Measuring Land Cover Changes in the Twin Cities Metro Area Using Remote Sensing Techniques

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Abstract

The Twin Cities Metro Area in Minnesota has realized drastic changes in land cover in the last few decades. As many people are moving back into the cities from the surrounding suburbs, these changes in land cover are becoming more noticeable. This study uses Geographic Information Systems and remote sensing to measure land cover change from 2007 to 2016. By interpreting satellite imagery, a clearer picture can be obtained as to where change is taking place and to what degree the changes are happening. Using a system of land cover classification, the unique classes can be mapped and analyzed to show the most prominent changes in the region. Using these classes, a collection of maps, along with statistical information, was produced to better understand the changes that have taken place.

Introduction

Urban growth has long been considered a sign of healthy economic activity. This urban growth is often accompanied by an increase in population coupled with an increase in infrastructure. This is a delicate balance: the ecological needs and the needs of human development (Yuan and Bauer, 2007). Often times, human development takes precedent as cities expand pushing farther out into the rural areas. The most intrusive form of growth utilizes impervious surfaces. Impervious surfaces, or built up areas, are places where we spend a majority of our time. They are houses, roads, bridges, buildings, offices, schools, and even parks. As cities continue to expand, more pressure is put on city planners and administrators to increase infrastructure. However, with the increase in infrastructure, cities see a decrease in green space and a shift in land use. As Xu (2007) writes, urban areas are predominantly built up areas, which were taken from existing ecosystems. This means they can have a dramatic effect on hydraulic systems, biodiversity, and local climate, such as causing urban heat islands.

While the need to reassess the expansion of these impervious surfaces is apparent, there are strategies to develop in a more sustainable way. City planners and government officials can utilize remote sensing data to better understand the region's needs and assess areas of concern. There are numerous ways to use multispectral images to obtain land cover classification changes. These interpretations are called classification techniques and consist of supervised and unsupervised methods. Unsupervised is

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letting the computer asses the pixel data from the image and classify the regions. Supervised classification utilizes polygonal test areas, which are polygons of like valued pixels of the same known land cover classification, for a more defined assessment. Using these classification techniques, one can determine the distribution of land cover classifications and the differences between them over time.

As the majority of the world's population shift their lives to urban areas, urbanization causes immense pressure on cities and governments to expand infrastructure. This leads to a change in land use from areas that were once agriculture or forested to areas of buildings, roads, and homes. As the world's population continues to grow, there will be more and more pressure to increase infrastructure spending. By using remote sensing and GIS techniques, government officials and city planners are able to see trends in population to better utilize the existing space. Areas that see significant population decrease could then be reverted into green space.

Study Area

The study area is the seven-county metropolitan area of Minneapolis and Saint Paul, Minnesota, USA (Figure 1). The counties include Anoka, Carver, Dakota, Hennepin, Ramsey, Scott, and Washington, with a total population of 3,033,634. The region includes a range of diverse land cover classifications, including over 900 lakes, residential areas, forests, and several prominent rivers (Yuan and Bauer, 2007). This metropolitan area is home to a majority of the state's population, which means it is more densely populated than the rural portions of the state, which results in more built up/residential areas.

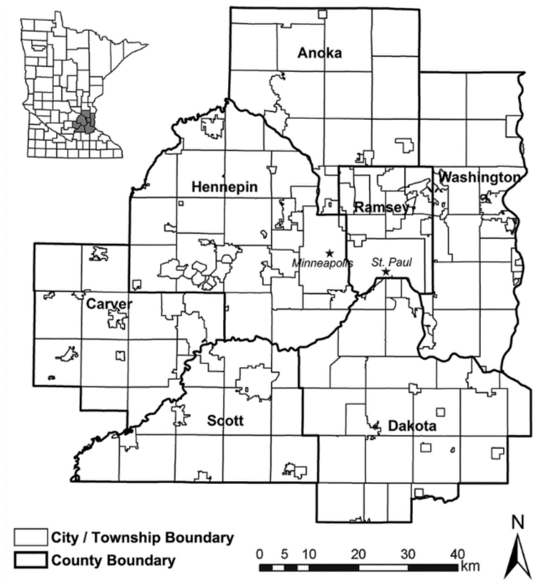

Figure 1. Twin Cities Metro Area.

Methods

Spatial Resolution

Raster images are comprised of individual cells. These individual pixel values have associated numerical values (Ferrato and Forsythe, 2013). Using these numerical values, impervious surfaces or "built up" areas can be mapped using remote sensing techniques.

The significant factor when dealing with remote sensing images is the scale (Nagendra, 2001). Scale can be applied in two ways; first is the extent of the analysis, and the second is the resolution of the remotely sensed images (Allen and Starr, 1982). The problem, however, is that the greater the extent of the image, the less resolution you have (Nagendra, 2001).

The most difficult part of working with remotely sensed images is deciding on the appropriate scale (or spatial resolution) for the environment you are working with (Woodcock and Strahler, 1987). Ferrato and Forsythe (2013) explain that there are four different types of spatial resolution: temporal, radiometric, spatial, and spectral. Spatial resolution is used when determining the quality of image and each needs to be taken into consideration when using multispectral images (Foody, 2002). For this study, two different temporal multispectral images were obtained. Due to the differences in vegetation and built up areas, summer images were used, as they best reveal the differences between urban and rural areas.

Another issue when dealing with multispectral images is the spectral and spatial resolution (Ferrato and Forsythe, 2013). These resolutions refer to the size of the individual cells of the images and the information inside them. These are the hard data used to determine the land use classification (Ferrato and Forsythe, 2013). For this study, two multispectral images were obtained from May 7, 2007 and August 11, 2016. The image in 2007 was taken from Landsat 5 TM and the 2016 image from Landsat 8 TM; both have a 30 meter resolution. All of the image analysis was done using ESRI's ArcMap.

Calculating Impervious Surfaces

Impervious surfaces are defined as "surfaces impenetrable by water including sidewalks, driveways, rooftops and parking lots" (Yuan and Bauer, 2007). Impervious surfaces are known to be a significant consideration for land use planners (Arnold and Gibbons, 1996). Stocker (1998) states there are four different ways to measure impervious surfaces: ground surveys, aerial interpretation, global positioning systems, and satellite interpretation. However, many of these data collection techniques are tedious and costly. The most efficient way to measure impervious surfaces is through satellite interpretation (Yuan and Bauer, 2007). In this assessment, using satellite imagery allows for the study of a large area without requiring many in-person measurements.

The initial step in understanding multispectral images is understanding the electromagnetic spectrum. This is the spectrum where all radiation is measured and classified. As Table 1 shows, all matter gives off some form of radiation. Humans can see some forms of radiation, which we call visible light. Visible light has a range of 400 nanometers to 700 nanometers with red light being in the 600-700 nanometer range. Infrared range is between 700-.5cm in wavelength. This study was focused on the red and the near infrared wave lengths with Landsat 8 band 6 as the mid infrared (1566-1551nm), 5 as the near infrared band (851-879nm), and 4 as the red band (636-673nm). For the Landsat 5 image, band 5 was the mid infrared (1550-1750nm), band 4 was the near infrared (770-900nm), and 3 was red (630-690nm).

Table 1. Components of the electromagnetic spectrum.

Wavelength	**Description**
<0.1 nm	Gamma Rays
0.1-10 nm	X-rays
10-400 nm	Ultraviolet
400-700 nm	Visible
700 nm to 1 mm	Infrared
1 mm to 1 cm	Microwaves
1 cm to 100 km	Radio waves
100-1000 km	Audio frequency

One tool for measuring impervious surfaces is called the Normalized Built up Index, or NDBI (Xu, 2007). The formula for the NDBI is expressed as follows:

$$NDBI = \frac{MIR - NIR}{MIR + NIR}$$

MIR is the band that contains the

mid infrared band and NIR is the band that contains the near infrared band (Xu, 2007). This equation is designed to expose all of the non-vegetative pixels in the images. The resulting values of each pixel are between -1 and 1, with areas that fall in the positive spectrum being built up areas (Saad and Tripathi, 2014). In Figures 2 and 3, impervious surfaces can be seen in the lighter areas, and the darker areas are the vegetative areas.

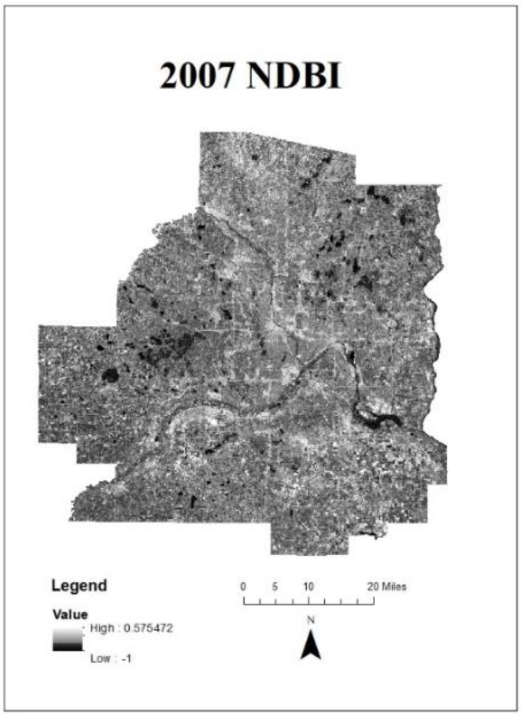

Figure 2. 2007 NDBI.

Another tool to measure impervious surfaces is the Normalized Vegetation Index (NDVI). Unlike the NDBI, the NDVI analyzes all of the areas that show high reflectivity in the near infrared and red bands. Healthy living plants give off high levels of infrared wavelengths and the NDVI will show areas with higher concentrations of vegetation. The formula for the NDVI is:

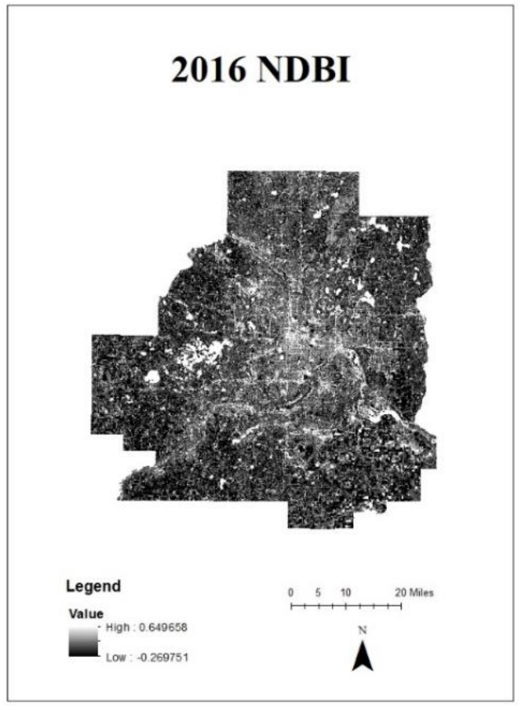

Figure 3. 2016 NDBI.

$$\text{NDVI} = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}}$$

The NDVI is a method for discerning the differences between vegetative and non-vegetative areas. In Figures 4 and 5, the lighter areas indicate higher concentrations of vegetation, and areas that are darker have less vegetation. This tool is different from the NDBI as it uses different bands for analysis. The near infrared band and red band highlight areas of healthy vegetation. In the resulting map, areas that have a pixel value in the positive number range tend to be the areas of vegetation. Conversely, areas in the negative numbers show areas that have little or no areas of vegetation. The results of these two indices were used to determine the accuracy of, and the differences between, the land cover classifications of the NDBI and NDVI.

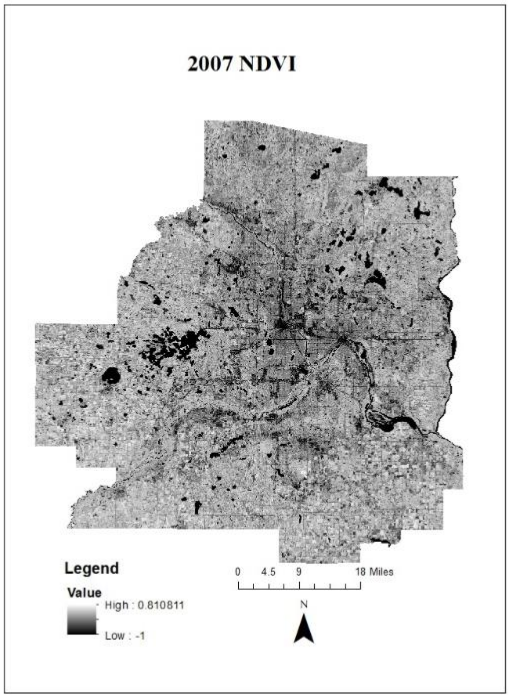

Figure 4. 2007 NDVI.

Classification

Once the NDBI is calculated, the classification needs to be assessed for accuracy (Foody, 2002). There are two different types of image classifications, supervised and unsupervised (Ferrato and Forsythe, 2013). Supervised classification takes into account known locations for certain land use types while unsupervised does not (Jensen, 2007).

In this analysis, the NDBI and the NDVI were used as a foundation for the land cover classification (Table 2). The NDBI should facilitate the identification of built up areas in the images, and the NDVI should facilitate the identification of vegetative areas.

The classification techniques were conducted using the data obtained from the NDBI and NDVI. These values are between 1 and -1 with all other values in between. The meaning of these values are based upon their respective signatures and represent distinct land cover classes.

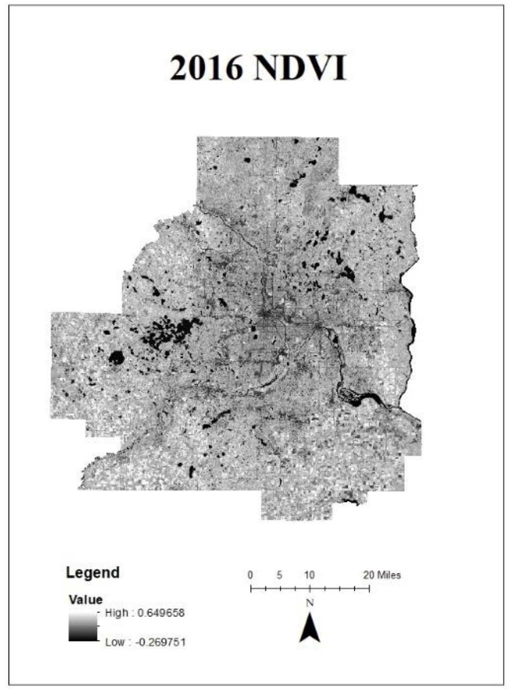

Figure 5. 2016 NDVI.

Table 2. Level 1 land cover classification.

Land cover classification	**Description**
Agriculture	crop fields
Forests	coniferous and deciduous forest
Urban/Built up	residential, commercial, roadways
Water/Wetland	rivers, streams, wetlands
Residential	areas that have a mix of houses and trees, grass, etc.

Both the 2007 and 2016 images were classified using a supervised classification system. A supervised classification was used to help mitigate errors produced by the extrapolation methods. Using the true color images as a reference, twenty training sample sites were assigned for each land cover classification using both the 2007 and 2016 images. From these training sites, signature files was created for both the 2007 and 2016 images. Using the signature file for both the 2007 and 2016 images, NDBI and NDVI were used as inputs for the maximum likelihood classification. The maximum likelihood classification was run using the signature files created earlier and was run for 2007 and 2016 for both NDBI and NDVI. This tool looks at the variance of all pixels in the designated training samples and uses this to classify the other like-valued pixels in each class. Appendices A and B show the maximum likelihood classification for the 2007 and 2016 NDBI. Appendices C and D show the 2007 and 2016 maximum likelihood classification for the NDVI.

Change Detection

Change detection maps are a way to highlight differences between two points in time. There are multiple ways to calculate change detection in remotely sensed data. The most common way is to take two multispectral images and subtract their cell values. The results of the NDBI and NDVI analyses were used for change detection, resulting in maps that exposed areas that were once vegetative and are now built up (Saad and Tripathi, 2014).

Issues with change detection maps can be quite profound. Ferrato and Forsythe (2013) state many factors can plague a change detection map, such as atmospheric conditions, instrument factors, temporal problems, and location. A hindrance of multispectral images is atmospheric conditions. Clouds have an impact on what the NDBI and NDVI will ultimately produce. Another issue commonly found in multispectral images is time of day or day of year. Much of what a multi spectral image captures is the radiation off of the earth, be it person, place or thing (Ferrato and Forsythe, 2013). Studying built up areas and vegetation is wholly dependent on trees, grass, and other vegetation giving off this radiation. It is important to take into account the time of year images are collected, as in winter, many trees are not producing NIR, and so change detection would be useless (Singh, 1989). Along with time of the year, time of day is important as well. Singh (1989) states there are several factors to watch out for, most notably, the difference in illumination. Much like time of year, time of day can have a dramatic effect on how an image is composed and might possibly deteriorate the quality of change detection results. By mitigating the possible errors that can occur in multispectral images, accurate and detailed maps can highlight areas of deep concern.

Accuracy Assessment

After each NDBI raster image was generated, an accuracy assessment was performed to evaluate how each pixel was classified. The accuracy assessment was performed by creating a point shapefile. Points were distributed in areas of known pixel values within the land cover classification. Once the points were assigned a known value, the Point to Raster tool was used to convert the points to test pixels. These test pixels were used as the control to assess the accuracy of the maximum likelihood classification. Next, the Point to Raster operation produced a confusion matrix. This resulting matrix was used to determine the accuracy through multiple criteria, including errors of omission and commission. An omission is a test pixel that should have been assigned to a class but was not. Commission is how many test pixels were incorrectly assigned to a class.

Results

Classification and Impervious Surfaces

As stated, each satellite image presents a different challenge when trying to interpret the data. The 2007 images appeared to have some surface interference, so some of the pixels for the NDBI and NDVI were classified incorrectly. However, the classification process yielded interesting results. For the 2007 NDBI result of the Twin Cities Metro Area, there were 6,088 acres of built up (impervious) surfaces, 22,061 forested, 1,664 water, 11,889 agriculture, and finally 21,774 residential (Figure 6). For the NDVI result, there were 5,090 acres of built up, 20,496 for forested, 1,661 for water, 10,289 for agriculture, and 21,774 for residential (Figure 7).

For the 2016 NDBI image, the surface reflectance appeared more consistent with what was expected. Water had a total area of 1,989 acres, forested 5,334 acres, residential 36,000 acres, built up 6,830 acres, and agriculture was 13,322 acres (Figure 6). For the 2016 NDVI image, there were 6,830 acres of built up, 5,334 acres of forested land, 1,989 of water, 13,322 of agriculture land, and 36,000 of residential land (Figure 7).

The NDVI classification yielded similar results to the NDBI based upon land cover classification. There were minor discrepancies between the forested land cover and residential. This issue could be due to the fact that most residential streets and houses have trees and other high infrared producing plants around them. The image resolution becomes a major factor in determining the accuracy of individual pixels. Also, the two different sensors on the Landsat images could have played a role in each classification, as the older model showed much of the residential land cover as forested and the newer Landsat 8 satellite showed it as residential.

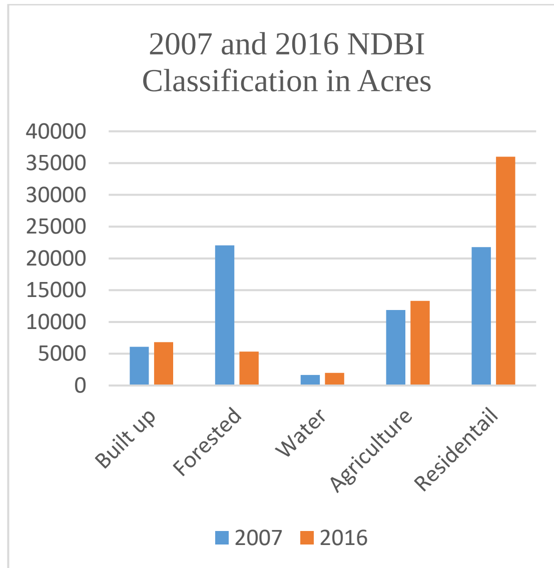

Figure 6. Graph of land cover in acres using NDBI.

Accuracy Assessment

The accuracy assessment for each year produced mixed conclusions. For each assessment, the ground truth percentages were found first. These ground truth percentages are based upon how many points were in each classification divided by the total number of points the maximum likelihood classification found for each separate land cover (Appendix E). For example, for the 2007 NDBI raster, 97% of the built up ground truth points were correctly classified. Finally, we have the overall accuracy, which is the total number of correctly classified points divided by the overall points. Kappa accuracy was also conducted for this assessment.

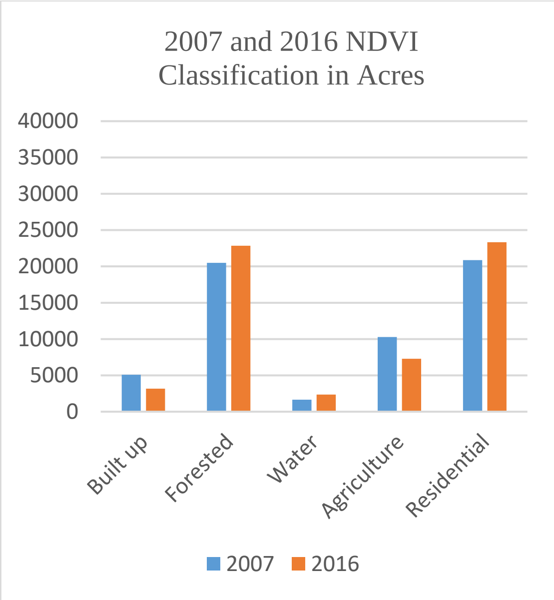

Figure 7. Graph of land cover classification using NDVI.

Kappa accuracy is a comparison of overall accuracy with expected accuracy allowing for a more refined accuracy assessment. Here, the accuracy was around 40% and the kappa 37% due to the abnormal reflectivity in the 2007 image. This signals that there were a lot of misclassified points. This is due to the fact that the reflectivity of the 2007 image was skewed and some of the pixel values were not consistent with the training samples. For the 2016 NDBI raster, the overall accuracy was 88% and the kappa was 85% (Appendix F). This signals that the expected and observed accuracy were much more consistent in the 2016 image.

For the NDVI rasters, the accuracy was assessed in the same way. For the 2007 NDVI raster, the overall accuracy was 73% and the kappa was 70% (Appendix G). For the individual ground truth accuracy, agriculture had an accuracy of 92%, built up 97%, forested 66%, residential 21%, and water 87%. As shown on the 2007 classification map, residential land cover was misclassified quite severely. Also, the forested omission test of the accuracy assessment had an omission rate of 39%, meaning several test points were misclassified as forested.

The 2016 NDVI raster had an overall accuracy of 77% with a kappa of 72% (Appendix H). The accuracy of the five land cover classifications were mostly consistent with the exceptions of forested and agriculture classes, which had accuracies of 79% and 25%, respectively. The accuracies were hampered by the same problem found in the 2007 image, as much of the misclassified agriculture class was classified as residential.

Tables 3 and 4 display the overall acres and square feet for each land cover classification along with the increase/ decrease in each between the 2007 and 2016 images for both the NDVI and NDBI.

Limitations

During the course of this study, many different problems arose. Many of the satellite images that were obtained were cloud covered or during a season when not much plant life was growing. This makes it difficult to use remote sensing techniques for interpretation. The reason for the skew in data for the 2007 images was due to this factor, as only one image for the entire summer season was useable. This, coupled with the limiting technological advances in 2007, makes this study unique in that older technology and newer technology were both used in this assessment.

Discussion/Conclusion

Using two different types of satellite images helps decrease errors in the cell values, but when a single raster image can include tens of thousands of raster cells,

Table 3. Changes in Land Cover 2007-2016 using NDBI.

2007 Classification	Acres	Square Feet
Water	1664.27	72495579.68
Residential	21774.68	948504985.3
Built Up	6087.58	266174843
Forested	22061.95	961018353.6
Agriculture	11889.11	517889599.1
2016 Classification	Acres	Square Feet
Water	1989.5	86662607.47
Residential	36000.73	156892003
Built up	6830.38	297532256.5
Forested	5334.41	232366768.2
Agriculture	13322.56	580330825.7
	Change in Acreage	Change in Square Feet
Water	325.23	14167027.79
Residential	14226.05	619687017.7
Built up	742.8	32357413.5
Forested	-16727.54	-728651585.4
Agriculture	1433.45	62441226.6

Table 4. Changes in Land Cover 2007-2016 using NDVI.

2007 Classification	Acres	Square Feet
Water	1661.98	72396000
Residential	20858.93	908615100
Built up	5090.38	221737200
Forested	20496.21	892815300
Agriculture	10289.39	44820600
2016 Classification	Acres	Square Feet
Water	2350.28	102378600
Residential	23329.61	1016238000
Built up	3160.46	137670000
Forested	22841.90	994993500
Agriculture	7290.32	317566500
	Change in Acreage	Change in Square Feet
Water	688.3	29982600
Residential	21270.68	9253764900
Built up	-1929.92	-84067200
Forested	2345.69	102178200
Agriculture	-2999.07	-272745900

errors will be produced but should be detected through accuracy assessments. By extracting the reflectance of certain cells and applying the NDBI and NDVI measures, areas that are distinctively vegetative or built up can be identified. Since the NDVI and NDBI are opposing indexes, it was expected to see each one have similar results as each measures the exact opposite characteristic; however, it is interesting to see that some discrepancies exist between them.

Impervious surfaces are a necessary evil for cities. Increasing the impervious footprint of cities also increases the quantity of storm water, which leads to pollution of the waterways and stress on the storm water infrastructure (Brabec, Schulte, and Richards, 2002). Unfortunately, it is not something many people consider in their day-to-day lives.

All the new infrastructure, such as roads and parking lots, that cities are building shed water to the storm sewers and could collect oil from vehicles or other pollutants. By mapping the direct changes that are happening to cities, city officials and lawmakers can have an idea of the areas that are most critical. Growing cities are hard to stop, but creating detailed accounts of what is being lost in the process can sway the communities' minds into better sustainable practices.

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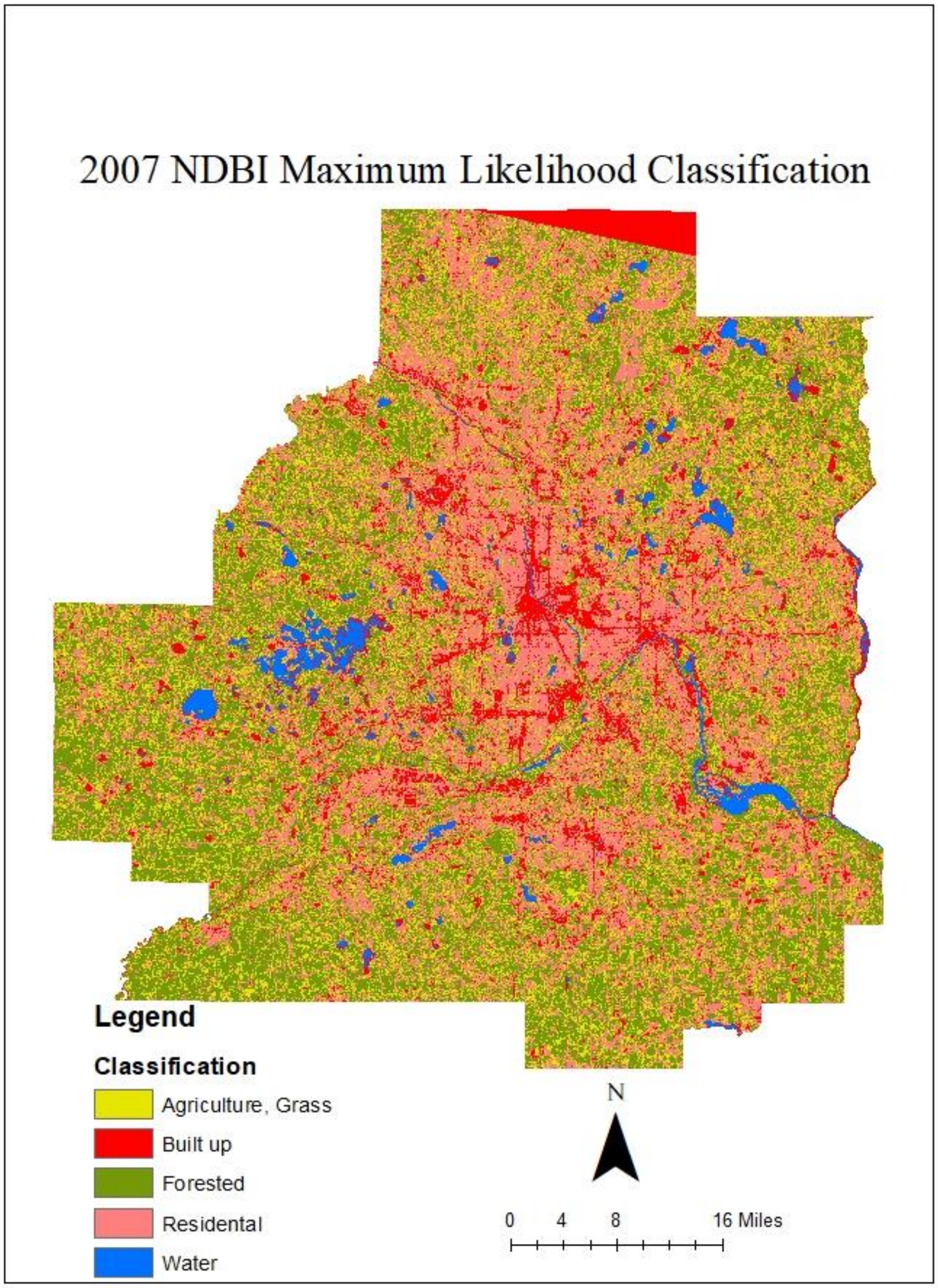
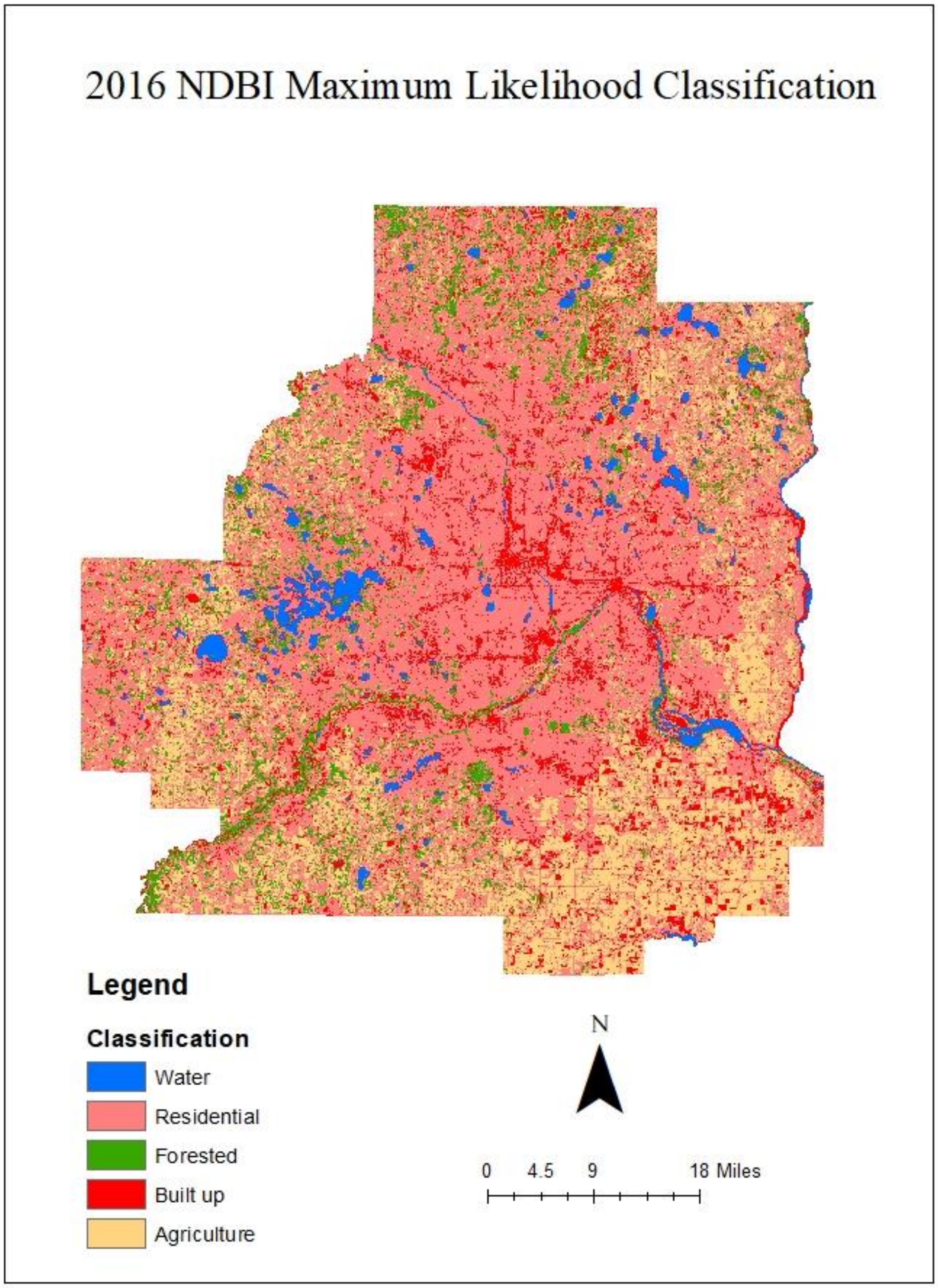
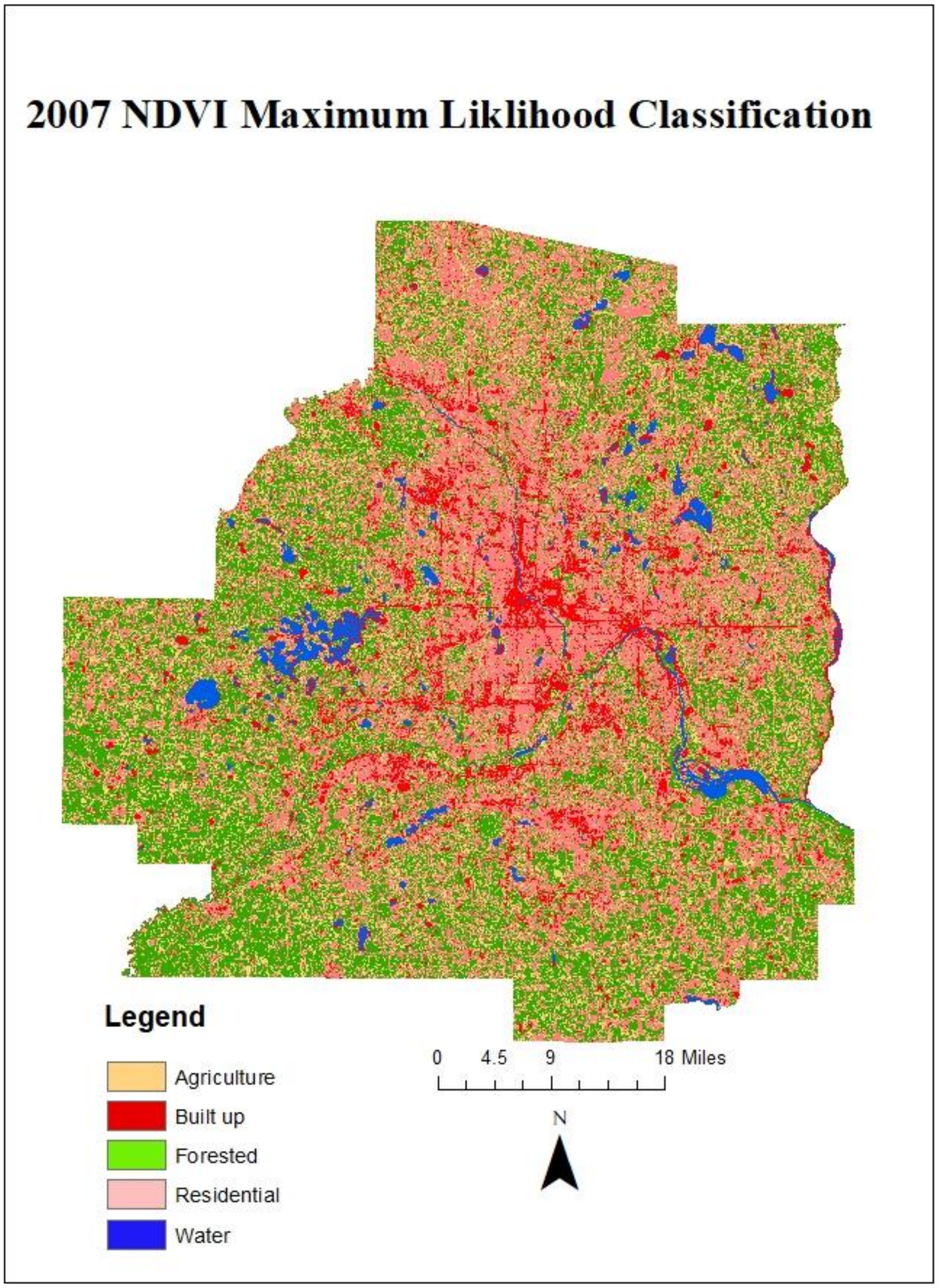
Appendix A. 2007 NDBI Maximum Likelihood Classification.



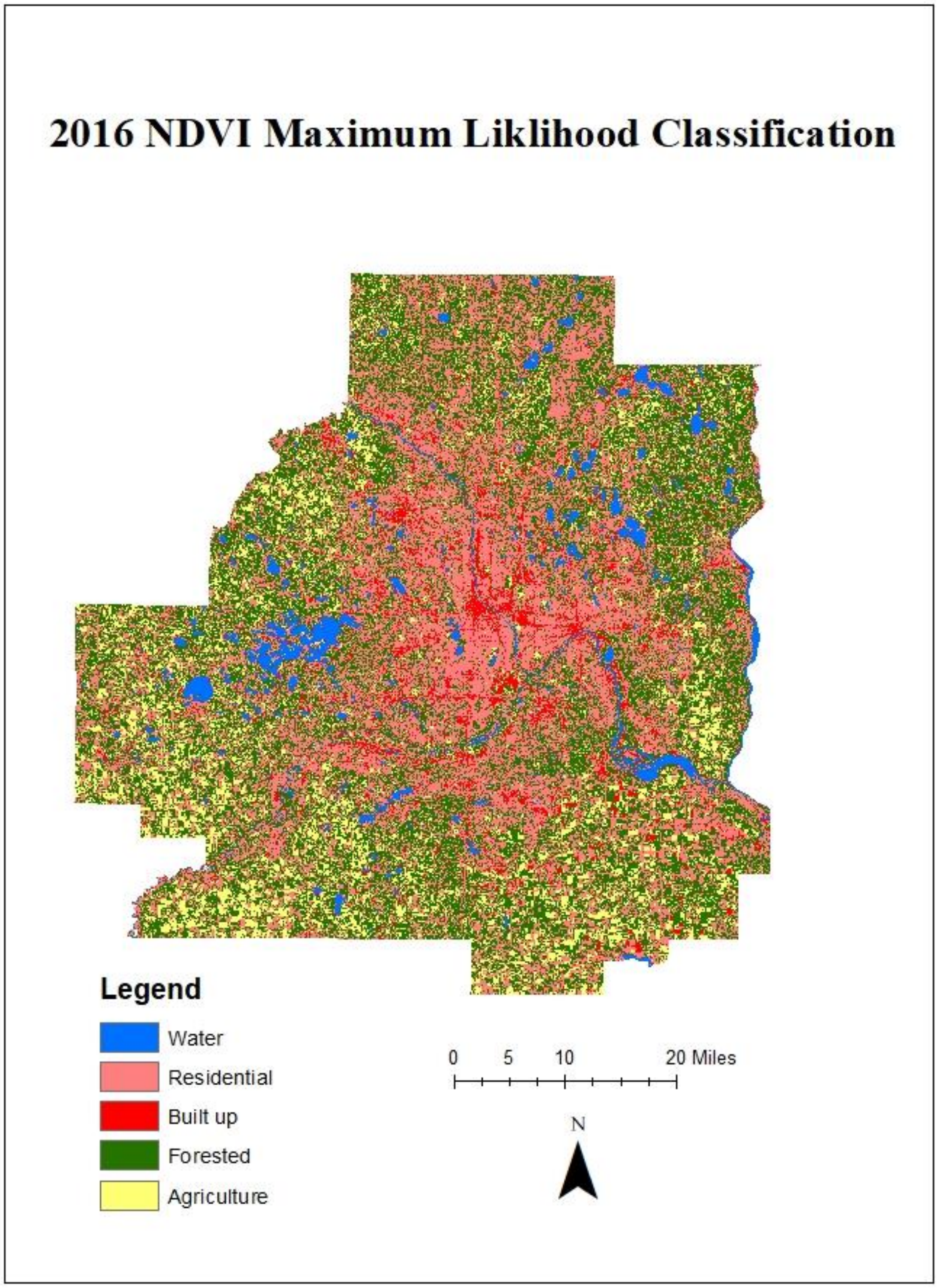
Appendix B. 2016 NDBI Maximum Likeihood Classification.



Appendix C. 2007 NDVI Maximum Likelihood Classification.



Appendix D. 2016 NDVI Maximum Likelihood Classification.



Appendix E. 2007 NDBI Accuracy Assessment.

	Built up	Forested	Water	Agriculture	Residential	Ground Truth
Built up	39	1	2	5	1	48
Forested	0	38	1	10	2	45
Water	1	0	35	5	0	41
Agriculture	0	1	0	16	3	20
Residential	0	0	2	4	34	46
Total	40	40	40	40	40	400
Ground Truth	Built up	Forested	Water	Agriculture	Residential	
Built up	97%	2%	5%	5%	2%	
Forested	0%	95%	2%	10%	5%	
Water	2%	0%	87%	12%	0%	
Agriculture	0%	2%	0%	65%	7%	
Residential	0%	0%	5%	7%	85%	
Commission	Correct	Reference		Overall	40.5%	
Built up	9	45	20%	Kappa	37.8%	
Forested	11	45	24%			
Water	6	41	14%			
Agriculture	4	20	20%			
Residential	6	46	13%			
Omission	Incorrect	Reference				
Built up	1	40	2.5%			
Forested	2	40	5%			
Water	5	40	12.5%			
Agriculture	24	40	60%			
Residential	6	40	15%			

Appendix F. 2016 NDBI Accuracy Assessment.

	Water	Residential	Built up	Forested	Agriculture	Ground Truth	
Water	23	0	0	0	0	23	
Residential	0	29	0	3	1	33	
Built up	8	2	31	0	2		
Forested	0	0	0	25	1	42	
Agriculture	0	0	0	2	26	26	
Total	31	31	31	30	30	153	
Ground Truth	Water	Residential	Built up	Forested	Agriculture		
Water	74%	0%	0%	0%	0%		
Residential	0%	94%	0%	100%	3%		
Built up	26%	6%	100%	0%	7%		
Forested	0%	0%	0%	83%	3%		
Agriculture	0%	0%	0%	7%	87%		
Commission	Correct	Reference					
Water	0	23	0%				
Residential	4	33	12%				
Built up	12	42	29%		Overall	88%	
Forested	1	26	4%		Kappa	83%	
Agriculture	2	28	7%				
Omission	Incorrect	Reference					
Water	8	31	26%				
Residential	2	31	6%				
Built up	0	31	0%				
Forested	5	30	17%				
Agriculture	4	30	13%				

Appendix G. 2007 NDVI Accuracy Assesment.

	Agriculture	Built up	Forested	Residential	Water	Ground Truth
Agriculture	38	0	12	2	1	53
Built up	0	40	0	24	1	65
Forested	3	0	28	0	0	31
Residential	0	1	0	9	3	13
Water	0	0	2	6	36	44
Total	41	41	42	41	41	
Ground Truth						
Agriculture	92%	0%	28%	4%	2%	
Built up	0%	97%	0%	58%	2%	
Forested	7%	0%	66%	0%	0%	
Residential	0%	2%	0%	21%	7%	
Water	0%	0%	4%	14%	87%	
Comission	Correct	Reference				
Agriculture	14	53	26%	Overall	73%	
Built up	25	65	38%	Kappa	70%	
Forested	3	31	9%			
Residential	4	13	30%			
Water	8	44	18%			
Omission	Incorrect	Reference				
Agriculture	3	41	7%			
Builtup	1	41	2%			
Forested	14	42	33%			
Residential	17	41	41%			
Water	5	41	12%			

Appendix H. 2016 NDVI Accuracy Assesment.

	Water	Residential	Built up	Forested	Agriculture	Ground truth
Water	40	0	1	0	0	41
Residential	1	37	1	6	13	58
Built up	0	0	39	0	2	41
Forested	0	4	0	31	16	51
Agriculture	0	0	0	2	10	12
Total	41	41	41	39	41	203
Ground Truth						
Water	97%	0	2%	0%	0%	
Residential	2%	90%	2%	15%	33%	
Built up	0	0	95%	0%	5%	
Forested	0	9%	0%	79%	41%	
Agriculture	0	0	0%	5%	25%	
Comission	Correct	Reference				
Water	1	41	2%			
Residential	21	58	36%	Overall	77%	
Built up	2	41	4%	Kappa	72%	
Forested	20	51	39%			
Agriculture	2	12	16%			
Omission	Incorrect	Reference				
Water	1	41	2%			
Residential	4	41	9%			
Built up	2	41	4%			
Forested	8	39	20%			
Agriculture	31	41	75%			