Elizaveta Gonchar
CP 6531
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Class Project

Hall County – Change Detection (1991-2013)

I. INTRODUCTION

The purpose of this project was to conduct a change detection analysis using remote sensing techniques, focusing on Hall county located northeast of Atlanta in Georgia. I was tasked with performing this change detection analysis by comparing three Landsat satellite images for Hall county corresponding to September 28, 1991, October 1, 2001, and November 10, 2013. Most of the components of this project were broken into six assigned Project Tasks that we completed throughout the semester. I conducted all my analyses within the ERDAS Imagine software.

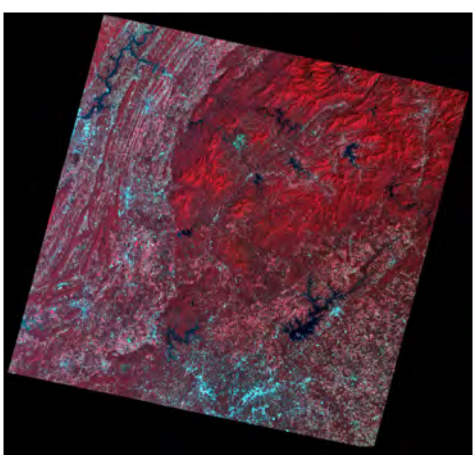
Prior to delving into my analysis method, I would like to note some characteristics of Hall county. I provide an image of where it is in Georgia on the right (Wikipedia contributors). Hall county consists of 1,017.9 km^2 of land and 94.0 km^2 of water. The largest city in Hall county is Gainesville and the most notable feature that I identified of the county is its proximity to Lake Lanier. According to the U.S. Census Bureau, Hall county experienced an 87.3% population increase from 1991 to 2013 indicating it was a county that likely underwent a significant expansion during this time. I believe a major source of growth for the county has been its proximity to Atlanta and Lake Lanier, though I was not able to verify this. This population growth signals to me that I would expect to see increases in urban features in Hall county across the three years.

For my change detection analysis, I closely followed the proposed steps from the class. The workflow that was implemented consisted of the following: subsetting, geocorrection, image enhancements, supervised and unsupervised classifications, and change detection analyses. I supplemented the results of my unsupervised classification with an NDVI change representation.

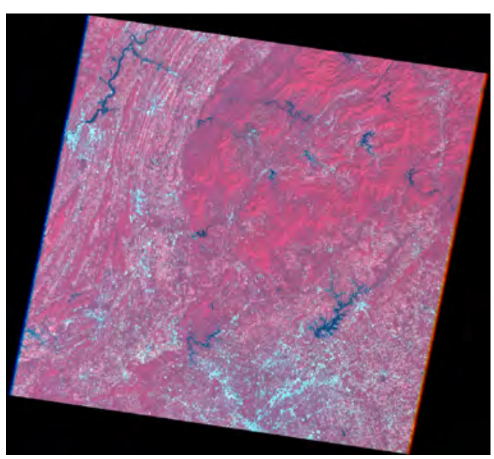
II. DATA SOURCES

I relied solely on the provided data: county boundary and Landsat imagery for the three years I considered. Below I present the original images I used for my analysis.

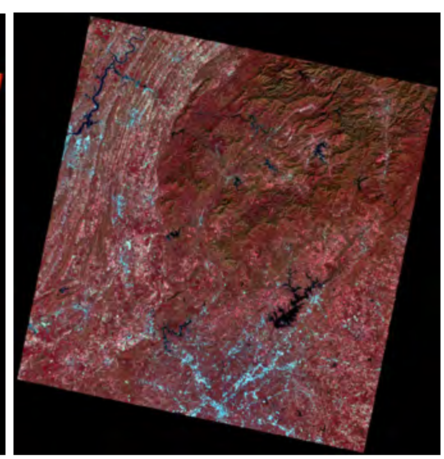
(a) 1991



(b) 2001



(c) 2013



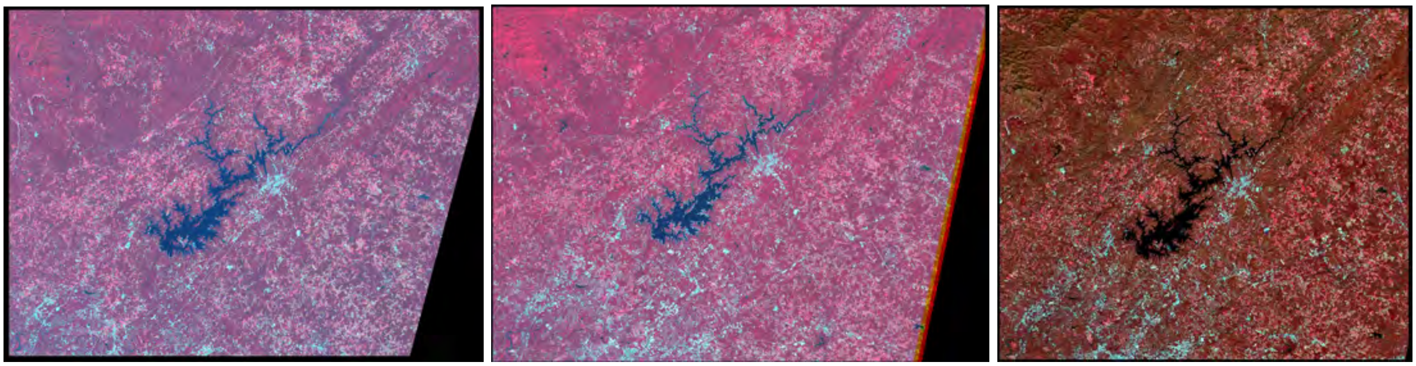
III. OPERATIONAL FLOW

A. DATA IMPORT – SUBSETTING

As mentioned above, my operational flow followed the order of the assigned project tasks: subsetting, geometric correction, image enhancement, supervised classification, unsupervised classification, and change detection.

I began by subsetting my images. Hall county is near the edge of the swath and this affected the results of the methods implemented for the previously submitted project tasks. Below I present the subsets I obtained of my images. I will note that, for the final image analysis, I adjusted my subsetted images such that they were the same size; I was able to do this only after the geocorrection had been implemented.

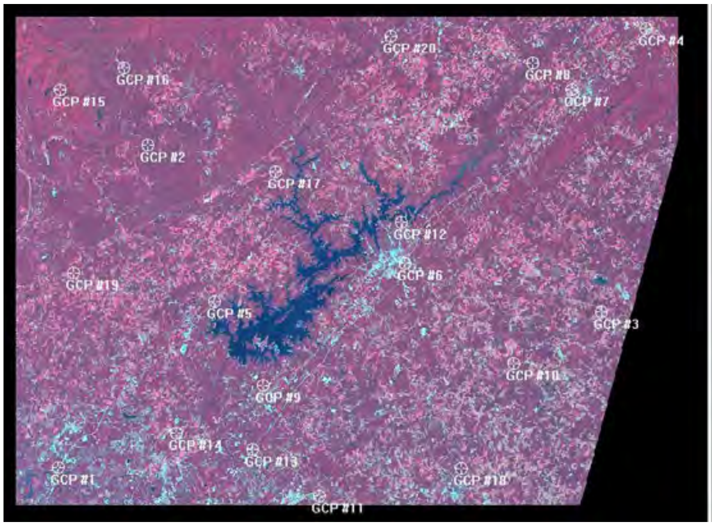
(a) 1991 (b) 2001 (c) 2013

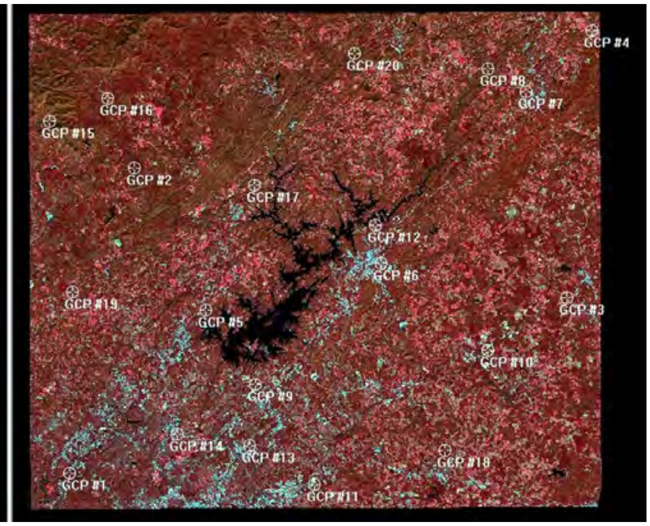


B. GEOMETRIC CORRECTION

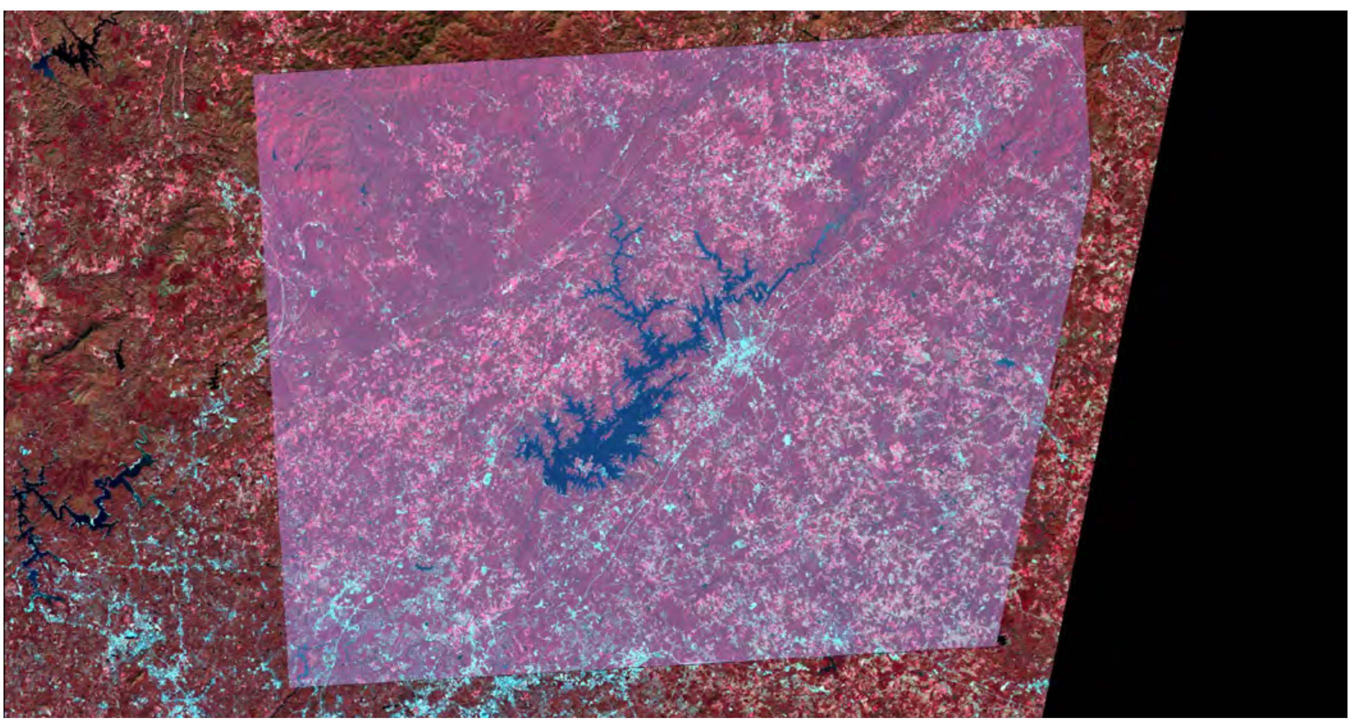
My second task was to geocorrect the images for the years 1991 and 2001 using the 2013 image as my reference. I made sure to apply the techniques discussed in class, particularly the need to include a GCP in each of the 9 matrix positions. As a personal note, I found this task particularly enjoyable and took time to ensure that all my RMSEs were below 0.1. The only difficulty I experienced was with reloading my constructed GCPS for one of the years. When I went back to reload the points, the input image's GCPs all shifted to the top left portion of the image. I was not able to resolve the issue, so I re-did the GCPs for that image and was able to get the results I present in the following two pages.

(a) 1991

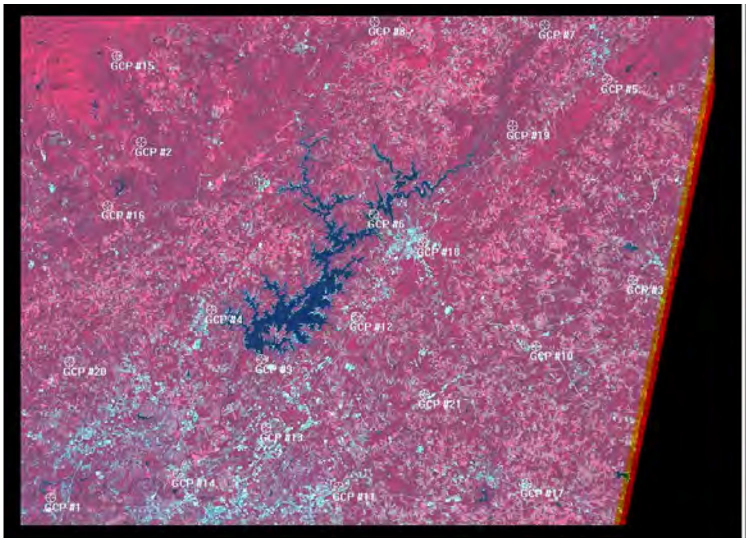


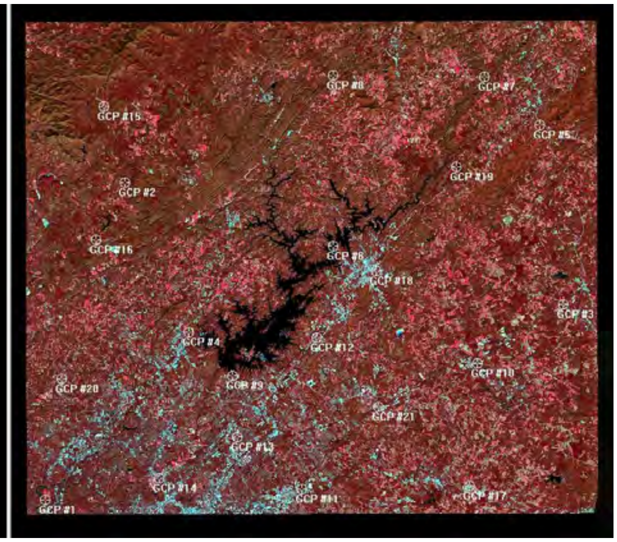


Point #	Point ID	>	Color	X Input	Y Input	>	Color	X Ref	Y Ref	Type	X Residual	Y Residual	RMS Error	Contrib.
1	GCP #1			202.917	-2142.266			746302.996	3766440.287	Control	-0.062	-0.076	0.098	1.443
2	GCP #2			629.493	-609.823			756370.499	3813096.310	Control	-0.017	-0.071	0.073	1.073
3	GCP #3			2787.720	-1403.668			822426.029	3793141.221	Control	-0.051	-0.080	0.095	1.396
4	GCP #4			3002.275	-56.863			826470.943	3833866.325	Control	-0.002	0.095	0.095	1.405
5	GCP #5			944.585	-1365.680			767132.495	3791316.217	Control	0.084	-0.012	0.085	1.257
6	GCP #6			1853.049	-1172.160			794017.784	3798421.772	Control	-0.039	-0.018	0.043	0.635
7	GCP #7			2648.043	-344.960			816370.156	3824606.071	Control	0.013	-0.034	0.036	0.538
8	GCP #8			2459.935	-217.717			810508.261	3828085.583	Control	-0.044	0.018	0.047	0.698
9	GCP #9			1176.775	-1750.534			774785.689	3779902.734	Control	0.054	0.059	0.080	1.181
10	GCP #10			2370.196	-1647.270			810352.630	3785105.952	Control	0.042	-0.061	0.074	1.088
11	GCP #11			1446.437	-2276.655			783794.232	3764622.065	Control	0.040	0.068	0.078	1.157
12	GCP #12			1835.054	-977.969			793135.237	3804209.187	Control	-0.028	0.075	0.080	1.185
13	GCP #13			1127.010	-2055.089			773831.158	3770692.948	Control	-0.036	0.081	0.089	1.307
14	GCP #14			762.023	-1977.916			762762.457	3772355.881	Control	0.004	0.008	0.009	0.136
15	GCP #15			208.446	-345.309			743290.793	3820275.952	Control	0.018	0.013	0.022	0.326
16	GCP #16			512.151	-244.342			752208.213	3823837.762	Control	-0.036	0.006	0.037	0.543
17	GCP #17			1233.652	-734.352			774689.024	3810437.869	Control	-0.021	-0.025	0.033	0.483
18	GCP #18			2119.857	-2145.091			803733.271	3769752.273	Control	0.001	-0.037	0.037	0.549
19	GCP #19			273.223	-1217.092			746773.439	3794279.296	Control	-0.001	0.033	0.033	0.490
20	GCP #20			1785.411	-94.324			790087.842	3830585.117	Control	0.081	-0.044	0.092	1.363

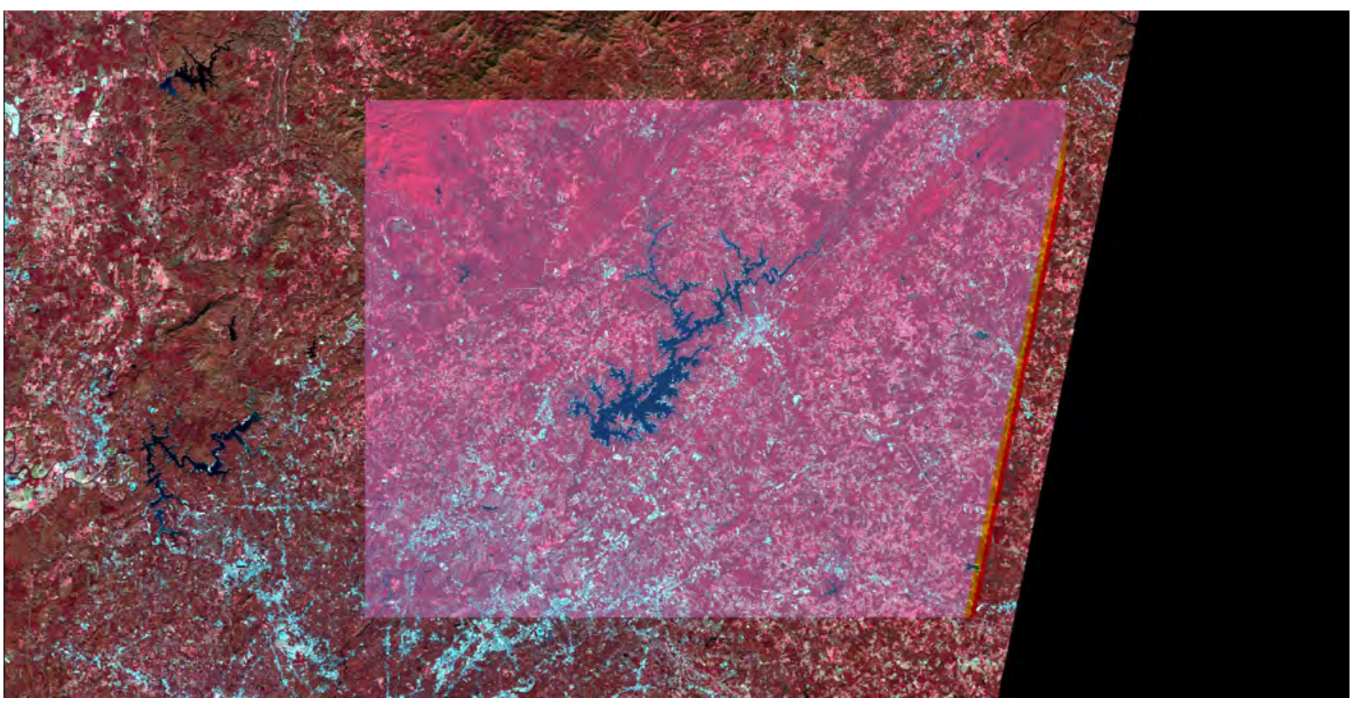


(b) 2001





Point #	Point ID	>	Color	X Input	Y Input	>	Color	X Ref.	Y Ref.	Type	X Residual	Y Residual	RMS Error	Contrib.
1	GCP #1			134.669	-2198.723			743101.767	3763368.136	Control	-0.009	-0.024	0.026	0.592
2	GCP #2			546.882	-574.515			755467.977	3812058.703	Control	0.000	-0.072	0.072	1.664
3	GCP #3			2780.186	-1206.173			822453.447	3793126.007	Control	-0.013	-0.013	0.018	0.423
4	GCP #4			867.512	-1341.444			765084.142	3789071.350	Control	-0.002	0.059	0.059	1.352
5	GCP #5			2663.501	-286.703			818955.246	3820689.109	Control	0.009	-0.059	0.059	1.365
6	GCP #6			1605.107	-904.700			787209.494	3802163.240	Control	0.037	0.000	0.037	0.839
7	GCP #7			2381.188	-38.968			810486.667	3828117.160	Control	-0.027	-0.008	0.028	0.637
8	GCP #8			1607.941	-26.349			787294.112	3828496.799	Control	-0.010	0.058	0.059	1.356
9	GCP #9			1092.817	-1566.865			771841.320	3782311.522	Control	-0.017	-0.014	0.022	0.497
10	GCP #10			2339.452	-1507.338			809234.511	3784098.182	Control	0.018	0.022	0.029	0.666
11	GCP #11			1444.184	-2147.892			782381.495	3764894.919	Control	0.044	0.037	0.057	1.321
12	GCP #12			1523.236	-1371.990			784751.647	3788155.793	Control	-0.018	0.046	0.050	1.142
13	GCP #13			1113.674	-1878.784			772465.567	3772961.439	Control	-0.050	0.014	0.052	1.192
14	GCP #14			715.193	-2090.661			760513.495	3766608.833	Control	-0.037	-0.002	0.037	0.854
15	GCP #15			438.584	-181.819			752220.748	3823834.335	Control	0.023	0.034	0.041	0.941
16	GCP #16			396.348	-865.856			750952.422	3803326.761	Control	-0.001	0.001	0.002	0.034
17	GCP #17			2299.317	-2135.464			808030.018	3765266.971	Control	0.021	-0.003	0.021	0.480
18	GCP #18			1825.332	-1032.013			793813.277	3798347.770	Control	-0.017	0.035	0.038	0.881
19	GCP #19			2235.050	-499.570			806103.728	3814308.549	Control	0.003	-0.015	0.016	0.363
20	GCP #20			221.240	-1579.110			745700.460	3781942.764	Control	0.036	-0.046	0.059	1.345
21	GCP #21			1833.837	-1729.119			794068.333	3777446.896	Control	0.008	-0.050	0.050	1.155



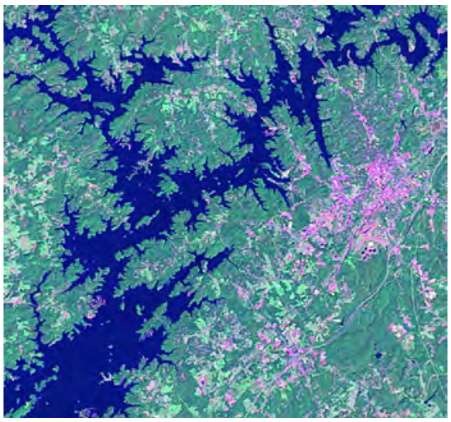
C. IMAGE ENHANCEMENT

We were next tasked with implementing image enhancement techniques that we discussed in class. In Project Tasks 3 and 4, we had the opportunity to implement spectral, spatial, and transformation image enhancements and identify what may work well for change detection and what may not.

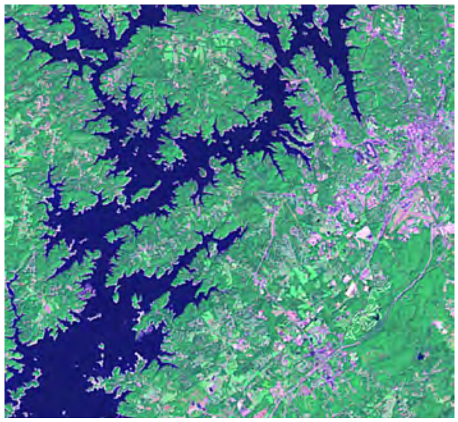
SPECTRAL & SPATIAL

I present the results of my tested image enhancements for Project Task 3 below. I will note that for my final analysis, my image enhancements centered around convolution filtering as well as variations in band combinations. The first enhancement I considered was one where I loaded RGB with the layers (6,4,2) and implemented a 5x5 Edge Enhance filter. The results are presented below.

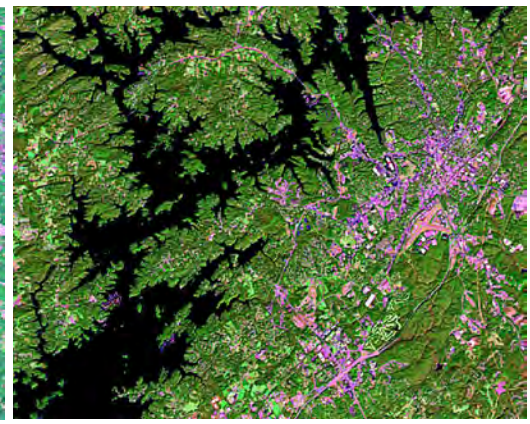
(a) 1991



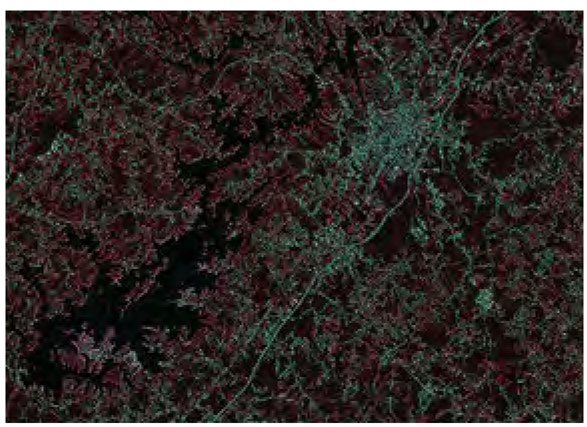
(b) 2001



(c) 2013

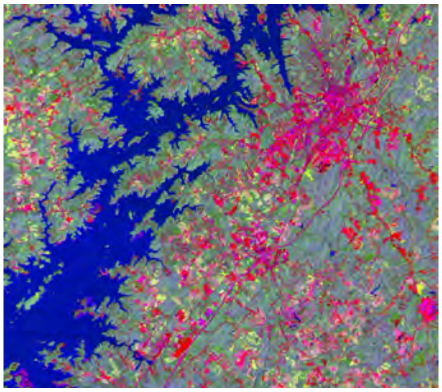


Next, I implemented a combination of an Edge Detect filter with the False Color IR band setting. While this may seem like a trivial combination now after I have worked with ERDAS Imagine more, at the time this combination was nuanced to me. Once I implemented this enhancement on the 1991 image, I concluded this image would not be helpful to me, so I opted to not implement it for the other years. I found that it could help identify roads but, since there were other options that offer more information available, this would not be optimal for me and so it was not pursued for the other images. I include the resulting image for 1991 below.

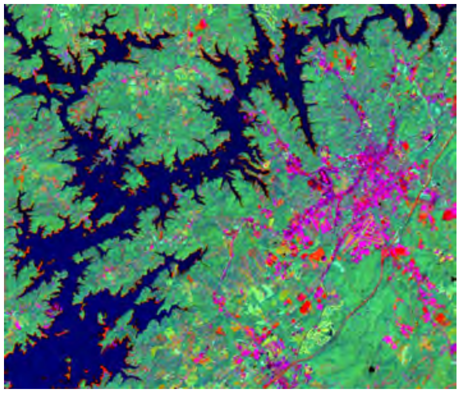


Lastly, I conducted a Principal Component Analysis (PCA) where I specified five factors. I will be honest in saying that I had an approximate understanding of how a PCA works in a remote sensing context, having studied it from a psychometric perspective in the past. I present the results of my attempted PCA but will refrain from providing an interpretation of the results as I conducted a PCA below, which I believe was more successful.

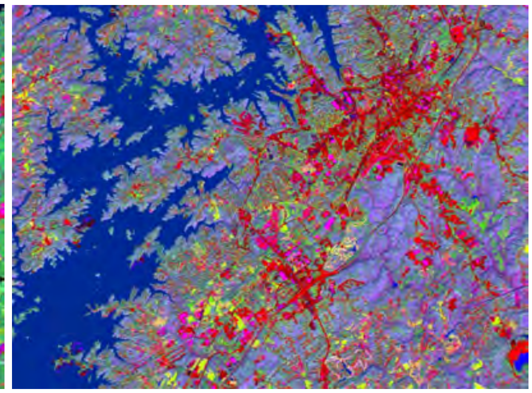
(a) 1991



(b) 2001



(c) 2013

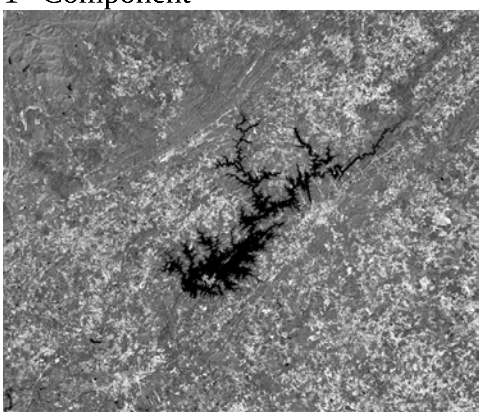


<u>TRANSFORMATION</u>

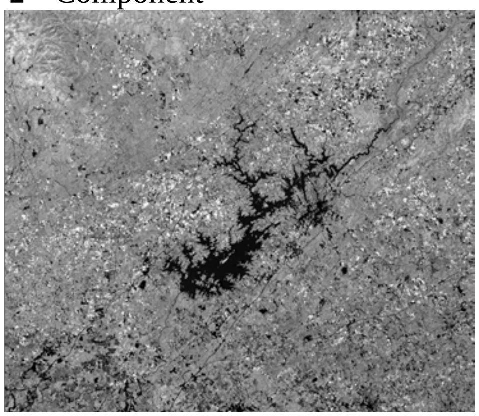
In addition to our spectral and spatial enhancements which we completed in Project Task 3, we conducted transformation enhancement techniques for Project Task 5. For this task, we were asked to compare the results of the Principal Component Analysis (PCA) to the Tassled Cap and consider what information they provide. I begin by presenting the results of my PCA below which was run on 3 components.

<u>1991</u>

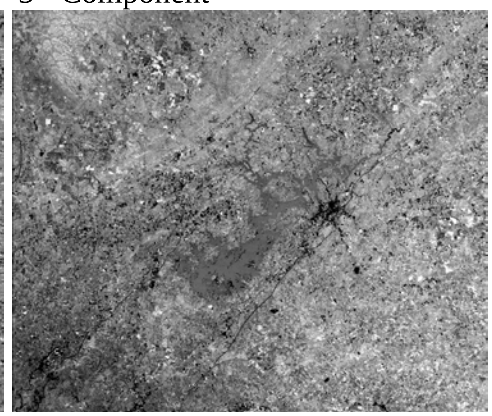
1st Component



2nd Component

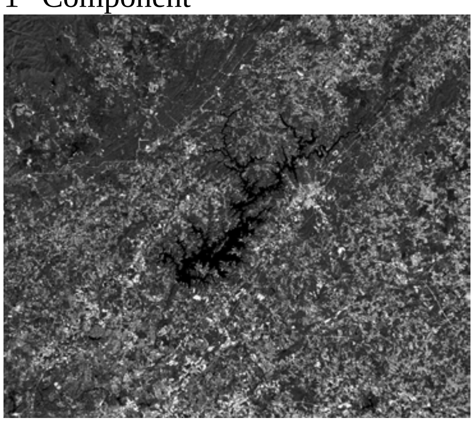


3rd Component

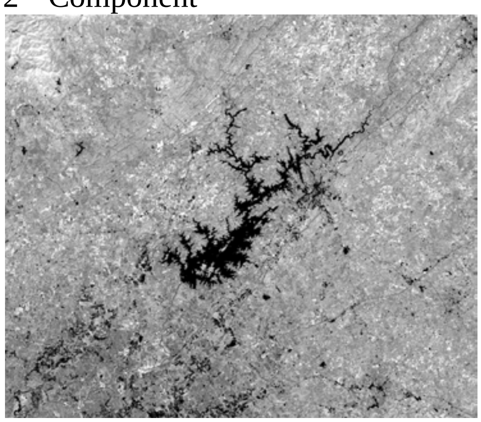


<u>2001</u>

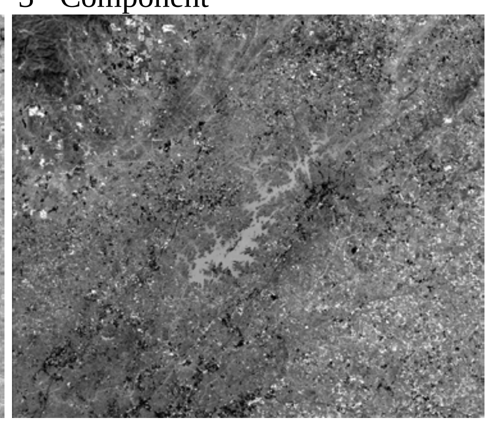
1st Component



2nd Component

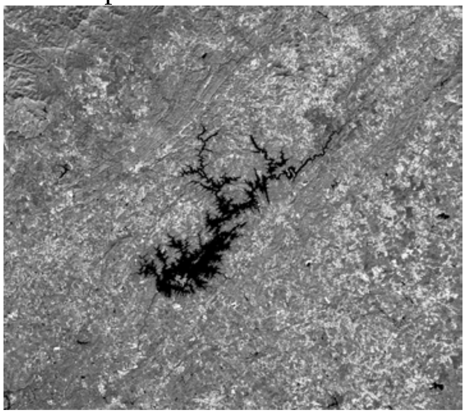


3rd Component

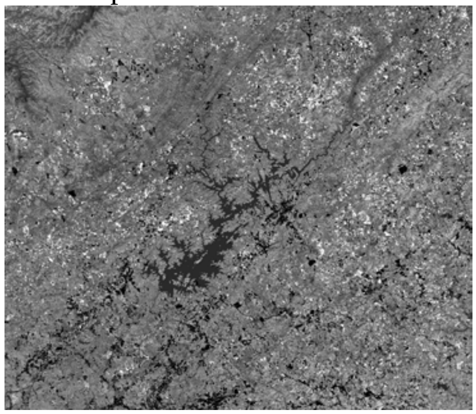


2013

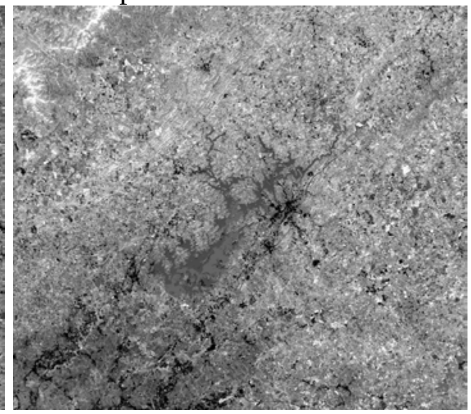
1st Component



2nd Component



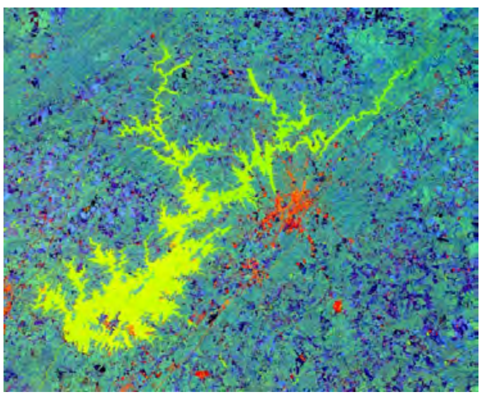
3rd Component



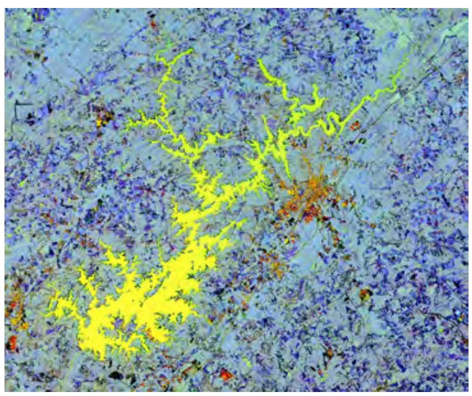
The results of the PCA were consistent with my expectations after learning about how the PCA works in a remote sensing framework; I discuss these expectations after my presentation of the Tasseled Cap. As I mentioned earlier in this paper, I realized after submitting Project Task 3 that PCA was not appropriate for that task.

I present the results of the Tasseled Cap enhancement below.

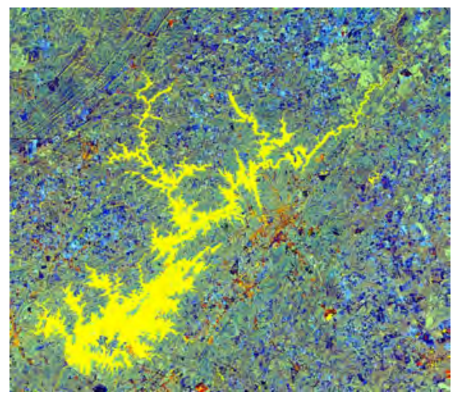
(a) 1991



(b) 2001



(c) 2013



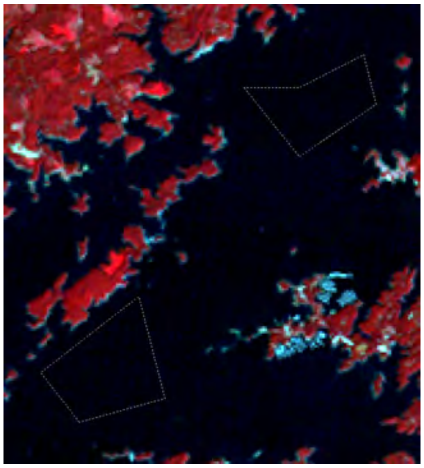
I provided the following comments and conclusions after implementing these two algorithms. As we are aware, both PCA and Tasseled Cap use linear combinations; there two differ in that PCA uses locally derived statistics, whereas as Tassel-Cap uses a predefined matrix of coefficients. The results I obtained for the PCA were consistent with the ones we discussed in lecture, where the 1st component had the most variance and we see more noise as we go to the 2nd and 3rd component. With Tasseled Cap, since we did not discuss the function at great length in class, I provided my own insights from the perspective of how the results may assist me in conducting a change detection analysis. I found that it is good at identifying vegetation but not consistent with urban features.

D. PATTERN RECOGNITION

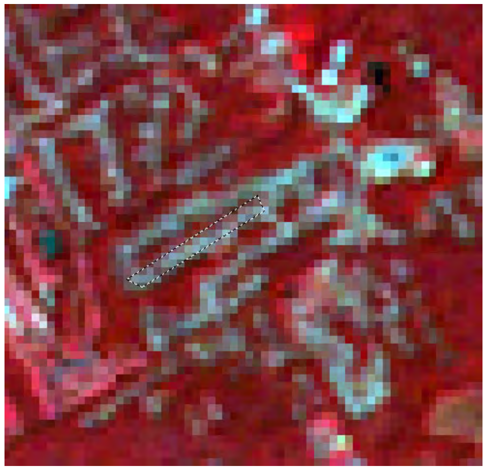
SUPERVISED

The next step in the project was captured in Project Task 5, which consisted of conducting a supervised classification on the images. Due to time constraints and general lack of confidence in my results, I implemented the supervised classification for the 1991 and 2001 images only. When I was identifying features, I supplemented my images with ground truth imagery from Google Earth imagery. For the 1991 image, I identified the following features of interest: lake/water, urban (residential, industrial, and commercial), cropland/grass, and forest. I provide sample images of the features used in implementing the supervised classification below.

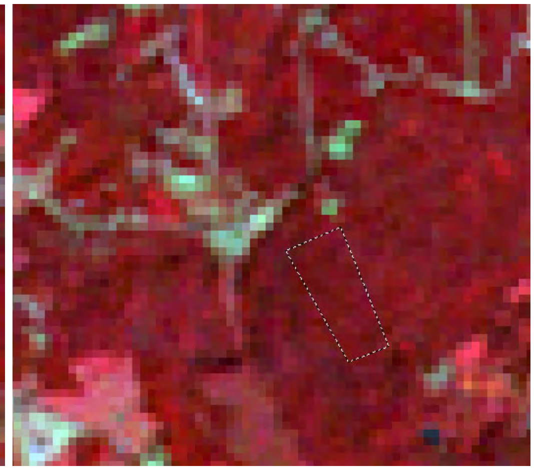
(a) Lake/Water



(b) Residential

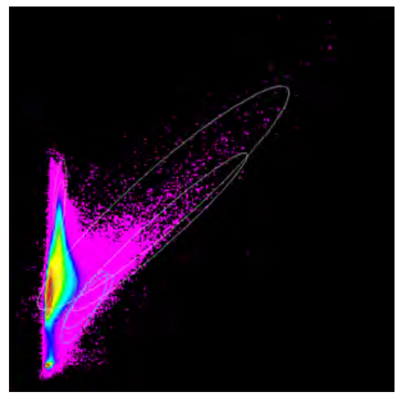


(c) Forest

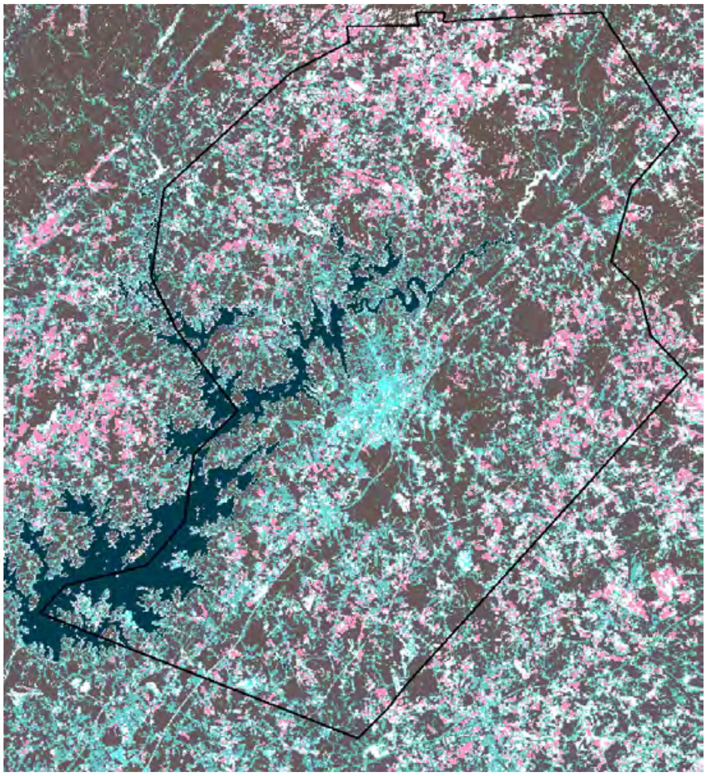


I provide my supervised class signatures below along with the feature space image, depicting band 2 on the x-axis and band 4 on the y-axis.

Class #	>	Signature Name	Color	Red	Green	Blue
1	▶	Lake1		0.000	0.227	0.294
2		Lake2		0.000	0.227	0.294
3		Residential1		0.406	0.802	0.823
4		Residential2		0.403	0.790	0.791
5		Forest1		0.395	0.366	0.385
6		Forest2		0.415	0.349	0.331
7		Industrial1		1.000	1.000	1.000
8		Industrial2		1.000	1.000	1.000
9		Cropland1		1.000	0.580	0.761
10		Cropland2		1.000	0.586	0.764
11		Urban1		0.296	1.000	1.000
12		Urban2		0.357	1.000	1.000



The image obtained from this classification is presented on the following page.

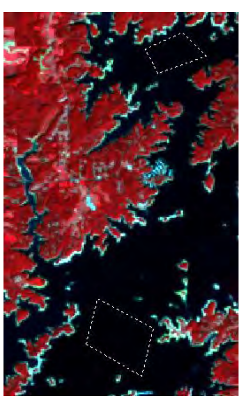


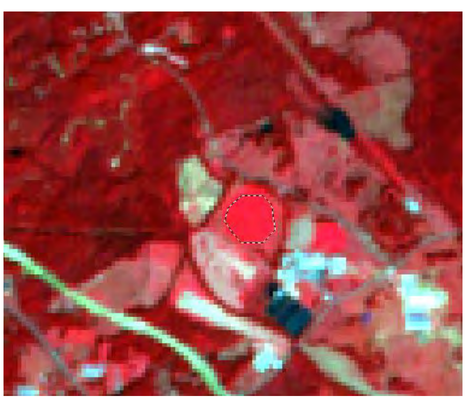
This image appears to provide reasonable classifications that may be helpful in a visual analysis of how the urban features may have evolved over time. Upon reviewing my proposed classifications, the issue that stands out to me most after having completed a more thorough classification for my change detection analysis is that I tried to separate out urban features into three separate entities: residential, industrial, and commercial. Based on my final analysis of pixel signatures, I am not confident that this was appropriate.

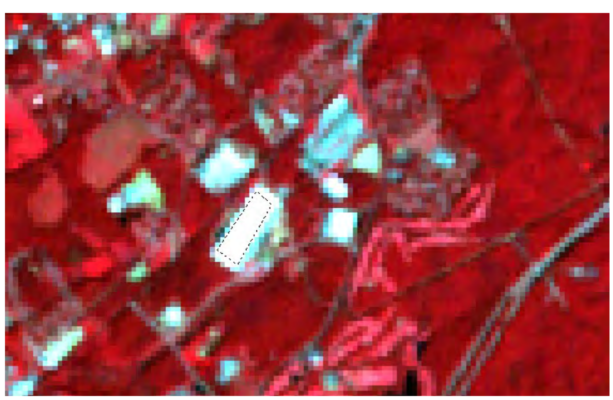
After conducting my supervised classification, which I did not use in my final change detection analysis, I was left with an question regarding some of the issues I came across during my classification: where does a house "stop" and a road "start?" As I was working to classify residential features as separate entities from roads, which I believe I classified as commercial as a simplification due to the similarities in signatures, I came across the issue of how does one visually separate roads and houses especially when there are other factors at play such as driveways and tree cover. This issue should have been a signal there that my proposed classes were problematic but, at the time, I was focused on meeting the project task's requirement of identifying 5-6 classes. I also found myself Commercial buildings appeared similar as roads making it difficult to differentiate them.

I will briefly provide the methods implemented in my 2001 image supervised classification but will note that my discussion of findings is well summarized in the above paragraph. Below I provide some examples of the clips used in my supervised classification.

(a) Lakes/water (b) Cropland/grass (c) Industrial

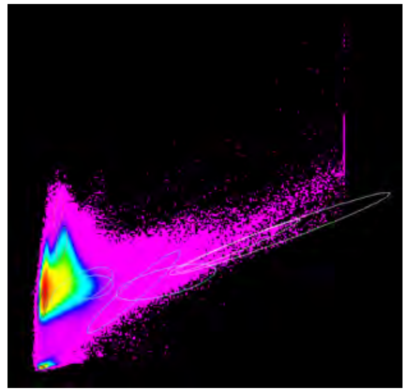




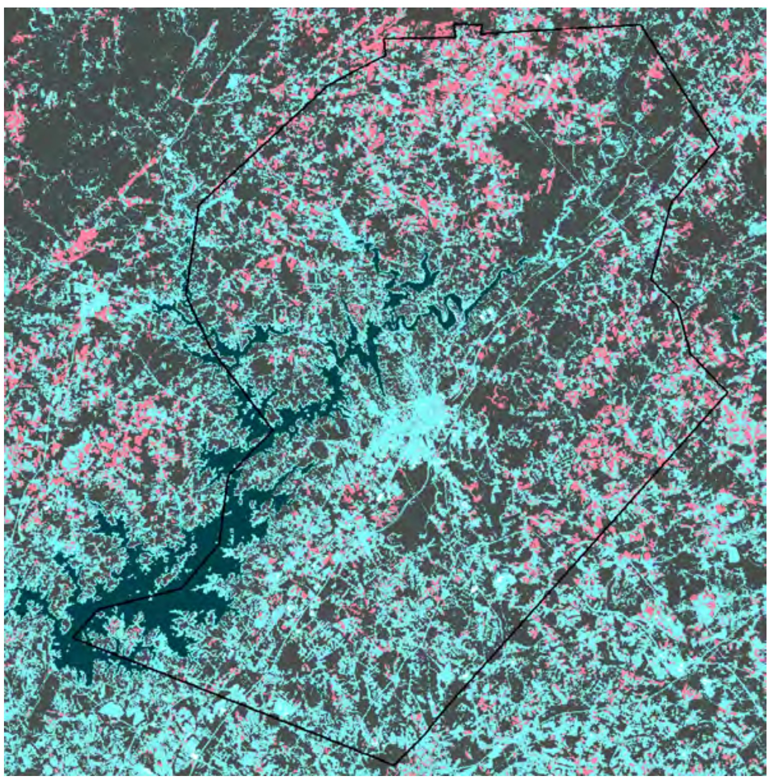


While I provided the results of two different attempts at image classification, I will provide only the latter attempt here for completion. Below I present the class signatures I identified alongside the feature space layer image which also consists of band 2 on the x-axis and band 4 on the y-axis.

Class #	>	Signature Name	Color	Red	Green	Blue
1	▶	Lake1		0.000	0.262	0.294
2		Lake2		0.000	0.262	0.284
3		Residential1		0.514	0.924	0.928
4		Residential2		0.514	1.000	1.000
5		Forest1		0.281	0.320	0.310
6		Forest2		0.294	0.295	0.282
7		Industrial1		1.000	1.000	1.000
8		Industrial2		1.000	1.000	1.000
9		Cropland1		1.000	0.446	0.564
10		Cropland2		1.000	0.518	0.614
11		Urban1		0.577	1.000	1.000
12		Urban2		0.456	1.000	1.000



Based on the results from both feature space images, I was proud of how consistent the signatures were within the feature spaces but the actual classifications were clearly not capturing as much of the variation as we would likely need for a comprehensive analysis.

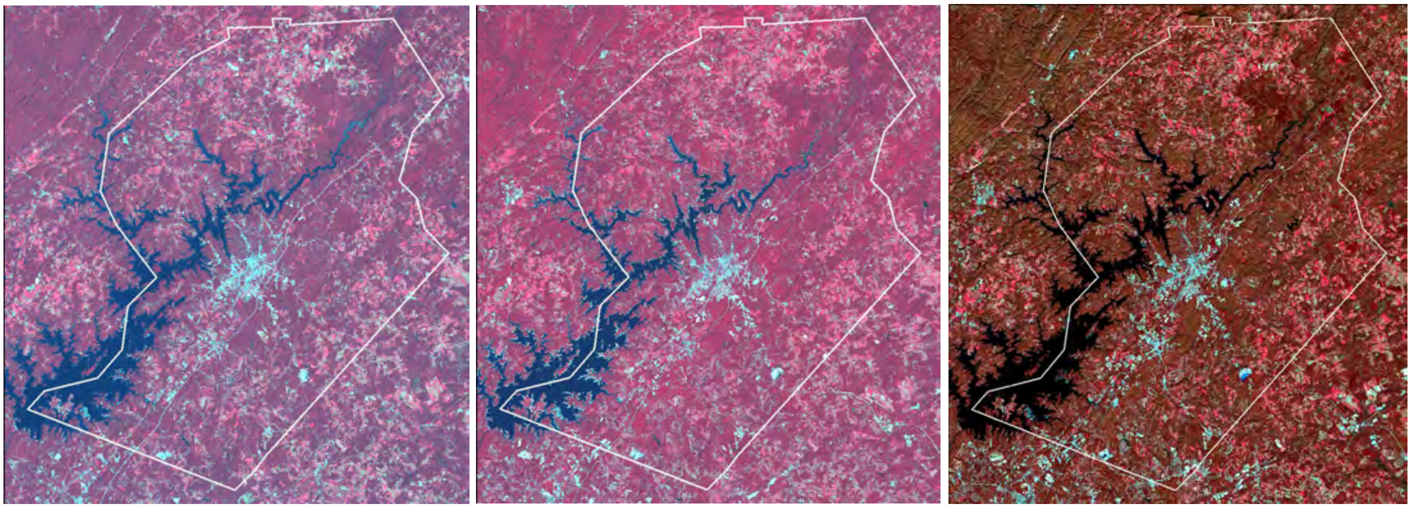


I was not confident with the resulting classifications for the supervised approach and decided to not use it for my change detection analysis.

UNSUPERVISED

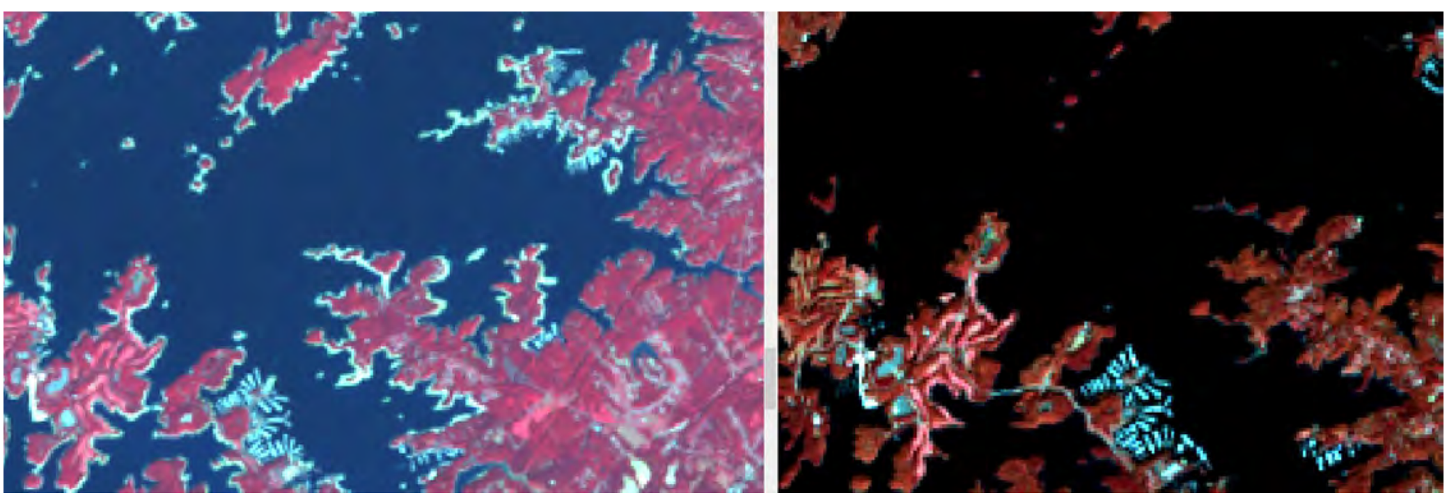
When I went to conduct my change detection process, I realized it would be best to clip the three images to the same size and closer to the boundaries of the county and to rerun the unsupervised image classification using the images presented below.

(a) 1991 (b) 2001 (2013)



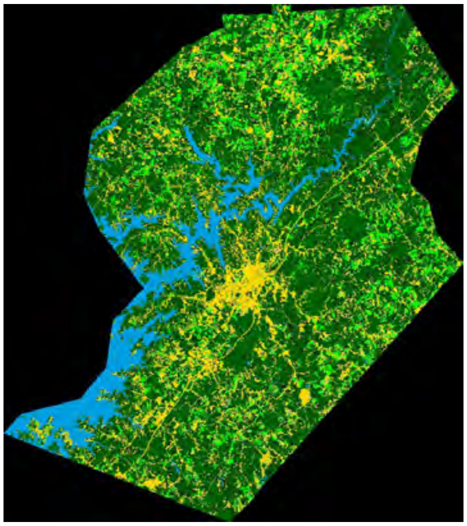
I went through classifying the generated classes from the unsupervised classification multiple times. I also tried varying the number of classes generated and adjusting whether to set the number of classes or to allow for a range. In the end, I settled on 50 classes and 1,500 iterations with a convergence threshold of 1. I ran this unsupervised classification on the three years of images.

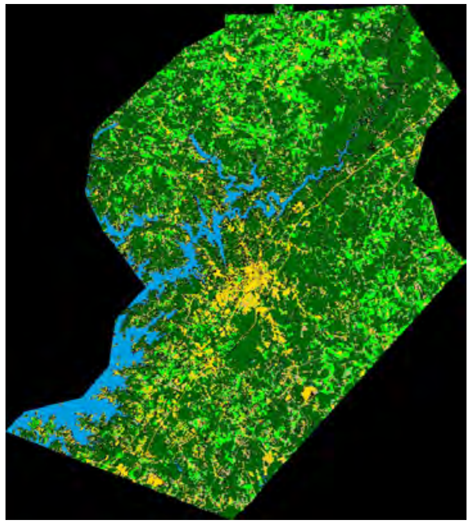
From there, I tried grouping the classes and identifying the features represented in each class. This is where I had the greatest difficulty. I went through grouping and identifying these classes multiple times for each image, each time uncovering a flaw or challenge that affected my groupings. For example, with the 2001 image, I discovered that, due to the unique shore lines that were generated in the image (presented below), the shoreline of Lake Lanier had signatures that were in the same class as the major urban areas. I was unable to separate the two and had to classify the shorelines in 2001 as urban areas. I also struggled with shadow classes because my identification of shadow classes was very much framed by where in the image, I would search to identify the class.

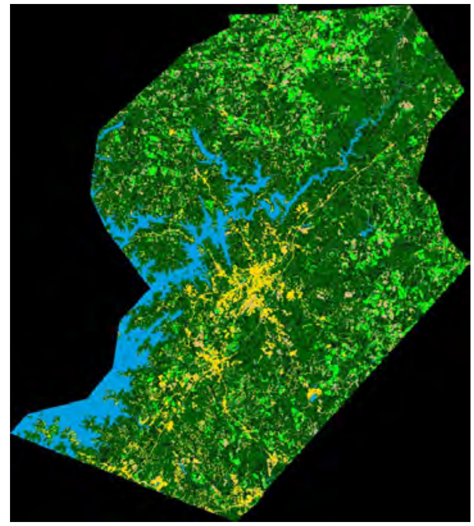


In the end, I was able to identify five features of interest (not including shadows): water, urban, grass, bareground, and forest. I tried to identify a sixth class but was not successful in doing identifying one. Below I provide my final recoded images across the three years. In the images, it appears that the urban center has declined but I believe this is the result of having higher resolution imagery which reduces the need for generalization of pixels in dense areas. I provide both visual and statistical evidence capturing how these features varied across the years.

(a) 1991 (b) 2001 (2013)



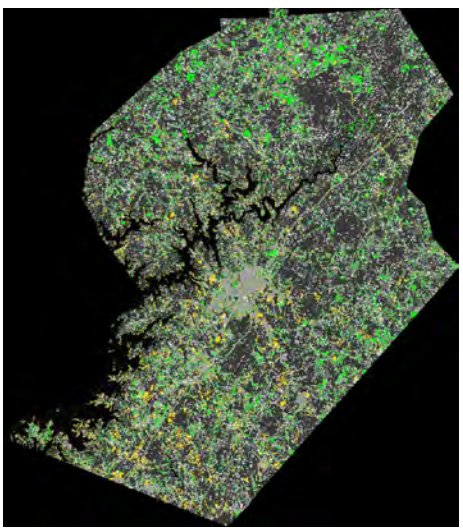


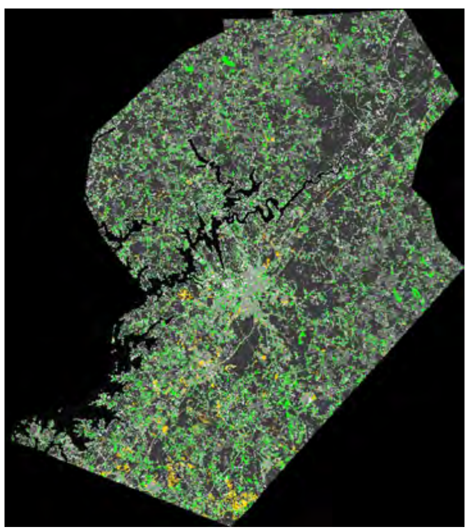


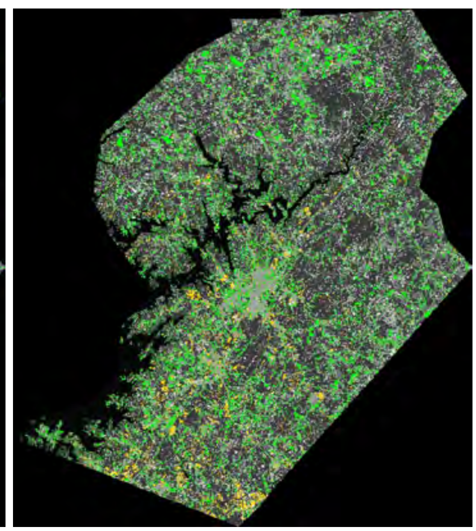
E. CHANGE DETECTION

Following the methodology presented in the Change Detection slides, I took the recoded images and conducted three matrix unions (1991-2001, 2001-2013, and 1991-2013). I obtained the following images.

(a) 1991 – 2001 (b) 2001 – 2013 (c) 1991 – 2013



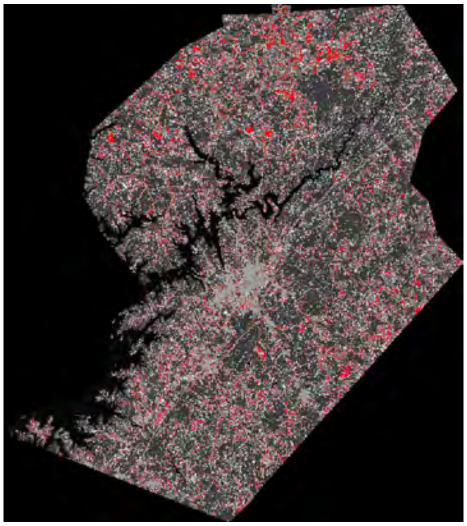




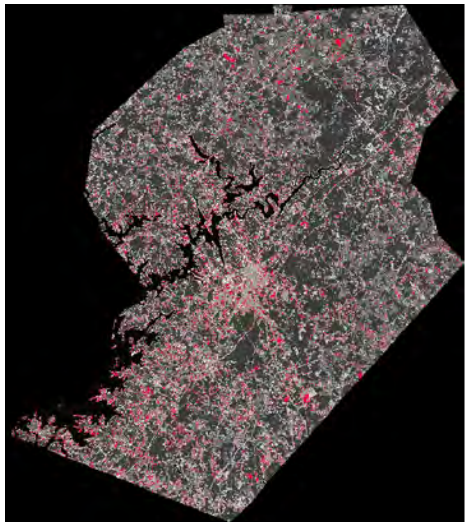
The images do not appear as depicted above by default. I opted to set all pixels that transitioned from the other features to vegetation features (trees and grass) as green and all pixels that transitioned from the other features to urban features as yellow. We can see from a visual inspection that it appears that Hall county underwent a great deal of vegetation growth. I will call attention to one oddity in the results and that is the fact that from 1991 to 2001 there was a great deal of shoreline urbanization along Lake Lanier; this is likely the result of a drought that occurred in August 2001[1] which likely affected Lake Lanier's water level in early October of that year. After generating these images, I was curious to see how much de-urbanization Hall county underwent across these years. I generated the images below by setting all the cells that indicated a change from urban features to any of the other features.

[1] Source: https://www.ncdc.noaa.gov/sotc/drought/200108

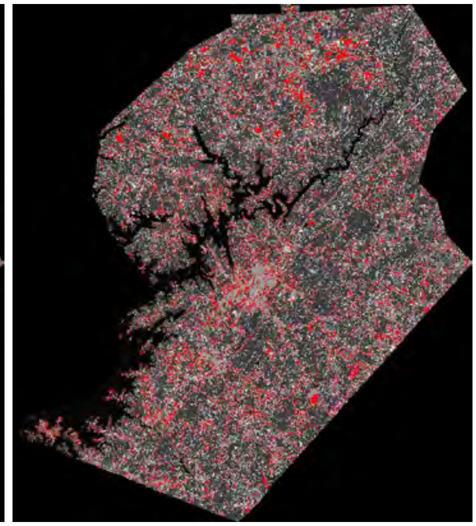
(a) 1991 – 2001



(b) 2001 – 2013



(c) 1991 – 2013



We can immediately see there was significant de-urbanization across the years. I will discuss this finding later in the paper when I compare these findings with those of a NDVI change detection analysis, but I will note now that these results are likely due to issues with the image classification as opposed to what actually took place in Hall county.

Along with generating these images, I generated the matrix which captures how the land cover changed across the years. I present the resulting matrices of my change detection below. First, I present the results in terms of changes in pixels.

1991 / 2001	Water	Tree	Grass	Urban	Bareground	Total - 1991
Water	77,082	2,958	557	5,658	970	87,225
Tree	209	482,914	22,419	27,212	22,093	554,847
Grass	8	27,887	79,285	8,457	12,416	128,053
Urban	187	20,726	36,079	60,479	22,674	140,145
Bareground	14	8,822	10,388	7,917	5,938	33,079
Total - 2001	77,500	543,307	148,728	109,723	64,091	

2001 / 2013	Water	Tree	Grass	Urban	Bareground	Total - 2001
Water	76,921	417	16	118	49	77,521
Tree	1,711	473,659	8,064	11,440	12,756	507,630
Grass	338	64,951	67,601	5,295	31,771	169,956
Urban	4,707	43,611	4,462	46,756	11,353	110,889
Bareground	609	41,388	9,175	5,827	12,838	69,837
Total - 2013	84,286	624,026	89,318	69,436	68,767	

1991 / 2013	Water	Tree	Grass	Urban	Bareground	Total - 1991
Water	95,137	8,655	35	381	89	104,297
Tree	2,027	471,652	9,007	20,660	17,826	521,172
Grass	59	55,393	47,234	6,258	21,456	130,400
Urban	1,294	76,722	17,854	39,394	19,156	154,420
Bareground	62	21,426	5,226	4,351	5,319	36,384
Total - 2013	98,579	633,848	79,356	71,044	63,846	

One aspect of these tables that I found concerning was that the totals obtained for 1991 and 2013 were not consistent between the tables. I wondered if this was an artifact of using the intersection function, that the pixels that intersected between images varied. Due to time constraints, I was unable to pursue this concern in depth.

Next, I provide the results of the changes in area as measured in acres.

1991 / 2001	Water	Forest	Grass	Urban	Bareground	Total - 1991
Water	17,142.6	657.8	123.9	1,258.3	215.7	19,398.4
Forest	46.5	107,397.6	4,985.9	6,051.8	4,913.4	123,395.1
Grass	1.8	6,201.9	17,632.6	1,880.8	2,761.3	28,478.3
Urban	41.6	4,609.4	8,023.8	13,450.2	5,042.6	31,167.5
Bareground	3.1	1,962.0	2,310.2	1,760.7	1,320.6	7,356.6
Total - 2001	17,235.6	120,828.7	33,076.3	24,401.8	14,253.5	

2001 / 2013	Water	Forest	Grass	Urban	Bareground	Total - 2001
Water	17,106.8	92.7	3.6	26.2	10.9	17,240.3
Forest	380.5	105,339.3	1,793.4	2,544.2	2,836.9	112,894.3
Grass	75.2	14,444.8	15,034.1	1,177.6	7,065.7	37,797.3
Urban	1,046.8	9,698.9	992.3	10,398.3	2,524.8	24,661.1
Bareground	135.4	9,204.5	2,040.5	1,295.9	2,855.1	15,531.4
Total - 2013	18,744.8	138,780.2	19,863.9	15,442.2	15,293.4	

1991 / 2013	Water	Forest	Grass	Urban	Bareground	Total - 1991
Water	21,158.0	1,924.8	7.8	84.7	19.8	23,195.1
Forest	450.8	104,893.0	2,003.1	4,594.7	3,964.4	115,906.0
Grass	13.1	12,319.1	10,504.6	1,391.7	4,771.7	29,000.3
Urban	287.8	17,062.6	3,970.6	8,761.0	4,260.2	34,342.2
Bareground	13.8	4,765.0	1,162.2	967.6	1,182.9	8,091.6
Total - 2013	21,923.5	140,964.5	17,648.4	15,799.8	14,199.0	

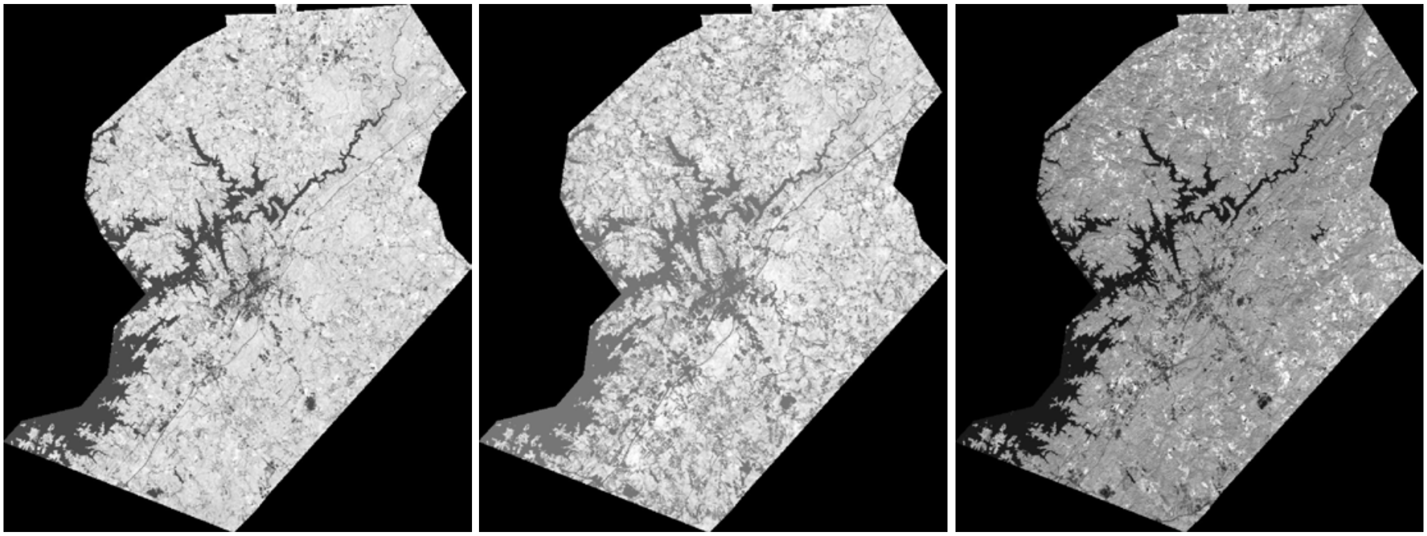
To give a better sense of what these tables are telling us, I generated a table which tells us the percent changes in the coverage of each feature.

	% Δ of Year Combinations		
Features	1991 – 2001	2001 – 2013	1991 – 2013
Water	-11.15	8.73	-5.48
Forest	-2.08	22.93	21.62
Grass	16.15	-47.45	-39.14
Urban	-21.71	-37.38	-53.99
Bareground	93.75	-1.53	75.48

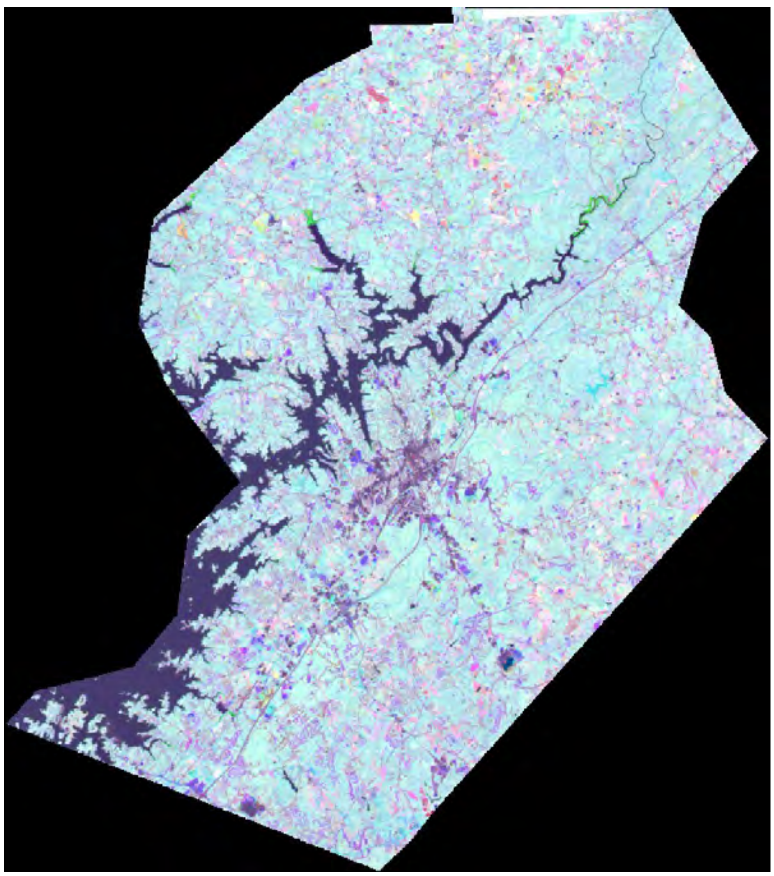
Note that the results affirm my findings from the visual inspection: vegetation (particularly trees/forest) features increased across the analyzed images and urban features declined across the three years. I will discuss these results in greater detail when I go through the sources of errors.

As a way of grounding my analysis, I continued my change detection analysis by conducting computing the NDVI for each year. I present the resulting images below.

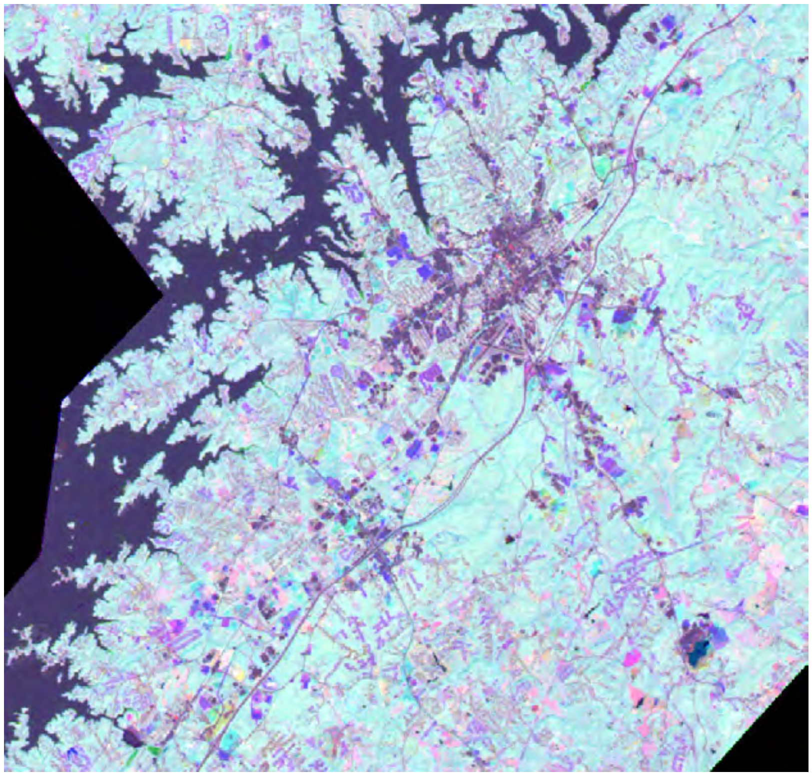
(a) 1991 (b) 2001 (c) 2013



I then stacked these three images to generate a single 3-layer image. This would allow me to visually identify changes that took place. I present the resulting image below.



For illustrative purposes, I loaded 1991 on Blue, 2001 on Green, and 2013 on Red. From the general image, we can see that Gainesville and the areas along the highway in the direction of Atlanta have experienced most of the urbanization. We can also see that northern portions of Hall County experienced minimal urbanization along with increased vegetation. To provide a better understanding of what this image tells us, I provide a zoom-in below.



I will note some areas of interpretation. We may interpret blue features as those that have been urbanized from 1991 to 2001. The darker aqua (not turquoise) areas are those features that were urbanized from 2001 to 2013. The pink features that are present throughout the image are those that likely went from unhealthy vegetation to healthy vegetation from 2001 to 2013. I was unable to identify a way to obtain statistics on the landcover changes from the NDVI estimation so I will rely on the visual interpretation to guide my discussion.

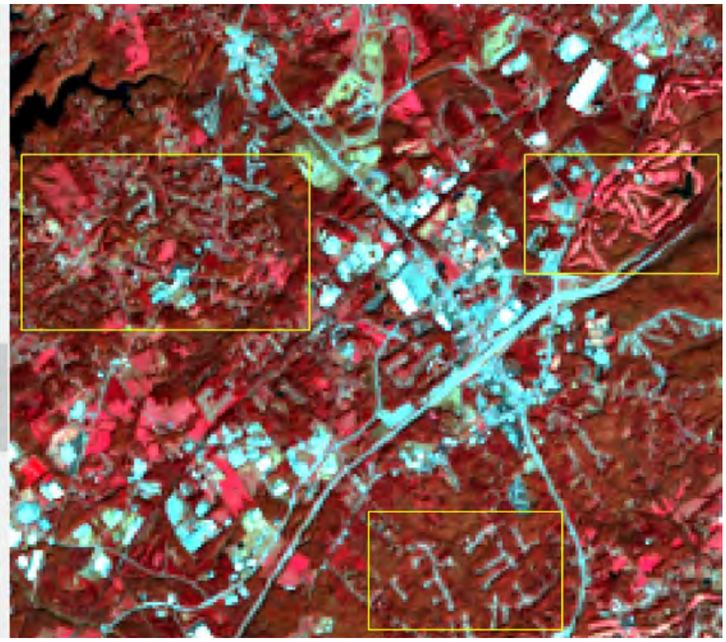
F. SOURCES OF ERROR

As I indicated in my interpretation of the results of my change detection using the unsupervised classification images, the unsupervised classification incorporated a great deal of subjectivity which resulted in errors in the class generation. For example, I had difficulty identifying baregrounds in the 1991 image; these types of subjective interpretations likely introduced a great deal of error into my classification results. I also suspect that the baregrounds results for 2013 were affected by seasonal variations due to reduced healthy grass throughout the county because 2013 was taken in November. There were also structural changes at play which affected how the changes were captured; for example, I identified at least one quarry which kept changing its features over time due to the changes in mining behaviors.

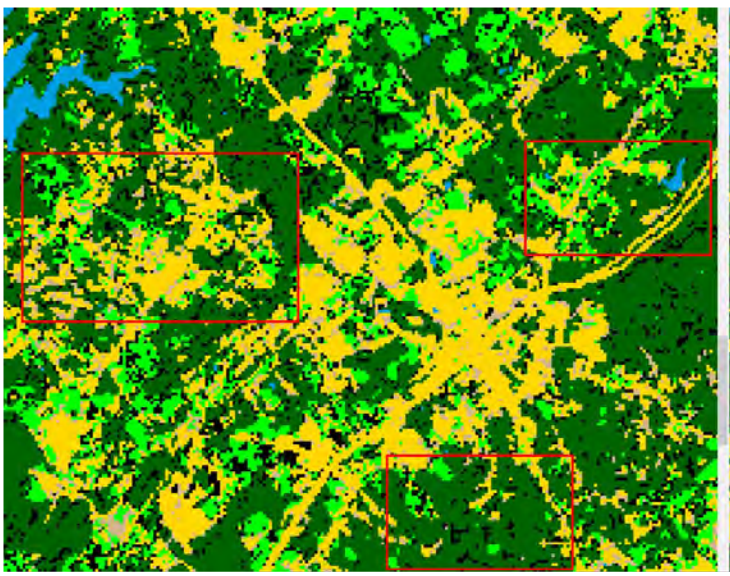
As a reminder, the images used ranged from September 28 to November 10 which means that tree cover changes affected urban feature identification. Alternatively, the variations in tree cover may have simply been the result of tree growth over the years. I found that roads and residential areas were prone to variations in land cover classification due to variations in tree coverage across the years as indicated by the boxed areas in the image below. I provide the relevant recoded images below which capture how these variations affected the feature classifications of the highlighted areas.

(a) 1991

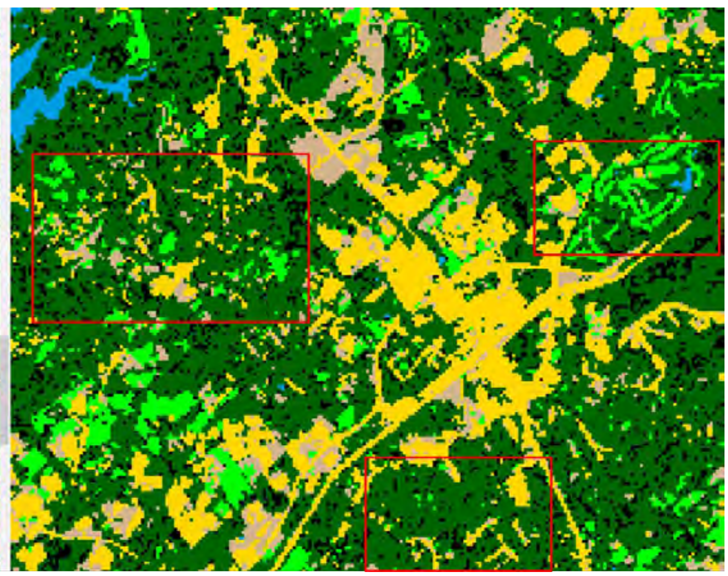
(b) 2013



(a) 1991



(b) 2013



One of the biggest limitations of my analysis was that I was only able to identify five groups consistently across the three images. These categories are fairly general and I feel that finding a way to specify more land-use type classes accurately would yield results that are more insightful for anyone interested in studying how the use of the land changes and how they relate to economic trends in regions. As I uncovered during my supervised classification, it is difficult to separate out urban spaces by use and, given my limited understanding of soil or vegetative differences, I was unable to specify the landcover classes in any greater depth.

Finally, minor issues with Lake Lanier led to variations in the estimation of urban features. One such example is that the boats at docks were registered as urban entities and the quantity of boats docked varied across time so that affected the count, especially since Hall county does not include the entire lake. As I mentioned earlier, 2001 introduced an overestimation of urban features due to the increased shoreline.

IV. CONCLUDING REMARKS

If we take the results of the NDVI analysis and unsupervised classification results to agree, it appears that the urbanization near Gainesville may have been offset by the increased vegetation in the Northern portion of Hall County. From the discussion I presented above, it is clear that it would be difficult to parse out how much of an effect the errors in my classification affected the results but, from the discussion, it is clear that they were present. It is important to note that some of these errors are from my lack of practice with this process, but some errors are introduced from the algorithm as the ground truth clearly shows that there are discrepancies between what happened and what the algorithm tells us happened. This calls attention to the need for subjectivity or ground truth when conducting remote sensing-based analyses. We saw this in the discussion of the 2001 Lake Lanier shoreline urban classification as well as tree cover growth over residential areas. This error appears to be a part of the process as I was not able to identify any way in which the user could manually override classifications for specific regions to account for any misclassifications that may arise. It is also important to reiterate that a great deal of errors from both supervised and unsupervised classifications stem from the users themselves as there are subjective user-specified inputs that both algorithms require that introduce these errors like the ones I discussed with my analysis.

Overall, I think my results provide anecdotal evidence that it may be best to conduct change detection analyses using multiple methods to get the full picture. With NDVI, we are not able to immediately obtain statistical data regarding land cover changes over time but, with the unsupervised classification, subjectivity played a role and introduced a great deal of errors. The biggest takeaway I had was that I did not fully comprehend how Project Tasks 3 through 6 came together and what roles they played in change detection; additionally, I feel that I learned a great about what errors or limitations I face when making decisions in how I conduct such analyses.

References

U.S. Census Bureau, Resident Population in Hall County, GA [GAHALL0POP], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/GAHALL0POP, November 25, 2020.

Wikipedia contributors. (2020, November 21). Hall County, Georgia. In Wikipedia, The Free Encyclopedia. Retrieved 20:56, December 2, 2020, from https://en.wikipedia.org/w/index.php?title=Hall_County,_Georgia&oldid=989820566