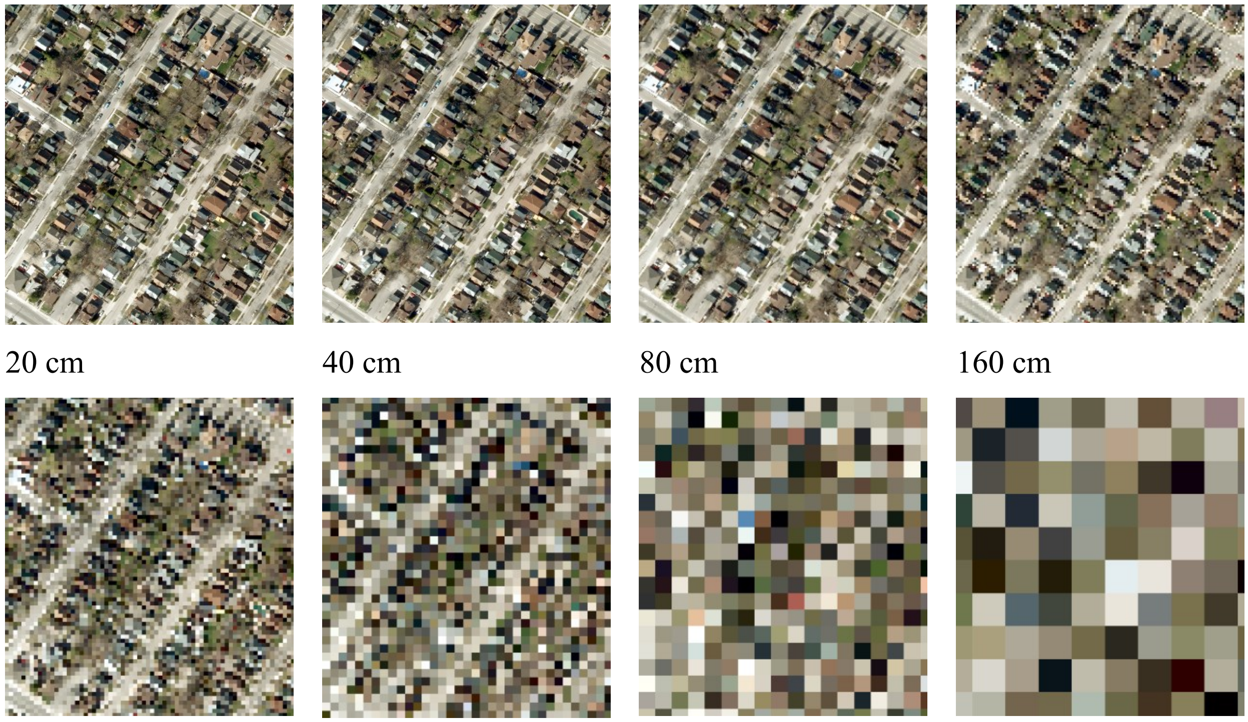


Accuracy of LC for the 2010 imagery - SVM



Accuracy of LC for the 2010 imagery - SAM

Appendix E



20 cm | 40 cm | 80 cm | 160 cm

320 cm | 640 cm | 1280 cm | 2560 cm

True colour samples of the 2010 imagery resampled to the required resolutions

Appendix F

Confusion matrix for 2010 LC Thematic Typology 1 at 20cm, MLC

		Sample Data Classes (m^2)									
		C. 1	C. 2	C. 3	C. 4	C. 5	C. 6	C. 7	C. 8	Total	User's (%)
Classified Result Classes	C. 1	12472	0	0	0	24	4138	0	0	16634	75.0
	C. 2	0	13994	2448	0	70	0	554	200	17266	81.0
	C. 3	0	1606	14918	0	893	0	1513	5	18936	78.8
	C. 4	0	43	0	20001	1	0	0	14	20059	99.7
	C. 5	8	780	65	0	18004	36	337	184	19414	92.7
	C. 6	7563	0	0	0	186	15824	0	1289	24863	63.6
	C. 7	0	2210	2580	0	666	0	17632	0	23087	76.4
	C. 8	0	1393	6	2	161	16	0	4310	5887	73.2
Total		20044	20025	20017	20004	20006	20014	20036	6006		
Producer's (%)		62.2	69.9	74.5	~100.0	90.0	79.1	88.0	71.8	Overall:	80.2%

Legend

C. 1	Grass	C. 2	Pitched Roof
C. 3	Pavement/Flat Roof	C. 4	Water
C. 5	Deciduous	C. 6	Coniferous
C. 7	Bare Ground and Soil	C. 8	Shadow

Confusion matrix for 2010 LC Thematic Typology 2 at 20cm, MLC

		Sample Data Classes (m^2)							
		C. 1	C. 2	C. 3	C. 4	C. 5	C. 6	Total	User's (%)
Classified Result Classes	C. 1	40019	0	0	0	1936	1173	43128	92.8
	C. 2	0	14734	2524	0	1314	239	18812	78.3
	C. 3	1	1647	15251	0	4842	10	21752	70.1
	C. 4	0	42	0	20001	2	14	20060	99.7
	C. 5	10	2179	2233	0	31024	4	35450	87.5
	C. 6	28	1423	9	2	923	4562	6946	65.7
Total		40057	20027	20017	20003	40041	6003		
Producer's (%)		99.9	73.6	76.2	~100.0	77.5	76.0	Overall:	85.9%

Legend

C. 1	Green Vegetation	C. 2	Pitched Roof
C. 3	Pavement/Flat Roof	C. 4	Water
C. 5	Brown Vegetation and Soil	C. 6	Shadow

Confusion matrix for 2010 LC Thematic Typology 3 at 20cm, MLC

		Sample Data Classes (m²)						
		C. 1	C. 2	C. 3	C. 4	C. 5	Total	User's (%)
Classified Result Classes	C. 1	40018	1	0	1934	1173	43127	92.8
	C. 2	1	26366	0	3870	156	30394	86.7
	C. 3	0	49	20001	4	14	20068	99.7
	C. 4	10	11006	0	33271	7	44295	75.1
	C. 5	28	2621	2	961	4652	8264	56.3
	Total	40057	40043	20004	40041	6003		
Producer's (%)		99.9	65.8	~100.0	83.1	77.5	Overall:	85.1%

Legend

C. 1	Green Vegetation	C. 2	Impervious Surfaces
C. 3	Water	C. 4	Brown Vegetation and Soil
C. 5	Shadow		

Confusion matrix for 2010 LC Thematic Typology 4 at 20cm, MLC

		Sample Data Classes (m²)					
		C. 1	C. 2	C. 3	C. 4	Total	User's (%)
Classified Result Classes	C. 1	74883	7851	0	223	82957	90.3
	C. 2	3930	29520	0	155	33604	87.8
	C. 3	4	49	20002	14	20068	99.7
	C. 4	1282	2624	2	5611	9519	59.0
	Total	80099	40043	20004	6003		
Producer's (%)		93.5	73.7	~100.0	93.5	Overall:	89.0%

Legend

C. 1	Pervious Surfaces	C. 2	Impervious Surfaces
C. 3	Water	C. 4	Shadow

Confusion matrix for 2010 LC Thematic Typology 1 at 40cm, MLC

		Sample Data Classes (m^2)									
		C. 1	C. 2	C. 3	C. 4	C. 5	C. 6	C. 7	C. 8	Total	User's (%)
Classified Result Classes	C. 1	12432	0	0	0	26	3399	0	0	15857	78.4
	C. 2	0	14173	2292	0	52	0	488	195	17201	82.4
	C. 3	0	1585	15107	0	755	0	1130	4	18581	81.3
	C. 4	0	30	0	20007	0	0	0	7	20044	99.8
	C. 5	5	721	54	0	18355	31	255	177	19568	93.8
	C. 6	7599	0	0	0	145	16564	0	1314	25625	64.6
	C. 7	0	2204	2565	0	555	0	18177	0	23500	77.3
	C. 8	0	1319	6	0	124	11	0	4304	5765	74.7
Total		20037	20032	20023	20007	20013	20005	20021	6002		
Producer's (%)		62.0	70.8	75.4	100.0	91.7	82.8	90.8	71.7	Overall:	81.5%

Legend

C. 1	Grass	C. 2	Pitched Roof
C. 3	Pavement/Flat Roof	C. 4	Water
C. 5	Deciduous	C. 6	Coniferous
C. 7	Bare Ground and Soil	C. 8	Shadow

Confusion matrix for 2010 LC Thematic Typology 2 at 40cm, MLC

		Sample Data Classes (m^2)							
		C. 1	C. 2	C. 3	C. 4	C. 5	C. 6	Total	User's (%)
Classified Result Classes	C. 1	40014	0	0	0	1855	1192	43062	92.9
	C. 2	0	14849	2375	0	1192	236	18652	79.6
	C. 3	1	1628	15409	0	4307	9	21353	72.2
	C. 4	0	29	0	20007	1	7	20044	99.8
	C. 5	8	2181	2232	0	31918	3	36341	87.8
	C. 6	19	1345	7	0	762	4554	6688	68.1
Total		40042	20032	20023	20007	40034	6002		
Producer's (%)		99.9	74.1	77.0	100.0	79.7	75.9	Overall:	86.7%

Legend

C. 1	Green Vegetation	C. 2	Pitched Roof
C. 3	Pavement/Flat Roof	C. 4	Water
C. 5	Brown Vegetation and Soil	C. 6	Shadow

Confusion matrix for 2010 LC Thematic Typology 3 at 40cm, MLC

		Sample Data Classes (m^2)						
		C. 1	C. 2	C. 3	C. 4	C. 5	Total	User's (%)
Classified Result Classes	C. 1	40014	0	0	1848	1194	43055	92.9
	C. 2	1	26680	0	3584	155	30420	87.7
	C. 3	0	36	20007	1	7	20051	99.8
	C. 4	8	10783	0	33817	5	44612	75.8
	C. 5	19	255	0	786	4642	8001	58.0
	Total	40042	40055	20007	40034	6002		
Producer's (%)		99.9	66.6	100.0	84.5	77.3	Overall:	85.6%

Legend

C. 1	Green Vegetation	C. 2	Impervious Surfaces
C. 3	Water	C. 4	Brown Vegetation and Soil
C. 5	Shadow		

Confusion matrix for 2010 LC Thematic Typology 4 at 40cm, MLC

		Sample Data Classes (m^2)					
		C. 1	C. 2	C. 3	C. 4	Total	User's (%)
Classified Result Classes	C. 1	75680	7662	0	213	83555	90.6
	C. 2	3336	29797	0	154	33287	89.5
	C. 3	1	35	20007	7	20050	99.8
	C. 4	1059	2561	0	5628	9248	60.9
	Total	80076	40055	20007	6002		
Producer's (%)		94.5	74.4	100.0	93.8	Overall:	89.7%

Legend

C. 1	Pervious Surfaces	C. 2	Impervious Surfaces
C. 3	Water	C. 4	Shadow

Confusion matrix for 2010 LC Thematic Typology 1 at 80cm, MLC

Sample Data Classes (m²)

Classified Result Classes	C. 1	C. 2	C. 3	C. 4	C. 5	C. 6	C. 7	C. 8	Total	User's (%)
C. 1	12217	0	0	0	26	2699	0	0	14941	81.8
C. 2	0	14382	2276	0	52	0	468	216	17395	82.7
C. 3	0	1490	15096	0	961	0	980	6	18253	82.7
C. 4	0	28	0	20006	0	0	0	3	20037	99.8
C. 5	4	710	45	0	18555	22	207	188	19732	94.0
C. 6	7811	0	0	0	113	17297	0	1318	26539	65.2
C. 7	0	2075	2554	0	498	0	18374	0	23500	78.2
C. 8	0	1347	6	0	96	8	0	4275	5732	74.6
Total	20032	20031	19976	20006	20021	20027	20030	6005		
Producer's (%)	61.0	71.8	75.6	100.0	92.7	86.4	91.7	71.2	Overall:	82.2%

Legend

C. 1	Grass	C. 2	Pitched Roof
C. 3	Pavement/Flat Roof	C. 4	Water
C. 5	Deciduous	C. 6	Coniferous
C. 7	Bare Ground and Soil	C. 8	Shadow

Confusion matrix for 2010 LC Thematic Typology 2 at 80cm, MLC

Sample Data Classes (m²)

Classified Result Classes	C. 1	C. 2	C. 3	C. 4	C. 5	C. 6	Total	User's (%)
C. 1	40044	0	0	0	1779	1182	43004	93.1
C. 2	0	15049	2356	0	1114	261	18780	80.1
C. 3	0	1518	15380	0	4015	14	20928	73.5
C. 4	0	26	0	20006	1	3	20036	99.9
C. 5	3	2056	2232	0	32463	5	36759	88.3
C. 6	12	1283	8	0	679	4540	6622	64.6
Total	40059	20031	19976	20006	40051	6005		
Producer's (%)	~100.0	75.1	77.0	100.0	81.1	75.6	Overall:	87.2%

Legend

C. 1	Green Vegetation	C. 2	Pitched Roof
C. 3	Pavement/Flat Roof	C. 4	Water
C. 5	Brown Vegetation and Soil	C. 6	Shadow

Confusion matrix for 2010 LC Thematic Typology 3 at 80cm, MLC

		Sample Data Classes (m^2)						
		C. 1	C. 2	C. 3	C. 4	C. 5	Total	User's (%)
Classified Result Classes	C. 1	40044	1	0	1751	1182	42977	93.2
	C. 2	0	26650	0	3377	185	30211	88.2
	C. 3	0	31	20006	0	3	20040	99.8
	C. 4	3	10681	0	34231	6	44922	76.2
	C. 5	12	1646	0	692	4629	7980	58.0
	Total	40059	40008	20006	40051	6005		
Producer's (%)		~100.0	66.6	100.0	85.5	77.1	Overall:	85.9%

Legend

C. 1 Green Vegetation; C. 2 Impervious Surfaces
C. 3 Water; C. 4 Brown Vegetation and Soil
C. 5 Shadow

Confusion matrix for 2010 LC Thematic Typology 4 at 80cm, MLC

		Sample Data Classes (m^2)					
		C. 1	C. 2	C. 3	C. 4	Total	User's (%)
Classified Result Classes	C. 1	76213	7425	0	240	82878	60.9
	C. 2	3078	29901	0	183	33163	90.2
	C. 3	0	31	20006	3	20040	99.8
	C. 4	819	2650	0	5580	9047	61.7
	Total	80110	40008	20006	6005		
Producer's (%)		95.1	74.7	100.0	92.9	Overall:	90.1%

Legend

C. 1 Pervious Surfaces; C. 2 Impervious Surfaces
C. 3 Water; C. 4 Shadow

Confusion matrix for 2010 LC Thematic Typology 1 at 160cm, MLC

Sample Data Classes (m^2)

Classified Result Classes	C. 1	C. 2	C. 3	C. 4	C. 5	C. 6	C. 7	C. 8	Total	User's (%)
C. 1	12147	0	0	0	18	2260	0	0	14426	84.2
C. 2	0	14356	2276	0	49	0	458	256	17395	82.5
C. 3	0	1518	15263	0	576	0	965	10	18332	83.3
C. 4	0	10	0	19983	0	0	0	0	19994	99.9
C. 5	5	765	33	0	18801	20	200	200	20024	93.9
C. 6	7887	0	0	0	79	17733	0	1313	27013	65.6
C. 7	0	2035	2435	0	376	0	18406	0	23252	79.2
C. 8	0	1275	3	0	79	5	0	4229	5591	75.6
Total	20040	19960	20009	19983	19978	20019	20029	6008		
Producer's (%)	60.6	71.9	76.3	100.0	94.1	88.6	91.9	70.4	Overall:	82.8%

Legend

C. 1	Grass	C. 2	Pitched Roof
C. 3	Pavement/Flat Roof	C. 4	Water
C. 5	Deciduous	C. 6	Coniferous
C. 7	Bare Ground and Soil	C. 8	Shadow

Confusion matrix for 2010 LC Thematic Typology 2 at 160cm, MLC

Sample Data Classes (m^2)

Classified Result Classes	C. 1	C. 2	C. 3	C. 4	C. 5	C. 6	Total	User's (%)
C. 1	40054	0	0	0	1828	1196	43077	93.0
C. 2	0	15096	2360	0	1129	294	18880	80.0
C. 3	0	1592	15634	0	3625	15	20867	74.9
C. 4	0	8	0	19983	0	0	19991	~100.0
C. 5	0	1958	2012	0	32845	5	36820	89.2
C. 6	5	1306	3	0	581	4498	6392	70.4
Total	40059	19960	20009	19983	40008	6008		
Producer's (%)	~100.0	75.6	78.1	100.0	82.1	74.9	Overall:	87.7%

Legend

C. 1	Green Vegetation	C. 2	Pitched Roof
C. 3	Pavement/Flat Roof	C. 4	Water
C. 5	Brown Vegetation and Soil	C. 6	Shadow

Confusion matrix for 2010 LC Thematic Typology 3 at 160cm, MLC

Classified Result Classes		Sample Data Classes (m^2)						
		C. 1	C. 2	C. 3	C. 4	C. 5	Total	User's (%)
	C. 1	40054	0	0	1756	1193	43003	93.1
	C. 2	0	27095	0	2977	215	30287	89.5
	C. 3	0	10	19983	0	0	19994	99.9
	C. 4	0	10394	0	34706	18	45117	76.9
	C. 5	5	2470	0	568	4582	7626	60.1
	Total	40059	39969	19983	40008	6008		
Producer's (%)		~100.0	67.8	100.0	86.7	76.3	Overall:	86.6%

Legend

C. 1	Green Vegetation	C. 2	Impervious Surfaces
C. 3	Water	C. 4	Brown Vegetation and Soil
C. 5	Shadow		

Confusion matrix for 2010 LC Thematic Typology 4 at 160cm, MLC

Classified Result Classes		Sample Data Classes (m^2)					
		C. 1	C. 2	C. 3	C. 4	Total	User's (%)
	C. 1	76672	7196	0	241	84109	91.2
	C. 2	2824	30313	0	207	33344	90.9
	C. 3	0	15	19983	0	19999	99.9
	C. 4	571	2445	0	5560	8576	64.8
	Total	80067	39969	19983	6008		
Producer's (%)		95.8	75.8	100.0	92.5	Overall:	90.8%

Legend

C. 1	Pervious Surfaces	C. 2	Impervious Surfaces
C. 3	Water	C. 4	Shadow

Confusion matrix for 2010 LC Thematic Typology 1 at 320cm, MLC

		Sample Data Classes (m^2)									
		C. 1	C. 2	C. 3	C. 4	C. 5	C. 6	C. 7	C. 8	Total	User's (%)
Classified Result Classes	C. 1	12104	20	0	0	10	2826	0	0	14961	80.9
	C. 2	0	13793	2109	0	96	0	492	174	16630	82.9
	C. 3	0	1845	15360	0	532	0	860	20	18616	82.5
	C. 4	0	20	0	20060	0	0	0	20	20101	99.8
	C. 5	0	727	41	0	19077	41	195	92	20173	94.6
	C. 6	7987	20	0	0	31	17060	0	1260	26358	64.7
	C. 7	0	2529	2468	0	338	0	18463	0	23798	77.6
	C. 8	0	1096	0	0	20	10	0	4434	5560	79.7
Total		20091	20050	19978	20060	20070	19937	20009	6001		
Producer's (%)		60.2	68.8	76.9	100.0	95.1	85.6	82.3	73.9	Overall:	82.3%

Legend

C. 1	Grass	C. 2	Pitched Roof
C. 3	Pavement/Flat Roof	C. 4	Water
C. 5	Deciduous	C. 6	Coniferous
C. 7	Bare Ground and Soil	C. 8	Shadow

Confusion matrix for 2010 LC Thematic Typology 2 at 320cm, MLC

		Sample Data Classes (m^2)							
		C. 1	C. 2	C. 3	C. 4	C. 5	C. 6	Total	User's (%)
Classified Result Classes	C. 1	40028	82	0	0	1884	1106	43100	92.9
	C. 2	0	14234	2161	0	1311	205	17910	79.5
	C. 3	0	1935	15616	0	3154	20	20726	75.3
	C. 4	0	20	20	20060	0	20	20101	99.8
	C. 5	0	2632	2202	0	33280	0	38113	87.3
	C. 6	0	1147	0	0	451	4649	6246	74.4
Total		40028	20050	19978	20060	40079	6001		
Producer's (%)		100.0	71.0	78.2	100.0	83.0	77.5	Overall:	87.5%

Legend

C. 1	Green Vegetation	C. 2	Pitched Roof
C. 3	Pavement/Flat Roof	C. 4	Water
C. 5	Brown Vegetation and Soil	C. 6	Shadow

Confusion matrix for 2010 LC Thematic Typology 3 at 320cm, MLC

		Sample Data Classes (m^2)						
		C. 1	C. 2	C. 3	C. 4	C. 5	Total	User's (%)
Classified Result Classes	C. 1	40028	72	0	1812	1106	43018	93.0
	C. 2	0	27290	0	2427	133	29850	91.4
	C. 3	0	31	20060	0	20	20111	99.7
	C. 4	0	10455	0	35359	10	45824	77.2
	C. 5	0	2181	0	481	4731	7393	64.0
	Total	40028	40028	20060	40079	6001		
Producer's (%)		100.0	68.2	100.0	88.2	78.8	Overall:	87.2%

Legend

C. 1	Green Vegetation	C. 2	Impervious Surfaces
C. 3	Water	C. 4	Brown Vegetation and Soil
C. 5	Shadow		

Confusion matrix for 2010 LC Thematic Typology 4 at 320cm, MLC

		Sample Data Classes (m^2)					
		C. 1	C. 2	C. 3	C. 4	Total	User's (%)
Classified Result Classes	C. 1	77650	7301	0	133	85084	91.3
	C. 2	2140	30556	0	133	32829	93.1
	C. 3	0	31	20060	31	20122	99.7
	C. 4	317	2140	0	5704	8161	69.9
	Total	80108	40028	20060	6001		
Producer's (%)		96.9	76.3	100.0	95.1	Overall:	91.6%

Legend

C. 1	Pervious Surfaces	C. 2	Impervious Surfaces
C. 3	Water	C. 4	Shadow

Confusion matrix for 2010 LC Thematic Typology 1 at 640cm, MLC

Sample Data Classes (m²)

Classified Result Classes	C. 1	C. 2	C. 3	C. 4	C. 5	C. 6	C. 7	C. 8	Total	User's (%)
C. 1	12452	41	0	0	0	2007	0	0	14500	85.9
C. 2	0	11551	1434	0	41	0	328	205	13558	85.2
C. 3	0	2048	16261	0	451	0	901	0	19661	82.7
C. 4	0	164	0	19948	0	0	0	0	20111	99.2
C. 5	0	614	41	0	19210	0	164	328	20357	94.4
C. 6	7086	82	0	0	0	18145	0	860	26173	69.3
C. 7	0	2089	2253	0	410	0	18801	0	23552	79.8
C. 8	0	2662	0	0	41	0	0	4547	7250	62.7
Total	19538	19251	19988	19948	20152	20152	20193	5939		
Producer's (%)	63.7	60.0	81.4	100.0	95.3	90.0	93.1	76.6	Overall:	83.3%

Legend

C. 1	Grass	C. 2	Pitched Roof
C. 3	Pavement/Flat Roof	C. 4	Water
C. 5	Deciduous	C. 6	Coniferous
C. 7	Bare Ground and Soil	C. 8	Shadow

Confusion matrix for 2010 LC Thematic Typology 2 at 640cm, MLC

Sample Data Classes (m²)

Classified Result Classes	C. 1	C. 2	C. 3	C. 4	C. 5	C. 6	Total	User's (%)
C. 1	39690	164	0	0	410	737	41001	96.8
C. 2	0	11960	1434	0	8806	328	22528	53.1
C. 3	0	2130	16507	0	2007	0	20644	80.0
C. 4	0	164	0	19948	0	0	20111	99.2
C. 5	0	2130	2048	0	27771	0	31949	86.9
C. 6	0	2703	0	0	1352	4874	8929	54.6
Total	39690	19251	19988	19948	40346	5939		
Producer's (%)	100.0	62.1	82.6	100.0	68.8	82.1	Overall:	83.2%

Legend

C. 1	Green Vegetation	C. 2	Pitched Roof
C. 3	Pavement/Flat Roof	C. 4	Water
C. 5	Brown Vegetation and Soil	C. 6	Shadow

Confusion matrix for 2010 LC Thematic Typology 3 at 640cm, MLC

		Sample Data Classes (m^2)						
		C. 1	C. 2	C. 3	C. 4	C. 5	Total	User's (%)
Classified Result Classes	C. 1	39690	164	0	696	737	41288	96.1
	C. 2	0	26255	0	2908	82	29245	89.8
	C. 3	0	164	19948	0	0	20111	99.2
	C. 4	0	8806	0	34161	0	42967	79.5
	C. 5	0	3850	0	2580	5120	11551	44.3
	Total	39690	39240	19948	40346	5939		
Producer's (%)		100.0	66.9	100.0	84.7	86.2	Overall:	86.2%

Legend

C. 1	Green Vegetation	C. 2	Impervious Surfaces
C. 3	Water	C. 4	Brown Vegetation and Soil
C. 5	Shadow		

Confusion matrix for 2010 LC Thematic Typology 4 at 640cm, MLC

		Sample Data Classes (m^2)					
		C. 1	C. 2	C. 3	C. 4	Total	User's (%)
Classified Result Classes	C. 1	77046	6062	0	246	83354	92.4
	C. 2	1884	29204	0	82	31171	93.7
	C. 3	0	164	19948	0	30111	99.2
	C. 4	1106	3809	0	5612	10527	53.3
	Total	80036	39240	19948	5939		
Producer's (%)		96.3	74.4	100.0	94.5	Overall:	90.8%

Legend

C. 1	Pervious Surfaces	C. 2	Impervious Surfaces
C. 3	Water	C. 4	Shadow

Confusion matrix for 2010 LC Thematic Typology 1 at 1280cm, MLC

Sample Data Classes (m^2)

Classified Result Classes	C. 1	C. 2	C. 3	C. 4	C. 5	C. 6	C. 7	C. 8	Total	User's (%)
C. 1	13926	1802	164	0	0	4260	0	0	20152	69.1
C. 2	0	5079	492	0	0	655	328	0	6554	77.5
C. 3	0	3604	16056	0	328	0	2458	492	22938	70.0
C. 4	0	0	0	19497	0	0	0	0	19497	100.0
C. 5	0	1311	164	0	19988	0	164	0	21627	92.4
C. 6	8243	1638	0	0	0	15729	0	1147	23757	66.2
C. 7	0	2294	2458	0	164	0	17695	819	23429	75.5
C. 8	0	3441	492	0	164	0	0	4260	8356	51.0
Total	19169	19169	19825	19497	20644	50644	50644	6717		
Producer's (%)	72.6	26.5	81.0	100.0	96.8	76.2	85.7	63.4	Overall:	76.7%

Legend

C. 1	Grass	C. 2	Pitched Roof
C. 3	Pavement/Flat Roof	C. 4	Water
C. 5	Deciduous	C. 6	Coniferous
C. 7	Bare Ground and Soil	C. 8	Shadow

Confusion matrix for 2010 LC Thematic Typology 2 at 1280cm, MLC

Sample Data Classes (m^2)

Classified Result Classes	C. 1	C. 2	C. 3	C. 4	C. 5	C. 6	Total	User's (%)
C. 1	39813	3113	164	0	0	819	43909	90.7
C. 2	0	6062	655	0	8256	0	15073	40.2
C. 3	0	3932	16712	0	4588	655	25887	64.6
C. 4	0	0	0	19497	0	0	19497	100.0
C. 5	0	2458	1802	0	24084	819	29164	82.6
C. 6	0	3604	492	0	4260	4424	12780	34.6
Total	39813	19169	19825	19497	51288	6717		
Producer's (%)	100.0	31.6	84.3	100.0	58.3	65.9	Overall:	75.6%

Legend

C. 1	Green Vegetation	C. 2	Pitched Roof
C. 3	Pavement/Flat Roof	C. 4	Water
C. 5	Brown Vegetation and Soil	C. 6	Shadow

Confusion matrix for 2010 LC Thematic Typology 3 at 1280cm, MLC

Classified Result Classes		Sample Data Classes (m^2)						
		C. 1	C. 2	C. 3	C. 4	C. 5	Total	User's (%)
	C. 1	39813	4260	0	0	819	44892	88.7
	C. 2	0	21627	0	8192	164	29983	72.1
	C. 3	0	0	19497	0	0	19497	100.0
	C. 4	0	9011	0	27361	1147	37519	72.9
	C. 5	0	4096	0	5734	4588	14418	31.8
	Total	39813	38994	19497	41288	6717		
Producer's (%)		100.0	55.5	100.0	66.3	68.3	Overall:	77.2%

Legend

C. 1	Green Vegetation	C. 2	Impervious Surfaces
C. 3	Water	C. 4	Brown Vegetation and Soil
C. 5	Shadow		

Confusion matrix for 2010 LC Thematic Typology 4 at 1280cm, MLC

Classified Result Classes		Sample Data Classes (m^2)					
		C. 1	C. 2	C. 3	C. 4	Total	User's (%)
	C. 1	71926	10650	0	655	83231	86.4
	C. 2	4096	24248	0	819	29164	83.1
	C. 3	0	0	19497	0	19497	100.0
	C. 4	5079	4096	0	5243	14418	36.4
	Total	81101	38994	19497	6716		
Producer's (%)		88.7	62.2	100.0	78.0	Overall:	82.6%

Legend

C. 1	Pervious Surfaces	C. 2	Impervious Surfaces
C. 3	Water	C. 4	Shadow

Confusion matrix for 2010 LC Thematic Typology 1 at 2560cm, MLC

		Sample Data Classes (m^2)									
		C. 1	C. 2	C. 3	C. 4	C. 5	C. 6	C. 7	C. 8	Total	User's (%)
Classified Result Classes	C. 1	17039	1966	0	0	0	5243	0	1311	25559	66.7
	C. 2	0	2621	655	0	0	655	0	655	4588	57.1
	C. 3	0	4588	13107	0	655	0	1311	1966	21627	60.6
	C. 4	0	1311	655	19005	0	0	0	0	20972	90.6
	C. 5	0	1966	1311	0	18350	0	0	0	21627	84.8
	C. 6	3277	655	0	0	0	15073	0	655	19661	76.7
	C. 7	0	2621	7864	0	0	0	19661	655	30702	63.8
	C. 8	0	6554	1311	0	655	0	0	1311	9830	13.3
Total		20316	22282	24904	19005	19661	20972	20972	6554		
Producer's (%)		83.9	11.8	52.6	100.0	93.3	71.9	93.8	20.0	Overall:	68.6%

Legend

C. 1	Grass	C. 2	Pitched Roof
C. 3	Pavement/Flat Roof	C. 4	Water
C. 5	Deciduous	C. 6	Coniferous
C. 7	Bare Ground and Soil	C. 8	Shadow

Confusion matrix for 2010 LC Thematic Typology 2 at 2560cm, MLC

		Sample Data Classes (m^2)							
		C. 1	C. 2	C. 3	C. 4	C. 5	C. 6	Total	User's (%)
Classified Result Classes	C. 1	40632	2621	0	0	655	655	44564	91.2
	C. 2	655	3277	655	0	7864	1966	14418	22.7
	C. 3	0	4588	14418	0	4588	2621	26214	55.0
	C. 4	0	1311	655	19005	0	0	20972	90.6
	C. 5	0	3277	7864	0	23593	655	35389	66.7
	C. 6	0	7209	1311	0	3932	655	13107	5.0
Total		41288	22282	24904	19005	40632	6554		
Producer's (%)		98.4	14.7	57.9	100.0	58.1	10.0	Overall:	65.7%

Legend

C. 1	Green Vegetation	C. 2	Pitched Roof
C. 3	Pavement/Flat Roof	C. 4	Water
C. 5	Brown Vegetation and Soil	C. 6	Shadow

Confusion matrix for 2010 LC Thematic Typology 3 at 2560cm, MLC

		Sample Data Classes (m^2)						
		C. 1	C. 2	C. 3	C. 4	C. 5	Total	User's (%)
Classified Result Classes	C. 1	41288	3277	0	655	1966	47186	87.5
	C. 2	0	19005	0	7209	2621	28836	65.9
	C. 3	0	2621	19005	0	0	21627	87.9
	C. 4	0	13763	0	26870	1311	41943	64.1
	C. 5	0	8520	0	5898	655	15073	4.3
	Total	41288	47186	19005	40632	6554		
Producer's (%)		100.0	40.3	100.0	66.1	10.0	Overall:	69.0%

Legend

C. 1	Green Vegetation	C. 2	Impervious Surfaces
C. 3	Water	C. 4	Brown Vegetation and Soil
C. 5	Shadow		

Confusion matrix for 2010 LC Thematic Typology 4 at 2560cm, MLC

		Sample Data Classes (m^2)					
		C. 1	C. 2	C. 3	C. 4	Total	User's (%)
Classified Result Classes	C. 1	57016	9175	0	655	66847	85.3
	C. 2	12452	26870	0	4588	43909	61.2
	C. 3	0	2621	19005	0	21627	87.9
	C. 4	12452	8520	0	1311	2282	5.9
	Total	81920	47186	19005	6554		
Producer's (%)		69.6	56.9	100.0	20.0	Overall:	67.4%

Legend

C. 1	Pervious Surfaces	C. 2	Impervious Surfaces
C. 3	Water	C. 4	Shadow