Final Report

1. Introduction

The land covers show the land use and environment shaped by natural and human beings, and studying the changes in land covers will help us to know how the natural environment changes and what influences bring to human society. To study the land cover changes, we have to learn the relative remote sensing tools and methods; change detection is an efficient way to research the land cover changes; it uses the relative bands from different satellite images to extract and detect the differences from the study area, and finally export to visual information to highlight the changing locations; it is very useful to detect the land cover changes because it will use reliable satellite information to export the visualized results about the changing in land covers in the certain study period.

Washington DC is the capital and also the political center of the U.S., and there are lots of changes in the city from 1991 to 1999 with the city development. Studying the land cover changes in Washington DC from 1991 to 1999 is important for us to discover how did the city develop in the 1990s and to help us analyze the city environment during this study period.

This final lab project is using ENVI software and related remote sensing methods to research the land cover changing in a certain area in a certain time period and mainly focuses on the change detection; this project will focus on the Washington DC area and will base on 09/16/1991 and 07/28/1999 georeferenced images in that area to analyze how certain land cover changed from 1991 to 1999. In the end, this final lab project will be generating some statistics and figures as the results to demonstrate how the landcover changes in Washington DC in the final report; also, the final report will also discuss what we learn from the results of different classification methods and the change detection maps.

2. Material and Methods

For the material we use, the 09/16/1991 and 07/28/1999 Landsat images will be the base image for us to input into the ENVI software and be processed; we are using both Landsat 5 and Landsat 7 satellite images to help us to do the analysis of change detection, and these images are already georeferenced and contain the bands we need. These Landsat images all have the same resolution which is 461 x 450, and also, they all have six bands for us to use; for the projection, they are using the method of Albers Conical Equal Area, and their basic unit is meter. Also, we will use a 1992 land cover classification dataset that includes twenty types of reference land covers in Washington DC that help us to identify the potential land covers in each location in Washington DC in the study period.

For the methods, we decide to divide it into several steps for doing this project and each step will use different methods. The first step is to load the two 1991 and 1999 Landsat images to the ENVI software and load them as RGB true color and then export them into two different images then do a comparison; we can directly see the visual difference of land covers changing between 1991 and 1999. After that, we will use the Write Function Memory Insertion method to generate a change detection map; for this step, we will need to create a blank band data then create a test band, and finally stack this test band and each Band 4 of different date images and then view as RGB image to see the differences of the land cover changing between the two dates. The third step will be to use two supervised image classifications to generate what the landcover types will look like and where they were located in Washington DC in 1991 and 1999; for this steps, we will create the ROIs for different land cover types such as water, commercial, low-density residential, high-density residential, irrigated lawns, and forest for the maximum likelihood classification and neural network methods, and then we will generate the classification images for each of these supervised image classifications. For step 4, we will need to analyze the change detection statistics of the land cover change between 1991 and 1999, and we will need to generate two change detection matrix tables to acquire the change detection statistics between 1991 to 1999 for maximum likelihood classification and neural network method. After that, for step 5, we will have to compare the statistics then to decide which kind of vegetation, forest or irrigated lawns, possessed the most amount of change between 1991 and 1999, and finally we have to create two change images for the certain vegetation class for maximum likelihood classification method and neural network classification method. At the same time, we also need to create two change images for the commercial class for maximum likelihood classification and neural network method because we will do the comparison of commercial and vegetation class change later. For step 6, we will create the threshold ROIs based on the change image band for the all the land cover types except commercial, to generate a merging ROI of displaying the pixels to show the change from all other land cover types to the commercial class using maximum likelihood classification method and neural network classification method. In addition, we also need to generate a merging ROI of showing the pixels to show the change from all other land cover types to the certain vegetation class we chose and using the maximum likelihood classification method and neural network classification method; in the end, we have to create a two final change detection map based on the two supervised classification methods for the commercial and vegetation class displaying on the base layer of 1999 greyscale image. Finally, we will have all of these statistics and figures results to help us analyze the land cover change from 1991 to 1999 and discuss the potential errors of doing this research, the main differences between the different classification methods, and the applications of the change detection map.

3. Results

The generating figures and tables are the output results. First, we could see the two RGB color Landsat images of the 1991 and 1999; for the comparison of these different date images *Figure 1A* and *Figure 1B*, we are hard to see the differences in land cover directly and most of the land covers possess similar coverage, and for example, we could see that the high-density residential and low-density residential areas are similar between 1991 and 1999. Also, from this comparison, we could directly see the most changing land covers are vegetation and commercial classes. Especially, when we look at the areas next to the Pentagon and the Reagan International Airport, the landcover changing is very obvious. After that, the change detection map produced by step 2 will show more indicated results of the land covers changing in Washington DC; the result of the change detection map which is *Figure 2* shows that land covers changing mainly happened in the area near the Potomac River, especially the areas near the Pentagon and the Reagan International Airport; we could see the map shows the changing points as the green color. After that, for the result of step 3, we will have four classification maps for 1991 and 1999 using the Maximum Likelihood method and Neural Network method. We could separate these images which are *Figure 3A, Figure 3B*, *Figure 3C*, and *Figure 3D* into different pairs to do different comparisons. For example, we could know from the results that when comparing the 1991 and 1999 Maximum Likelihood classification maps, which is comparing the *Figure 3A* and *Figure 3B*, we could see some land covers extend a lot such as the commercial class. In addition, when we compare the 1999 Maximum Likelihood classification map and the 1999 Neural Network classification map, which is comparing the *Figure 3B* and *Figure 3D,* we could see the one using the Neural Network method is display the more accurate classifications; for example, the Maximum Likelihood method incorrectly marks some locations belonging to Irrigated Lawns but actually, they belong to Forest class and the Neural Network classification map showing the more accurate information. After that, for the result of step 4, we have four statistics tables in hand, and they show the percentage of the change detection statistics for the Maximum Likelihood method and Neural Network method, the square kilometer of the change detection statistics for the Maximum Likelihood method and Neural Network method; for *Table 1A and Table 1C*, we could see the class with the most percentage change is Irrigated Lawns no matter what supervised classification method are using. In *Table 1B*, when we use the Maximum Likelihood method, we could see that Low-density Residential possess the most area changes to other classes between 1991 and 1999. However, *Table 1D* uses the Neural Network method to show that High-density Residential possess the most area changes to other classes between 1991 and 1999. Furthermore, for step 5, the results of *Figure 4A* and *Figure 4C* show that the Irrigated Lawns class is the one vegetation class have the most amount of change no matter using the Maximum Likelihood method and Neural Network method; from the comparison of these figures, the main difference is that the most amount of change locations for the Irrigated Lawns class are near the Potomac River. Also, *Figure 4B* and *Figure 4D* show that the change images for the commercial class of the Maximum Likelihood method and Neural Network method are similar. Finally, step 5 creates the final change detection maps using different supervised classification methods for the commercial and vegetation classes; from the comparison of *Figure 5A* and *Figure 5B*, the map by the Neural Network method has less change in Irrigated Lawns vegetation class but more change in commercial class than the one by the Maximum Likelihood method.

4. Discussion

During the study period, if we consider the percentage of the change detection statistics, we could see that the Irrigated Lawns areas appear to have more significant changes. When we look at *Table 1A* and *Table 1C*, we could know that the Irrigated Lawns possess around 45.4% class changes for the Maximum Likelihood method and around 71.2% class changes for the Neural Network method. However, when we consider the square kilometer of the change detection statistics, Low-density Residential and High-density Residential areas appear to have more significant changes. When we look at *Table 1B* and *Table 1D*, we could find that for the Maximum Likelihood method, the Low-density Residential areas possess around 26 square kilometers of class changes, but for the Neural Network method, the High-density Residential areas possess around 31 square kilometers of class changes. When we reference *Figure 3D*, we can see that the Irrigated Lawns areas are mainly located upstream of the Potomac River, and the Low-density and High-density Residential areas are mainly located in the center, north, southwestern, and southeastern Washington DC and the distribution are very scattered. However, these changes are not easy to see from the preliminary insight; also, the commercial areas have obvious changes during the study period.

When comparing the final change detection maps with the preliminary insight image, we could see the similarity and differences. The similarity is that we could see the commercial areas obviously increasing from 1991 to 1991 in all the final detection maps and the preliminary insight image. The first difference is that the preliminary insight image does not show the obvious change of vegetation class as the same as the final detection maps. When we look at *Figure 2*, we could see the green areas, which are the most changing areas, mostly are the commercial areas. However, when we see *Figure 5A* and *Figure 5B*, we could see the vegetation class change is scattered and obvious on different supervised classification methods. The second difference we could notice is that the final change detection maps all show more changing areas of the commercial class than the preliminary insight image. *Figure 5A* and *Figure 5B* show the changing commercial areas are scattered, but *Figure 2* displays that there are only a few small commercial changing areas concentrated in the center of Washington DC.

We could find out that when we analyze the classification of the output figures and statistics, it is different than directly analyzing the original RGB images, and also, the different classification methods, the image quality, and terrain distortions will influence results and bring some potential errors. One of the possible sources of error is the different accuracy of classification. We know that the Maximum Likelihood method and Neural Network method are supervised classification methods, however, they have different algorithms that will influence the accuracy of the classification results; generally, the Neural Network method has a more complex algorithm for processing the data and low down the possible error that leads to more accurate classification results. Also, the quality of images will low down the readable information of land covers from the images and influence our ability to create the ROIs that will increase the errors for the classification results. In addition, the other aspect we should consider is the terrain distortion problem; it also increases the error and impacts our final classification results. Furthermore, some land covers may have seasonal changes, and if the images are acquired during a different season, they may not accurate and will produce an error on the final classification because the distribution of some certain land covers will change with the seasonal changes.

There are some major differences in the results when using the Maximum Likelihood method and Neural Network method. The first difference is that some land cover classes will be underestimated or overestimated when using different classification methods. For example, in this lab project, the result of the 1999 Maximum Likelihood classification map obviously overestimated the coverage of the Irrigated Lawns; when we compare the *Figure 3B* and *Figure 1B*, we can see that the coverage of Irrigated Lawns is not that large and lots of locations should be labeled as Forest instead of Irrigated Lawns, and we could find that from the *Figure 3D*, the classification map using Neural Network method, mostly will correctly mark these locations as Forest. Secondly, we could know another major difference in the results using different classification methods is the accuracy. In general, the Neural Network method will have fewer errors, and the accuracy is mostly larger than the Maximum Likelihood method. When we do a comparison of the *Figure 3B* and *Figure 3D*, we could see in the *Figure 3B*, that there are some small points displayed in the middle of the Potomac River incorrectly labeled as Commercial areas, however, they should be labeled as Water and it is a very obvious error when using the Maximum Likelihood method; when we look at the

Figure 3D, those error points disappear and they all correctly labeled as Water. These differences prove that the Neural Network method will provide a better classification result than using the Maximum Likelihood method.

Producing a change detection map is useful, and it has lots of practical applications. Firstly, it could help people doing the research on environmental protection. By making a change detection map, we could directly view how the land covers changes over time in certain locations, and we could use the result to make a plan of how and where to protect the land cover and also could know the recovering situation of some land covers after the land covers destroyed by natural hazards. Secondly, creating a change detection map could help the government in urban planning. With the change detection map, governments could know the development of the vegetation coverage and urban coverage which will help them to establish an appropriate urban design plan that considers the urban development and environment protection. Also, producing a change detection map could help us to know how climate change affects our environment and land covers. In addition, governments could also use a change detection map to do the property revenue assessment and find out if any unauthorized constructions or activities of destroying the greenery in residential areas.

Appendix

Figure 1A - Original RGB true color composite of the 1991 Landsat image (label its date)

Figure 1B - Original RGB true color composite of the 1999 Landsat image (label its date)

Figure 2 - Change detection map of the Landsat images as RGB composite (write function memory insertion method)

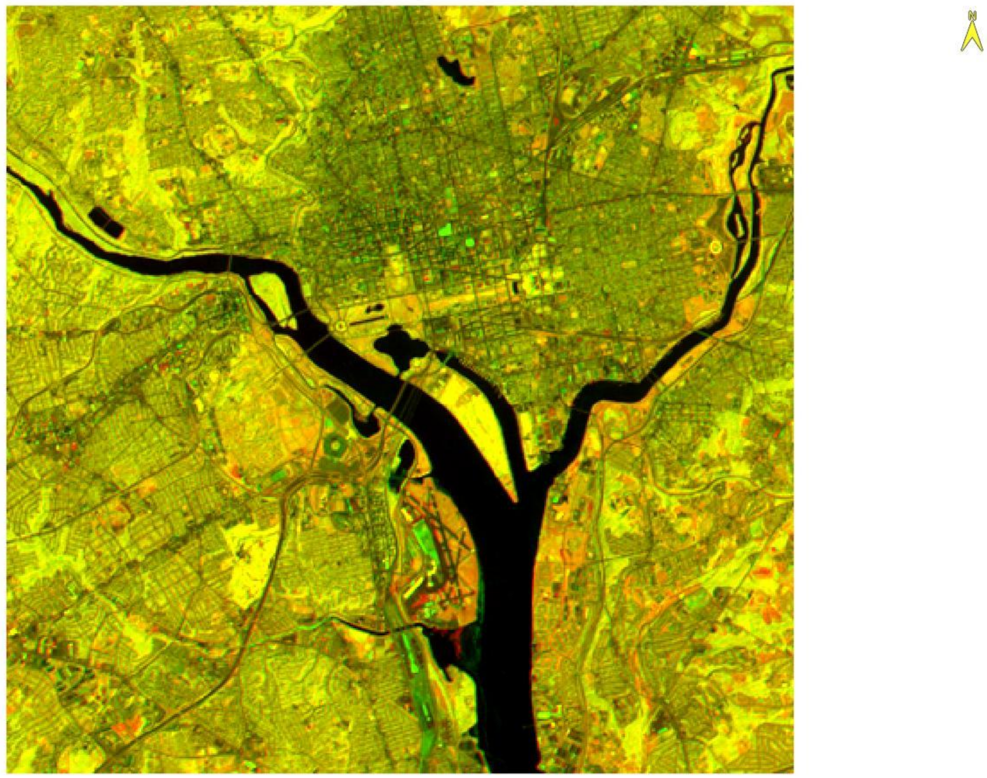

Figure 3A – Maximum Likelihood classification map for 1991

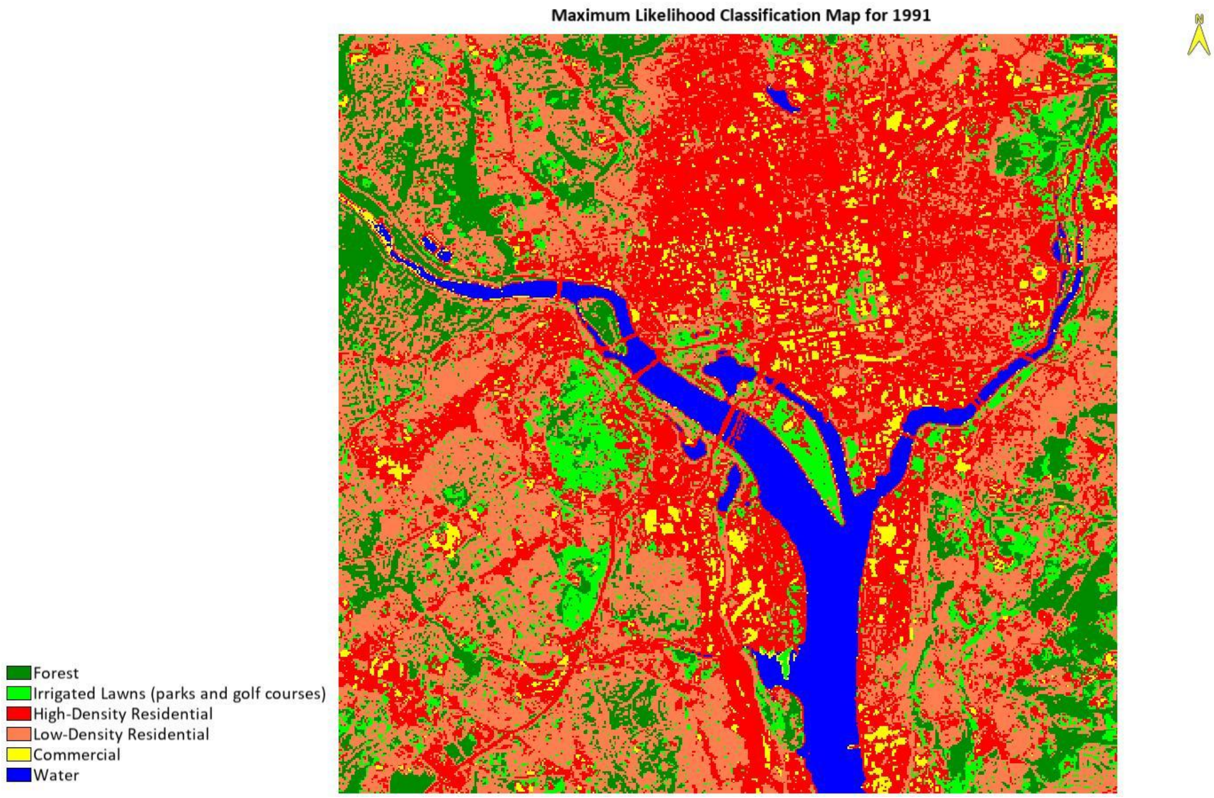

Figure 3B – Maximum Likelihood classification map for 1999

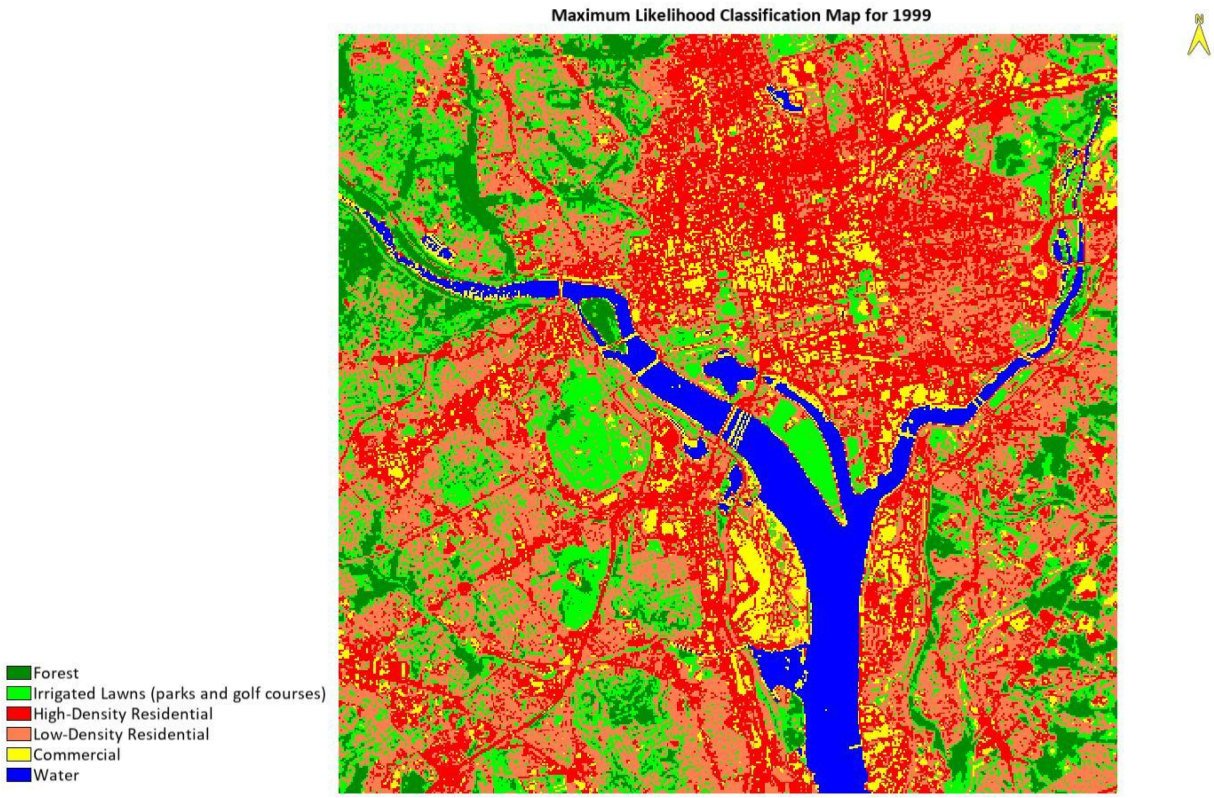

Figure 3C – Neural Network classification map for 1991

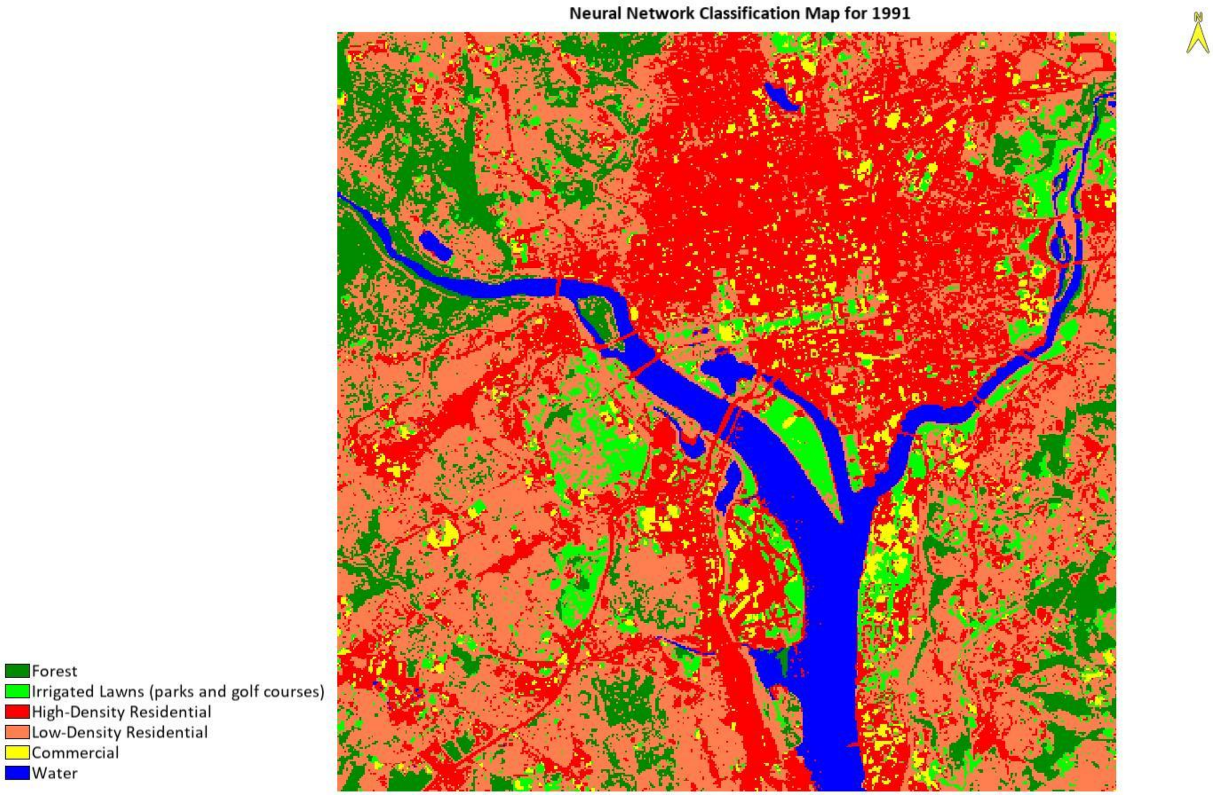

Figure 3D – Neural Network classification map for 1999

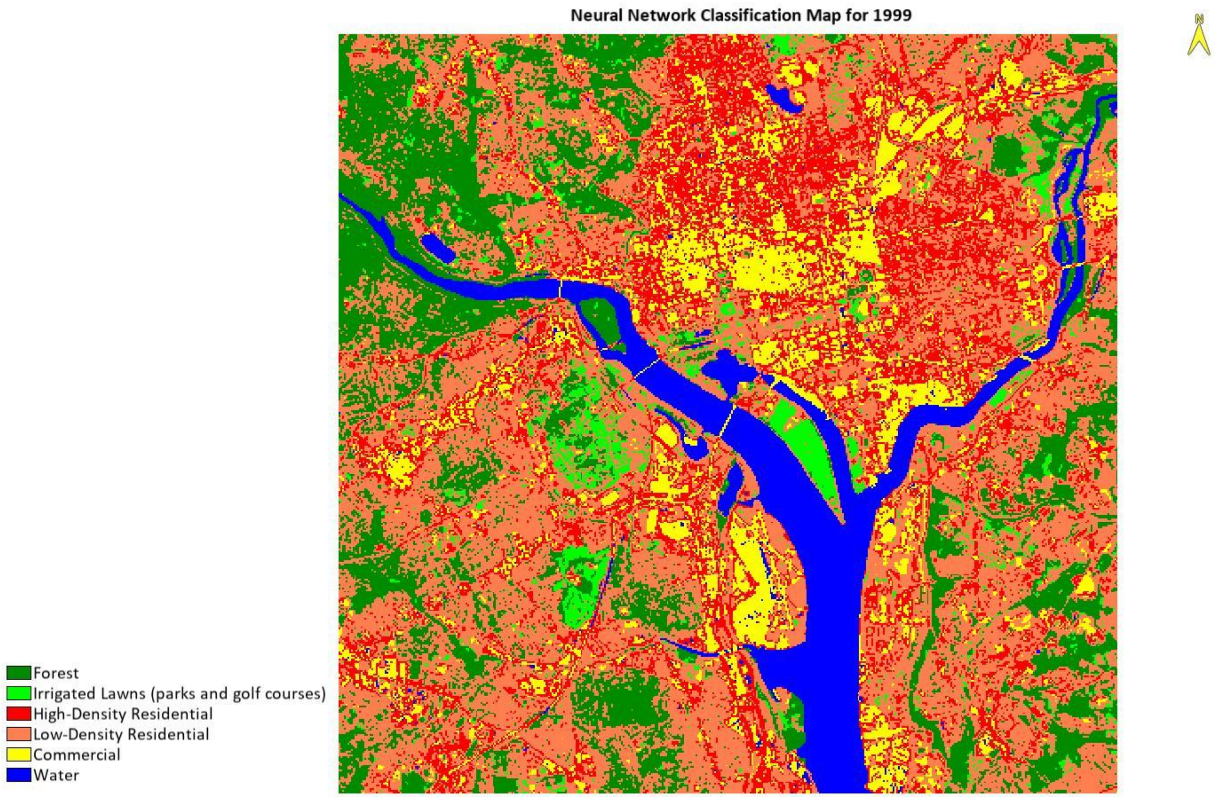

Table 1A – Change Detection Statistics Report (Percentage) for the Maximum Likelihood method

Change Detection Statistics (Initial State: maximum_likelihood_1991, Final State: maximum_likelihood_1999)

File Options Help

Percentage | Area (Square Km) | Reference

		Initial State							
		Forest	ted Lawns (parks and golf cour	High-Density Residential	Low-Density Residential	Commercial	Water	Row Total	Class Total
Final State	Unclassified	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Forest	57.449	3.413	0.060	3.614	0.011	0.000	100.000	100.000
	Irrigated Lawns (parks and golf courses)	31.450	54.591	3.911	20.474	2.180	0.120	100.000	100.000
	High-Density Residential	1.824	5.907	60.234	15.027	32.309	0.675	100.000	100.000
	Low-Density Residential	8.061	30.732	20.064	59.593	6.321	0.000	100.000	100.000
	Commercial	1.216	4.970	14.514	1.284	55.545	5.044	100.000	100.000
	Water	0.000	0.388	1.217	0.008	3.634	94.161	100.000	100.000
	Class Total	100.000	100.000	100.000	100.000	100.000	100.000		
	Class Changes	42.551	45.409	39.766	40.407	44.455	5.839		
	Image Difference	-29.582	101.950	-18.382	-9.392	99.868	3.700		

Table 1B – Change Detection Statistics Report (Area – square Km) for the Maximum Likelihood method

Change Detection Statistics (Initial State: maximum_likelihood_1991, Final State: maximum_likelihood_1999)

File Options Help

Percentage | Area (Square Km) | Reference

Initial State

Final State	Forest	ted Lawns (parks and golf cour	High-Density Residential	Low-Density Residential	Commercial	Water	Row Total	Class Total
Unclassified	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Forest	12.84	0.53	0.04	2.33	0.00	0.00	15.74	15.74
Irrigated Lawns (parks and golf courses)	7.03	8.49	2.51	13.19	0.18	0.01	31.42	31.42
High-Density Residential	0.41	0.92	38.67	9.68	2.64	0.08	52.40	52.40
Low-Density Residential	1.80	4.78	12.88	38.39	0.52	0.00	58.37	58.37
Commercial	0.27	0.77	9.32	0.83	4.54	0.60	16.34	16.34
Water	0.00	0.06	0.78	0.01	0.30	11.29	12.44	12.44
Class Total	22.35	15.56	64.21	64.43	8.17	11.99		
Class Changes	9.51	7.06	25.53	26.03	3.63	0.70		
Image Difference	-6.61	15.86	-11.80	-6.05	8.16	0.44		

Table 1C – Change Detection Statistics Report (Percentage) for the Neural Network method

Change Detection Statistics (Initial State: neural_network_1991, Final State: neural_network_1999)

File Options Help

Percentage | Area (Square Km) | Reference

		Initial State							
		Forest	ited Lawns (parks and golf cour	High-Density Residential	Low-Density Residential	Commercial	Water	Row Total	Class Total
Final State	Unclassified	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Forest	86.654	7.137	0.218	20.060	0.147	0.742	100.000	100.000
	Irrigated Lawns (parks and golf courses)	0.972	28.840	0.255	2.570	2.193	0.007	100.000	100.000
	High-Density Residential	0.787	5.141	47.035	7.586	16.793	0.134	100.000	100.000
	Low-Density Residential	9.568	54.729	24.367	67.844	26.482	0.782	100.000	100.000
	Commercial	0.804	4.049	25.495	1.132	54.189	0.080	100.000	100.000
	Water	1.216	0.104	2.631	0.807	0.196	98.256	100.000	100.000
	Class Total	100.000	100.000	100.000	100.000	100.000	100.000		
	Class Changes	13.346	71.160	52.965	32.156	45.811	1.744		
	Image Difference	60.706	-52.746	-39.870	2.626	177.523	16.173		

Table 1D – Change Detection Statistics Report (Area – square Km) for the Neural Network method

Change Detection Statistics (Initial State: neural_network_1991, Final State: neural_network_1999)

File Options Help

Percentage | Area (Square Km) | Reference

		Initial State							
		Forest	ted Lawns (parks and golf cour	High-Density Residential	Low-Density Residential	Commercial	Water	Row Total	Class Total
Final State	Unclassified	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Forest	18.54	0.93	0.13	14.67	0.01	0.10	34.38	34.38
	Irrigated Lawns (parks and golf courses)	0.21	3.76	0.15	1.88	0.16	0.00	6.16	6.16
	High-Density Residential	0.17	0.67	27.44	5.55	1.23	0.02	35.07	35.07
	Low-Density Residential	2.05	7.13	14.21	49.62	1.95	0.11	75.06	75.06
	Commercial	0.17	0.53	14.87	0.83	3.98	0.01	20.39	20.39
	Water	0.26	0.01	1.53	0.59	0.01	13.23	15.64	15.64
	Class Total	21.39	13.03	58.33	73.14	7.35	13.47		
	Class Changes	2.85	9.27	30.90	23.52	3.37	0.23		
	Image Difference	12.99	-6.87	-23.26	1.92	13.04	2.18		

Figure 4A – Change image (black/white) for one vegetation class (indicate if Forest or Irrigated Lawns) – Maximum Likelihood method

Irrigated Lawns

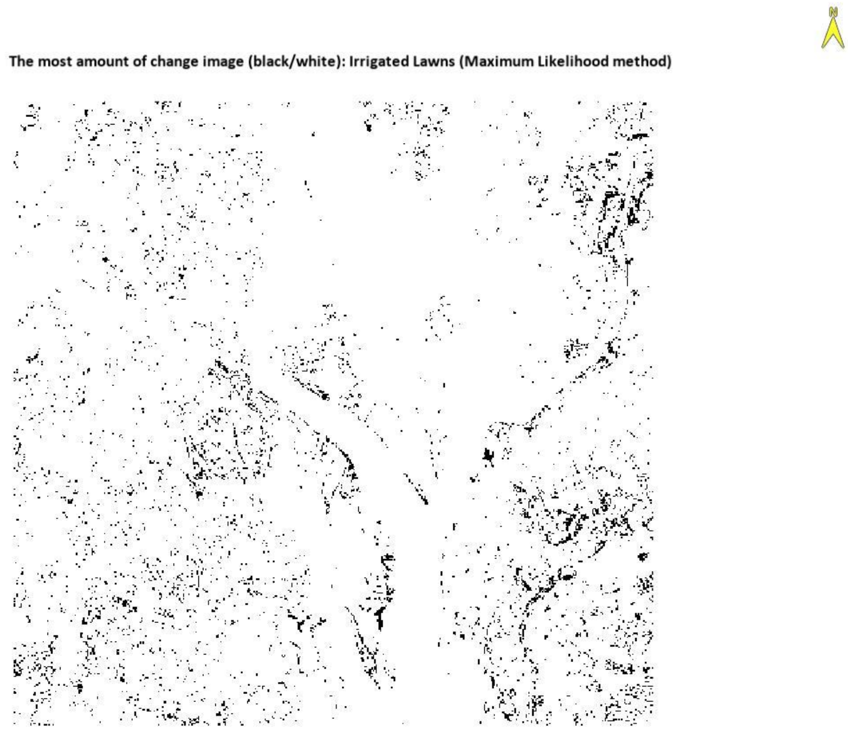

Figure 4B – Change image (black/white) for the Commercial class – Maximum Likelihood method

Figure 4C – Change image (black/white) for one vegetation class (indicate if Forest or Irrigated Lawns) – Neural Network method

Irrigated Lawns

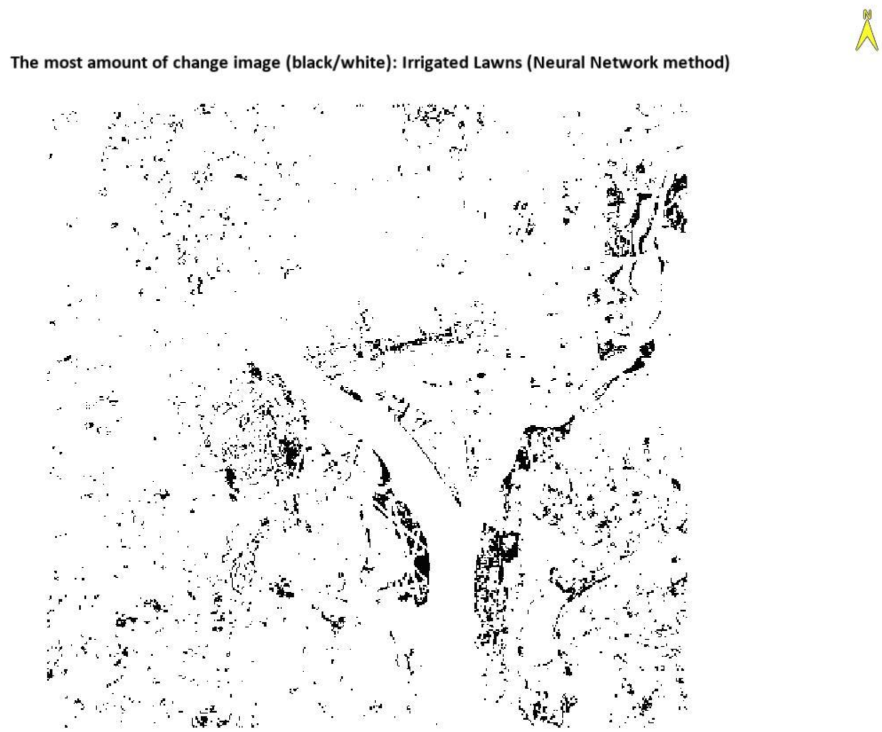

Figure 4D – Change image (black/white) for the Commercial class – Neural Network method

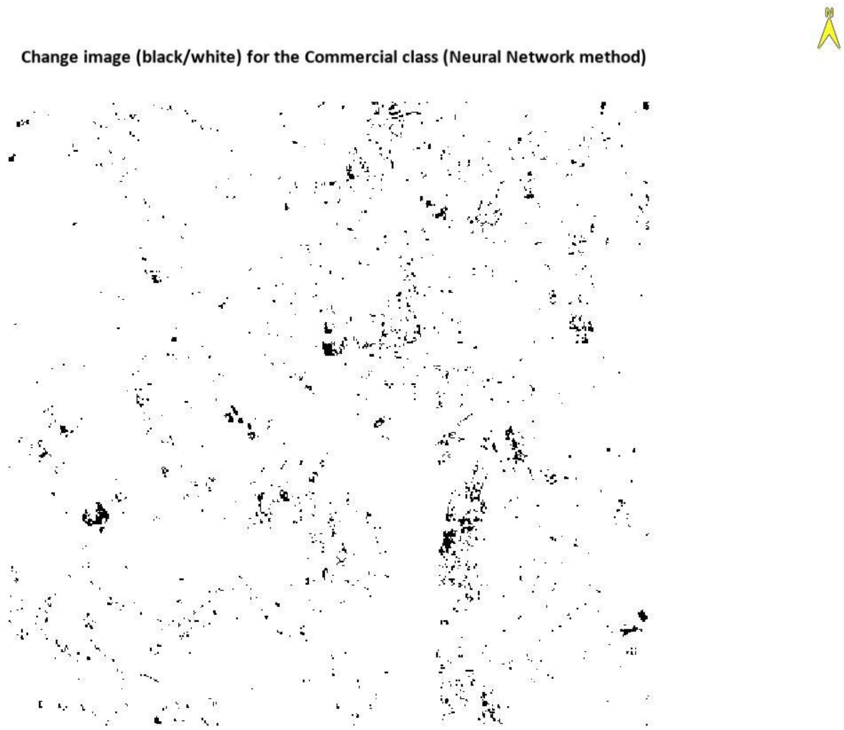

Figure 5A – Final change detection map produced by the Maximum Likelihood method for the Commercial and vegetation areas on the greyscale ’99 image (with title and legend)

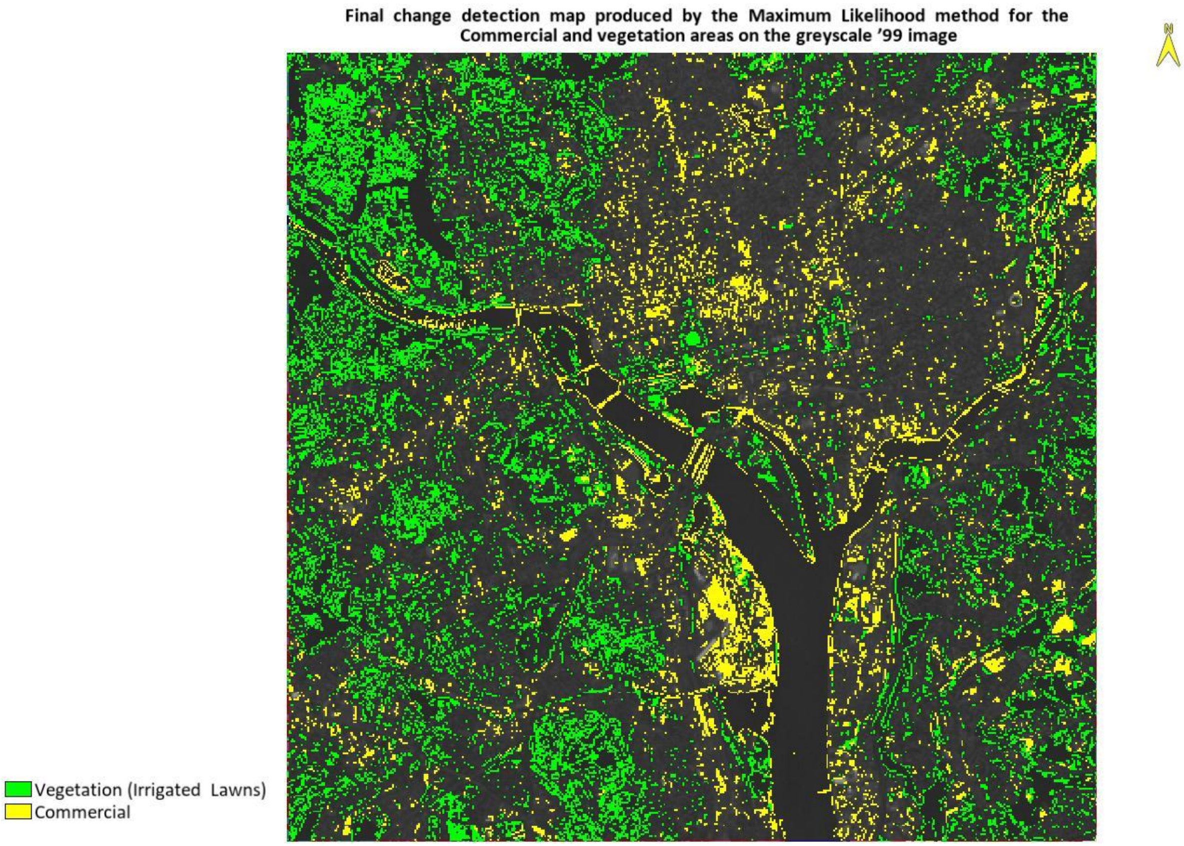

Figure 5B – Final change detection map produced by the Neural Network method for the Commercial and vegetation areas on the greyscale ’99 image (with title and legend)