LAND USE AND LAND COVER CHANGE DETECTION: A TWENTY YEAR COMPARATIVE STUDY OF PASCO COUNTY, FLORIDA

1 Introduction

Our planets vegetation has changed as a result of the action of humans and its inactions as well. This change has affected food production with direct consequence (Julien et al 2011). Land use and land cover change has affected both humans and the physical environment and also plays a fundamental role in various environmental and socioeconomic applications from local to the global scales (Chunhao Zhu & Yingkui Li, 2013).

The comparison of two to three land use maps over a long period of time is very vital to determine the trend and pattern of these land cover change (Chunhao Zhu & Yingkui Li, 2013). The interpretation of land use and land cover change involves some classification algorithms. Although the Maximum Likelihood Classifier is the most common method of classification (Chunhao Zhu & Yingkui Li, 2013), there are other types of classifiers such as the Minimum Distance Classifier.

One major process in the Land Cover classification is to access for the accuracy of said classification. Li and Wang (2009) suggested that accuracies greater than 80 percent in overall accuracy was the ideal quality of the land cover changing detection. Zhu and Li (2013) also suggest that one effective way to assess accuracy is through the use of field work or surveys or the use of high resolution aerial photos to obtain ground reference data. Field survey and high resolution aerial photographs can be very expensive and time consuming (Chunhao Zhu & Yingkui Li, 2013), however, with the introduction of Google Earth and free high resolution satellite images provided through the internet, most areas within the United States and some parts of the world, it is now easier to conduct field surveys without leaving the comfort at home. As a result of this, high resolution images from Google Earth have provided ways to obtain ground reference data for assessment accuracy of land use and land cover classification (Chunhao Zhu & Yingkui Li, 2013, Clark & Aide, 2011).

1.1 Aim and Objective

The major goal for this project is to conduct a land cover chage analysis for Pasco County over a twenty year period to ascertain how much change has occurred over this period.

Some of the objectives to accomplish this goal include:

- Make a supervised classification of the 1993,1998, 2003 and 2008 Landsat TM satellite image data;
- Make a supervised classification of 2013 Landsat OLI/TIRS satellite image data;
- Compare all classified images for changes;
- Report any change in tables diagrams and figures.

Study Area

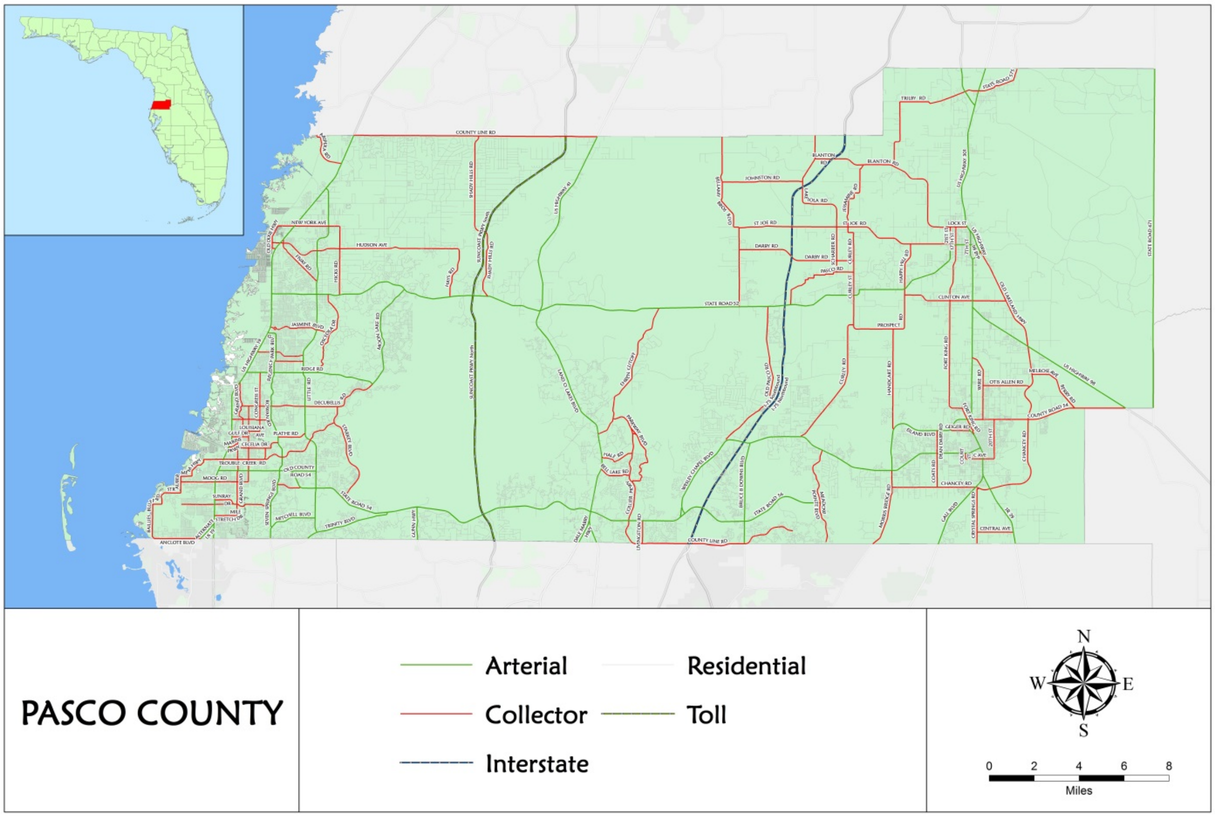

Figure 1: **Map of Pasco County, Florida**

Pasco County, located in Florida, was created on June 2nd, 1887 from the southern part of Hernando County. It is named after Samuel Pasco who was elected to the US senate. New Port Richey is the largest city in the county and Dade City is the county seat. Pasco, Hernando, Hillsborough and Pinellas counties, make up the Tampa-St. Petersburg-Clearwater Metropolitan Statistical Area.

Pasco County is bordered by Hernando County in the North, Sumter County in the Northeast, Polk County in the Southeast, Hillsborough County in the South and Pinellas County in the Southwest. Pasco County is regarded as one of the fastest growing counties in the country with a population of 464,697 according to the 2010 population census. The county is blessed with numerous parks and trails such as the Gulf of Mexico, and several nudist resorts. Pasco County has a total area of 865.95 square miles, with 744.85 square miles comprising of land and 123.10 square mile comprising of water ("Pasco County, Florida," 2015).

2 Methodology

2.1 Data

The data used for this project was a 1993, 1998, 2003 and 2008 TM Landsat image and a 2013 Operational Land Imager (OLI), commonly referred to as Landsat 8. Landsat 8 is a relatively new satellite image which was launched on February 11, 2013. Landsat 8 has eleven bands; nine of these bands are OLI spectral bands while the remaining two are thermal infrared sensor (TIRS) spectral bands. The bands, wavelengths and resolutions of Landsat 8 is shown in the table below. The Thematic Mapper (TM) has 4 multispectral scanner bands and 7 thematic mapper bands. The thematic mapper bands have a higher resolution than the multispectral scanner which was the reason why it was chosen for my analysis in this project. All satellite images were downloaded from the US Geological Survey website.

Table 1: Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) bands

Spectral Band	**Wavelength**	**Resolution**
Band 1 - Coastal / Aerosol	0.433 - 0.453 µm	30 m
Band 2 - Blue	0.450 - 0.515 µm	30 m
Band 3 - Green	0.525 - 0.600 µm	30 m
Band 4 - Red	0.630 - 0.680 µm	30 m
Band 5 - Near Infrared	0.845 - 0.885 µm	30 m
Band 6 - Short Wavelength Infrared	1.560 - 1.660 µm	30 m
Band 7 - Short Wavelength Infrared	2.100 - 2.300 µm	30 m
Band 8 - Panchromatic	0.500 - 0.680 µm	15 m
Band 9 - Cirrus	1.360 - 1.390 µm	30 m
Band 10 - Long Wavelength Infrared	10.30 - 11.30 µm	100 m
Band 11 - Long Wavelength Infrared	11.50 - 12.50	100 m

Source: Wikipedia, 2014

2.2 Method

2.2.1 Supervised classification

Supervised classification is a much more accurate method for mapping classes, but depends heavily on the cognition and skills of the image specialist. The strategy is simple: the specialist must recognize conventional classes (real and familiar) or meaningful (but somewhat artificial) classes in a scene from prior knowledge, such as, personal experience with the region, by experience with thematic maps, or by on-site visits. This familiarity allows the specialist to choose and set up discrete classes (thus supervising the selection) and the, assign them category names. The specialists also locate training sites on the image to identify the classes. Training sites are areas representing each known land cover category that appear fairly homogeneous on the image (as determined by similarity in tone or color within shapes delineating the category). Specialists locate and circumscribe them with polygonal boundaries drawn (using the computer mouse) on the image display. For each class thus outlined, mean values and variances of the DNs for each band used to classify them are calculated from all the pixels enclosed in the site. More than one polygon can be established for any class. When DNs are plotted as a function of the band sequence (increasing with wavelength), the result is a spectral signature or spectral response curve for that class. In reality the spectral signature is for all of the materials within the site that interact with the incoming radiation. Classification now proceeds by statistical processing in which every pixel is compared with the various signatures and assigned to the class whose signature comes closest. A few pixels in a scene do not match and remain unclassified, because these may belong to a class not recognized or defined) ("End to End Remote Sensing Tutorial Page 1-17," n.d.). Using ENVI, training areas was used to extract Regions of Interests (ROIs). These ROIs were used to identify the five deferent classes to be used to the classification purposes, post classification and other purposes as the progressed. These classes include Built-Up Area, Forest, Wetlands, Grasslands, and Water.

The maximum likelihood method of supervised classification was chosen for this classification. Maximum likelihood classification assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class. Unless a probability threshold is selected, all pixels are classified. Each pixel is assigned to the class that has the highest probability (i.e., the maximum likelihood).

2.2.2 Post Classification

Confusion Matrix (Use Ground Truth Regions of Interest)

This involves the use of the ground truth ROIs generated to calculate and display the confusion matrix. This report pairs ROIs with the classes of a classification image to show what percentage of the ROI pixels were or were not contained in a resulting class. To display a confusion matrix report using ROIs for ground truth:

1. From the Toolbox, select **Classification > Post Classification > Confusion Matrix Using Ground Truth ROIs**. The Classification Input File dialog appears.
2. Select a classification input file and perform optional spatial and spectral subsetting, then click **OK**. The Ground Truth Input File dialog appears.
3. Select a ground truth classification input file and perform optional spatial and spectral subsetting, then click **OK**. The Match Classes Parameters dialog appears.
4. Match the ground truth ROIs with the classification result classes by selecting the matching names in the two lists and clicking **Add Combination**. The class combinations are shown in a list at the bottom of the dialog. If the ground truth and classification classes have the same names, they are automatically matched.

To remove a class match from the list, select the combination name. The two class names reappear in the lists at the top of the dialog.

5. Click **OK**. The Confusion Matrix Parameters dialog appears.
6. Select the **Pixels** and/or the **Percent** check boxes.
7. Click the **Yes** or **No** toggle for **Report Accuracy Assessment**.
8. Enter an output error filename, and click **OK**.

The report shows the overall accuracy, kappa coefficient, confusion matrix, errors of commission (percentage of extra pixels in class), errors of omission (percentage of pixels left out of class), producer accuracy, and user accuracy for each class. Producer accuracy is the probability that a pixel in the classification image is put into class x given the ground truth class is x. User Accuracy is the probability that the ground truth class is x given a pixel is put into class x in the classification image. The confusion matrix output shows how the accuracy assessments are calculated (“Calculate Confusion Matrices (Using ENVI) | Exelis VIS Docs Center,” n.d.).

Overall Accuracy

The overall accuracy is calculated by summing the number of pixels classified correctly and dividing by the total number of pixels. The ground truth image or ground truth ROIs define the true class of the pixels. The pixels classified correctly are found along the diagonal of the confusion matrix table which lists the number of pixels that were classified into the correct ground truth class. The total number of pixels is the sum of all the pixels in all the ground truth classes. The overall accuracy was calculated for all classified satellite images. The results are shown in the results and analysis section of this report (“Calculate Confusion Matrices (Using ENVI) | Exelis VIS Docs Center,” n.d.).

Kappa Coefficient

The kappa coefficient (κ) is another measure of the accuracy of the classification. It is calculated by multiplying the total number of pixels in all the ground truth classes (N) by the sum of the confusion matrix diagonals (xkk), subtracting the sum of the ground truth pixels in a class times the sum of the classified pixels in that class summed over all classes (), and dividing by the total number of pixels squared minus the sum of the ground truth pixels in that class times the sum of the classified pixels in that class summed over all classes. The results from the calculated kappa coefficients are shown in the results and analysis section of this report (“Calculate Confusion Matrices (Using ENVI) | Exelis VIS Docs Center,” n.d.).

Confusion Matrix (Pixels)

The confusion matrix is calculated by comparing the location and class of each ground truth pixel with the corresponding location and class in the classification image. Each column of the confusion matrix represents a ground truth class and the values in the column correspond to the classification image’s labeling of the ground truth pixels. The confusion matrix was calculated for all satellite images. The results are shown in table in the results and analysis section of this report (“Calculate Confusion Matrices (Using ENVI) | Exelis VIS Docs Center,” n.d.).

Confusion Matrix (Percent)

The Ground Truth (Percent) table shows the class distribution in percent for each ground truth class. The values are calculated by dividing the pixel counts in each ground truth column by the total number of pixels in a given ground truth class. The percentages of the accuracies of each classes identified during the supervised classification are shown in tables. (“Calculate Confusion Matrices (Using ENVI) | Exelis VIS Docs Center,” n.d.).

Error of Commission

Errors of commission represent pixels that belong to another class that are labeled as belonging to the class of interest. The errors of commission are shown in the rows of the confusion matrix. The ratio of the number of pixels classified incorrectly by the total number of pixels in the ground truth class forms an error of commission (“Calculate Confusion Matrices (Using ENVI) | Exelis VIS Docs Center,” n.d.).

Error of Omission

Errors of omission represent pixels that belong to the ground truth class but the classification technique has failed to classify them into the proper class. The ratio of the number of pixels classified incorrectly by the total number of pixels in the ground truth class forms an error of omission (“Calculate Confusion Matrices (Using ENVI) | Exelis VIS Docs Center,” n.d.).

Producer Accuracy

The producer accuracy is a measure indicating the probability that the classifier has labeled an image pixel into Class A given that the ground truth is Class A (“Calculate Confusion Matrices (Using ENVI) | Exelis VIS Docs Center,” n.d.).

User Accuracy

User accuracy is a measure indicating the probability that a pixel is Class A given that the classifier has labeled the pixel into Class A. (“Calculate Confusion Matrices (Using ENVI) | Exelis VIS Docs Center,” n.d.).

2.2.3 Change Detection Analysis

Change Detection Analysis encompasses a broad range of methods used to identify, describe, and quantify differences between images of the same scene at different times or under different conditions. You can use many of ENVI's tools (such as Band Math or Principal Components Analysis) independently, or in combination, as part of a change detection analysis. In addition, the routines found under the Toolbox menu Change Detection offer a straightforward approach to measuring changes between a pair of images that represent an initial state and final state. Use Change Detection Statistics for classification images.

Change Detection Statistics

Use Change Detection Statistics to compile a detailed tabulation of changes between two classification images. The changes detected using this routine differ significantly from a simple differencing of the two images. While the statistics report does include a class-for-class image difference, the analysis focuses primarily on the initial state classification changes; that is, for each initial state class, the analysis identifies the classes into which those pixels changed in the final state image. ENVI can report changes as pixel counts, percentages, and areas. In addition, you can produce a special type of mask image (classification masks) that provide a spatial context for the tabular report. The class masks are ENVI classification images with class colors matching the final state image, making it easy to identify not only where changes occurred but also the class into which the pixels changed.

The input images must be coregistered or georeferenced. For the most accurate results, carefully coregister the images before processing. If the input images are not coregistered, ENVI uses the available map information to automatically coregister the images, using the initial state image as the base if re-projection or resampling is required.

From the Toolbox, select Change Detection > Change Detection Statistics.

The Select the ‘Initial State’ Image dialog appears.

Select a classification image representing the initial state and perform optional spatial subsetting, then click OK. The Select the ‘Final State’ Image dialog appears.

Select a classification image representing the final state and perform optional spatial subsetting, then click OK. The Define Equivalent Classes dialog appears.

Match the classes from the Initial and final state images by selecting the matching names in the two lists and clicking Add Pair.

Add only the classes you wish to include in the change detection analysis (you do not have to pair all classes). The class combinations are shown in a list at the bottom of the dialog. If the classes in each image have the same names, they are automatically paired.

Click OK. The Change Detection Statistics Output dialog appears.

Select the Report Type. You may choose any combination of Pixels, Percent, and Area.

Click the Output Classification Mask Images? toggle button to specify whether or not to create class masks.

If the Output Classification Mask Images? toggle button is Yes, select output to File or Memory.

Click OK. If an Area Report was requested but the initial state image does not have pixel sizes defined, the Define Pixel Sizes for Area Statistics dialog displays.

Enter the pixel sizes.

Click OK. ENVI adds the resulting output to the Layer Manager and opens the statistics in the Change Detection Statistics window.

The Change Detection Statistics Report

The Change Detection Statistics window contains all of the statistics tables that you selected from the Report Type field in the Change Detection Statistics Output dialog box, separated by tabs. It also contains a Reference tab, which includes additional information about the analysis, such as the names of the input images and the equivalent class pairings. Below is a sample Change Detection Statistics Report.

The statistics tables list the initial state classes in the columns and the final state classes in the rows. However, the columns include only the selected (paired) initial state classes, while the rows contain all of the final state classes. This is required for a complete accounting of the distribution of pixels that changed classes. For each initial state class (that is, each column), the table indicates how these pixels were classified in the final state image. For example, the table above shows that 999 pixels initially classified as "Estuarine Aquatic Bed" changed into the "Unconsolidated Shore" class in the final state image.

The Class Total row indicates the total number of pixels in each initial state class, and the Class Total column indicates the total number of pixels in each final state class. The table above shows that 211,633 pixels were classified as "Estuarine Aquatic Bed" in the initial state image.

The Row Total column is a class-by-class summation of all final state pixels that fell into the selected initial state classes.

Note: This may not be the same as the Final State Class Totals because it is not required that all initial state classes be included in the analysis.

The Class Changes row indicates the total number of initial state pixels that changed classes. In the table above, the total Class Changes for "Water" is 8,193 pixels. In other words, 8,193 pixels that were initially classified as "Water" changed into final state classes other than water.

The Image Difference row is the difference in the total number of equivalently classed pixels in the two images, computed by subtracting the Initial State Class Totals from the Final State Class Totals. An Image Difference that is positive indicates that the class size increased. For example, in table above, the "Water" class grew by 467,119 pixels.

Select the tabs along the top of the Change Detection Statistics dialog to show equivalent information for the class changes in terms of Percentage and Area. In the Percent report (not shown here) the increase in the size of the Water class corresponds to a growth of 21%:

(final state - initial state) / initial state = (390381 - 322763) / 322763 = 0.209

Additional Features of the Change Detection Statistics Report

Options from the Change Detection Statistics Report dialog menu bar are:

To change the floating-point precision displayed in the report, select Options > Set Report Precision.

To convert the units for the Area report, select Options > Convert Area Units.

To save the statistics reports to an ASCII text file, select File > Save to Text File. The Save Change Detection Stats to Text dialog appears; you can optionally add a descriptive line of header text to the file being written. The data is saved in a tab delimited format to facilitate importing into other software programs.

The Classification Mask Images

The classification masks complement the statistics tables by spatially identifying which initial state pixels changed classes, and into which class they changed. By examining the masks, you can often see patterns of changes. The masks can also help highlight coregistration errors.

ENVI saves the class mask images as a multi-band image with one mask for each paired class. To help identify the class into which a pixel changed, the masks are stored as ENVI classification images with the class assignments (names, colors, and values) matching the final state. A value of zero in the mask indicates that no change occurred from the initial to the final state; non-zero values indicate a change.

To differentiate pixels that did not change classes from those that changed into the Unclassified class (which typically has a classification value of zero), pixels that changed into the Unclassified class are assigned a value equal to the number of final state classes plus one, and color coded white. For example, in the sample analysis shown in the figure above, the final state image contains 6 classes; therefore, any pixel in the mask that changed into the unclassified class would be assigned a value of 7.

2.2.4 **Majority/Minority Analysis**

The majority/minority analysis is used to apply majority or minority analysis to classification image. The majority filter analysis was used to change the spurious pixels within a large single class to that class. A 5 x 5 kernel size was used for this analysis. The center pixel in the kernel is replaced with the class value that the majority of the pixels in the kernel has. The majority filter was used to filter out the unnecessary pixels within the classified image. The results from this analysis is shown in the results and analysis section of this project

3 Results and Analysis

3.1 Image Classification

3.1.1 1993 Image Classification

Figures 4.1 and 4.2 shows the 1993 classified image and filtered classified image of Pasco County. The filtered Image shows a clearer picture of the 1993 land use and land cover image of Pasco County. Using the 5 x 5 majority filter, the 1993 classified image was filtered and cleaned to remove specs and falsely classified pixels.

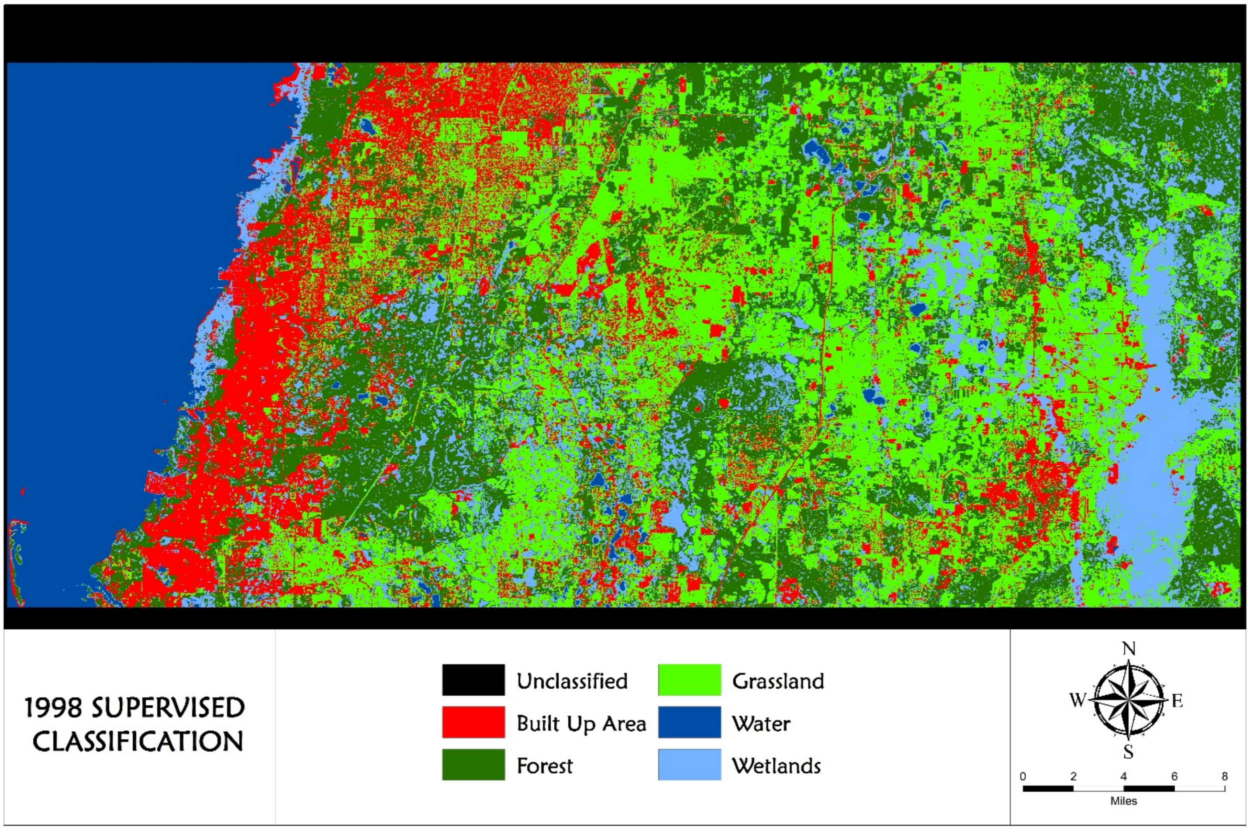

Fig 3.1: 1993 Supervised Classification

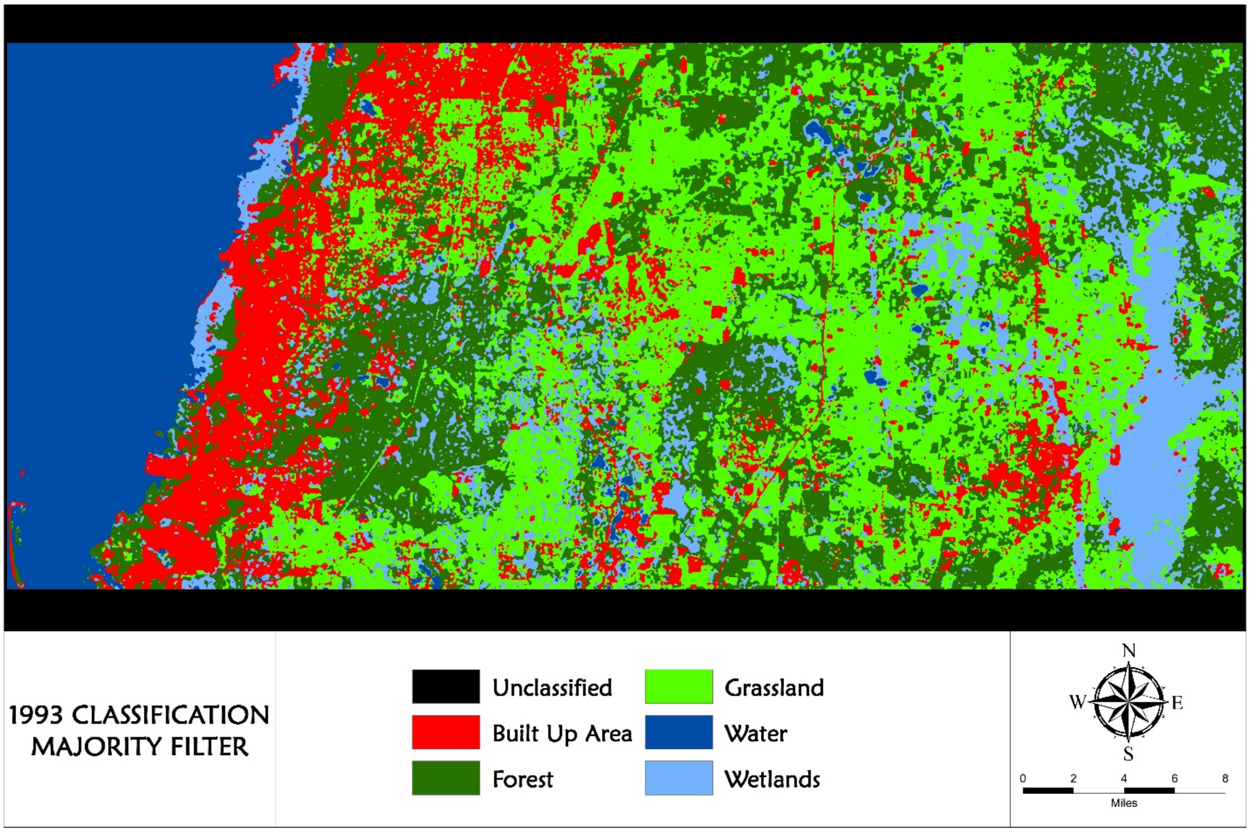

Fig 4.2: 1993 Majority Filtered Classification of Pasco County

3.1.1.1 Confusion Matrix

The calculation of the overall accuracy of the 1993 image classification showed a 99.7415% accuracy of the pixels within the ROIs selected for each of the class. This result was further acknowledged when the result of the calculated kappa coefficient showed a 0.9916 score out of a possibility of 1. This overall accuracy and kappa coefficient were able to achieve this level of accuracy due to the careful extraction of the classes within the images. Another reason was because the classes generated for this analysis were more of a general purpose rather than show more detail image classes

From tables the below, it can be observed that all classes have a high degree of accuracy. None of the classes generated was lower than 90 percent. Of the 5 classes forest and wetlands recorded the lowest with 98.45% and 98.62% level of accuracy respectively. This level of accuracy

Table 3.1: Ground truth Pixels

Class	Built Up Area	Forest	Grassland	Water	Wetlands	Total
Built Up Area	7520	4	73	62	1	7660
Forest	0	7371	0	0	42	7413
Grassland	50	10	6752	0	0	6812
Water	0	0	0	118824	0	118824
Wetlands	0	102	2	26	3074	3204
Total	**7570**	**7487**	**6827**	**118912**	**3117**	**143913**

Table 3.2: Ground truth Percentage

Class	Built Up Area	Forest	Grassland	Water	Wetlands	Total
Built Up Area	99.34	0.05	1.07	0.05	0.03	5.32
Forest	0	98.45	0	0	1.35	5.15
Grassland	0.66	0.13	98.9	0	0	4.73
Water	0	0	0	99.93	0	82.57
Wetlands	0	1.36	0.03	0.02	98.62	2.23
Total	**100**	**100**	**100**	**100**	**100**	**100**

3.1.1.2 Errors of Omission and Commission

The table below shows that wetlands had the highest percentage of commission error with a percentage of 4.06 (130/3204 pixels), while forest had the highest percentage in omission with a percentage of 1.55% (116/7487). This means that 4.06% of other classes were classified in error as wetlands while the classifier classified 1.55% of other classes as forest. The other percentages

Table 3.3: Errors of commission and omission

Class	Commission (Percent)	Omission (Percent)	Commission (Pixels)	Omission (Pixels)
Built Up Area	1.83	0.66	140/7660	50/7570
Forest	0.57	1.55	42/7413	116/7487
Grassland	0.88	1.1	60/6812	75/6827
Water	0	0.07	0/118824	88/118912
Wetlands	4.06	1.38	130/3204	43/3117

3.1.1.3 Producer and User Accuracies

The table below shows very high accuracies in both the producer and user accuracies. None of accuracies fell below 0.5 level of error during class. The table below shows the levels of producer and user accuracies for the 1993 image classification.

Table 3.4: Producer and user accuracies

Class	Prod. Acc. (Percent)	User Acc. (Percent)	Prod.Acc. (Pixels)	User Acc. (Pixels)
Built Up Area	99.34	98.17	7520/7570	7520/7660
Forest	98.45	99.43	7371/7487	7371/7413
Grassland	98.9	99.12	6752/6827	6752/6812
Water	99.93	100	118824/118912	118824/118824
Wetlands	98.62	95.94	3074/3117	3074/3204

3.1.2 1998 Image Classification

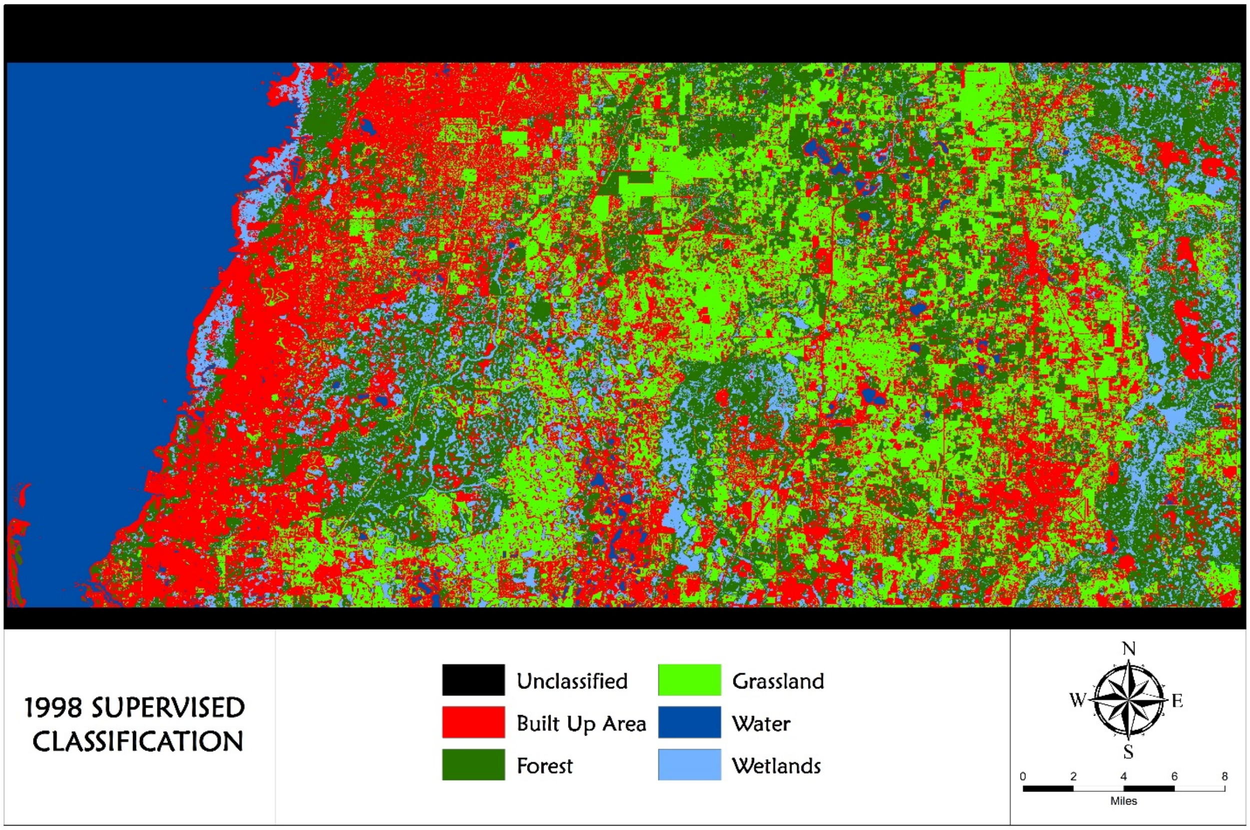

Fig: 3.3: 1998 Classified Image of Pasco County

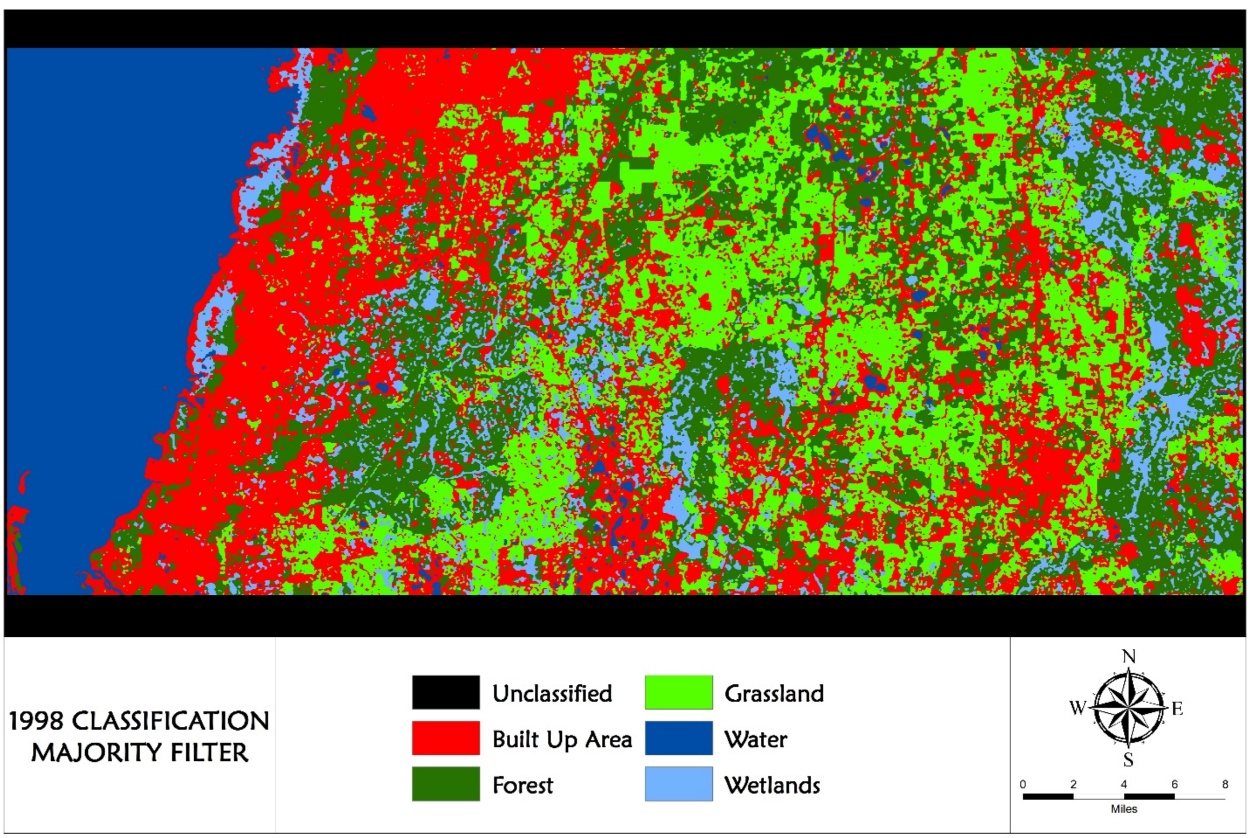

Fig.3.4: 1998 Majority Filtered Classification of Pasco County

3.1.2.1 Confusion Matrix

The confusion matrix calculation of the 1998 satellite image of Pasco County showed an overall accuracy of 99.1% and a kappa coefficient of 0.9871. This result shows a highly accurate and precise classification of the satellite image. This result was further substantiated with the breakdown of the accuracies of each of the classes shown in tables 4.5 and 4.6. The result showed that none of classes fell below the 95% accuracy mark. Of the five classes, forest was recoded to have the lowest with 97.26% of the pixels selected being accurate.

Table 3.5: Ground truth Pixels

Class	Built Up Area	Forest	Grassland	Water	Wetlands	Total
Built Up Area	5889	1	3	1	0	**5894**
Forest	0	11556	0	0	69	**11625**
Grassland	0	1	3809	0	0	**3810**
Water	0	1	0	20198	0	**20199**
Wetlands	0	323	0	0	2636	**2959**
Total	**5889**	**11882**	**3812**	**20199**	**2705**	**44487**

Table 3.6: Ground Truth Percentage

Class	Built Up Area	Forest.sh	Grassland	Water	Wetlands	Total
Built Up Area	100	0.01	0.08	0	0	**13.25**
Forest	0	97.26	0	0	2.55	**26.13**
Grassland	0	0.01	99.92	0	0	**8.56**
Water	0	0.01	0	100	0	**45.4**
Wetlands	0	2.72	0	0	97.45	**6.65**
Total	**100**	**100**	**100**	**100**	**100**	**100**

3.1.2.2 Errors of Omission and Commission

The errors of commission shows that wetlands had a commission error of 10.92 percent; Built-Up Area, Forest and Grassland all had errors less than 1% while water had no error or commission at all. Built-up Area and Water had no error of omission, while Grassland had less than one percent of omission error and forest and wetlands had the highest omission of 2.74% and 2.55% respectively.

Table 3.7: Errors of commission and omission

Class	Commission (Percent)	Omission (Percent)	Commission (Pixels)	Omission (Pixels)
Built Up Area	0.08	0	5/5894	0/5889
Forest	0.59	2.74	69/11625	326/11882
Grassland	0.03	0.08	1/3810	3/3812
Water	0	0	1/20199	1/20199
Wetlands	10.92	2.55	323/2959	69/2705

3.1.2.3 Producers and Users Accuracies

The producer and user accuracies show a high level of accuracies with built-up area and water having a 100% producer accuracy level respectively, while water has a user accuracy of 100%. None of the accuracies of the classes in this land use and land cover analysis recorded an accuracy level that was less than 95%.

Table 3.8: Producer and user accuracies

Class	Prod. Acc. (Percent)	User Acc. (Percent)	Prod. Acc. (Pixels)	User Acc. (Pixels)
Built Up Area	100	99.92	5889/5889	5889/5894
Forest	97.26	99.41	11556/11882	11556/11625
Grassland	99.92	99.97	3809/3812	3809/3810
Water	100	100	20198/20199	20198/20199
Wetlands	97.45	89.08	2636/2705	2636/2959

3.1.3 2003 Image Classification

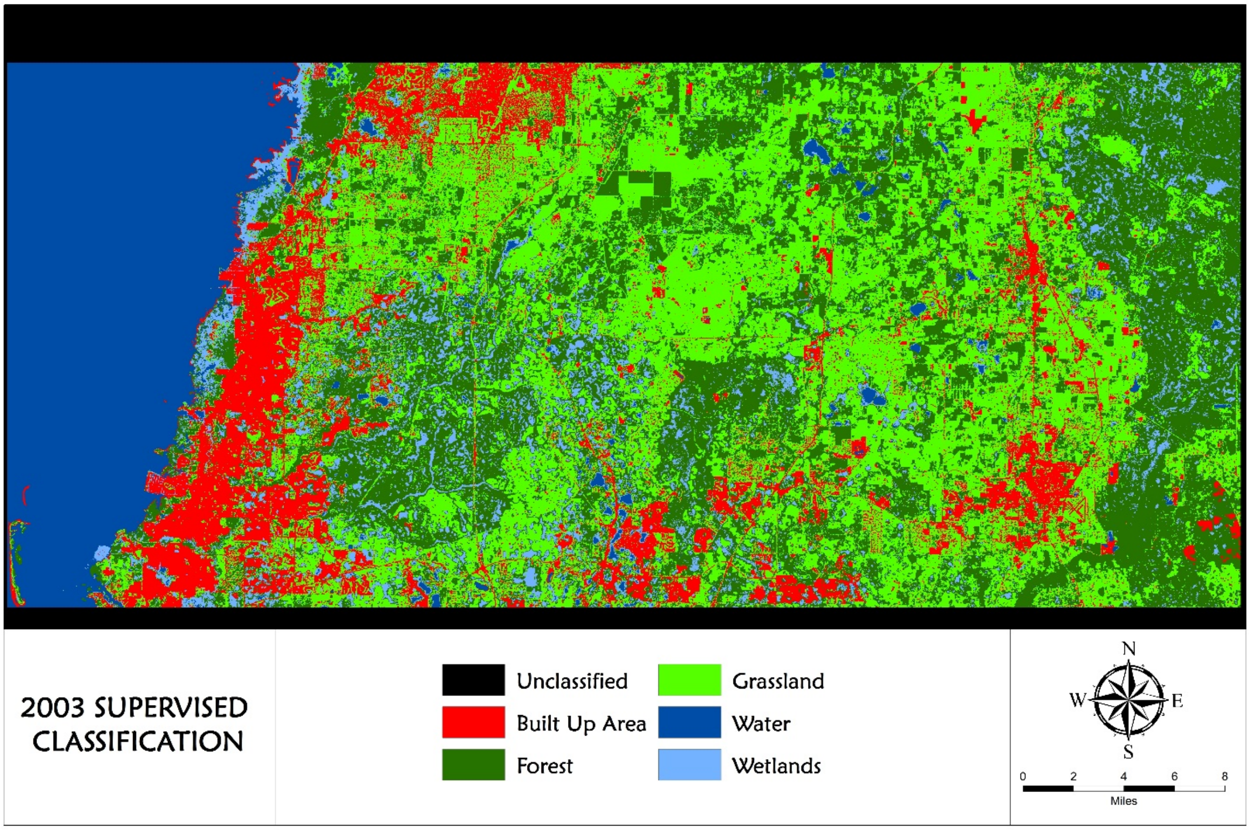

Fig: 3.5: 2003 Classified Image of Pasco County

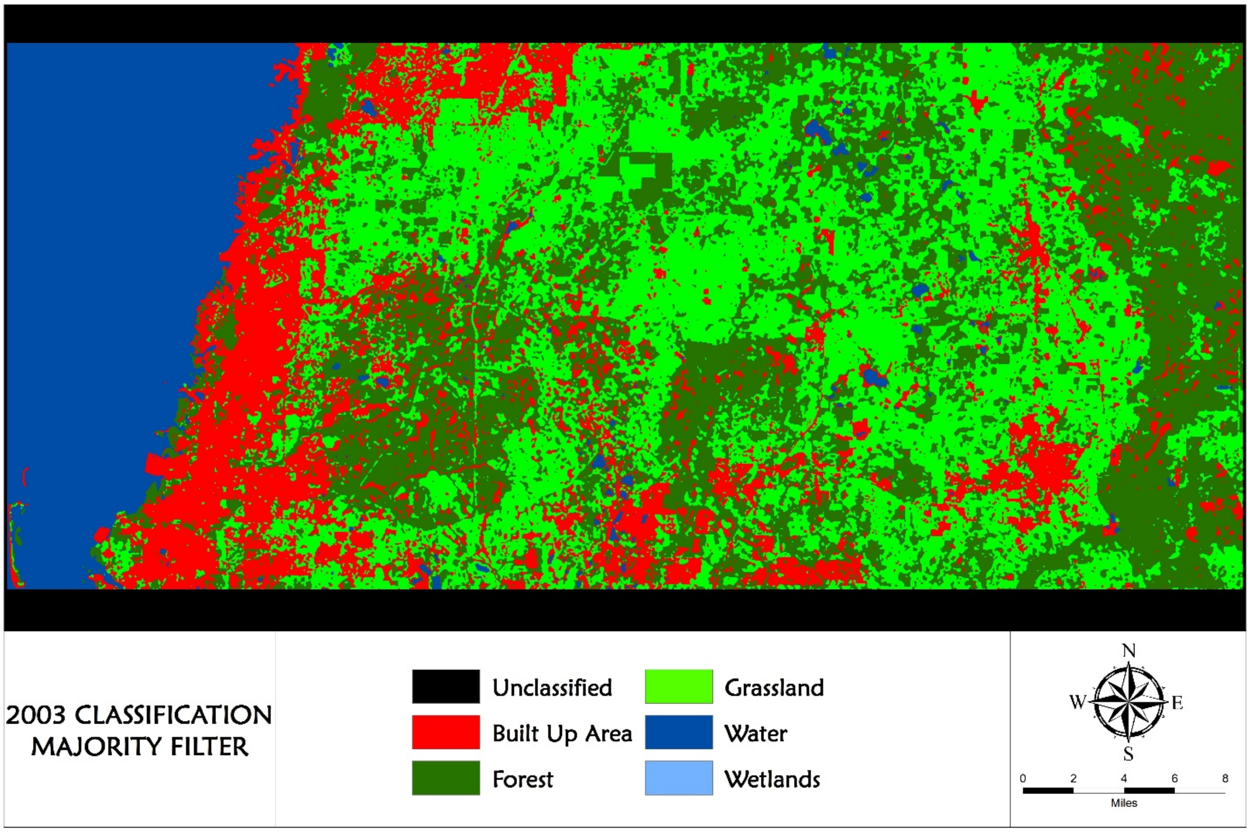

Fig.3.6: 2003 Majority Filtered Classification of Pasco County

3.1.3.1 Confusion Matrix

The confusion matrix calculation of the 2003 land use and land cover classified image showed an overall accuracy of 98.86% and a kappa coefficient of 0.9764. The ground truth showed that the forest class had the lowest percentage of 94.68% with water ranking as the highest percentage of 99.91%. Other details about the ground truth accuracies are shown in tables 4.9 and 4.10.

Table 3.9: Ground Truth Pixels

Class	Built Up Area	Forest	Grassland	Water	Wetlands	Total
Built Up Area	5319	0	25	31	0	**5375**
Forest	0	15422	0	0	40	**15462**
Grassland	71	9	5672	0	0	**5752**
Water	0	0	0	55980	0	**55980**
Wetlands	0	858	0	18	1647	**2523**
Total	**5390**	**16289**	**5697**	**56029**	**1687**	**85092**

Table 3.10: Ground truth percentages

Class	Built Up Area	Forest	Grassland	Water	Wetlands	Total
Built Up Area	98.68	0	0.44	0.06	0	**6.32**
Forest	0	94.68	0	0	2.37	**18.17**
Grassland	1.32	0.06	99.56	0	0	**6.76**
Water	0	0	0	99.91	0	**65.79**

Wetlands	0	5.27	0	0.03	97.63	**2.97**
Total	**100**	**100**	**100**	**100**	**100**	**100**

3.1.3.2 Errors of Omission and Commission

The table below shows that wetlands had the highest error of commission with a total of 34.72% being classified as another class. Water had the lowest error with no error at all. Forest and wetlands had the highest errors of omission of 5.32% and 2.37% respectively. Other classes had less than 2% errors o omission.

Table 3.11: Errors of commission and omission

Class	Commission (Percent)	Omission (Percent)	Commission (Pixels)	Omission (Pixels)
Built Up Area	1.04	1.32	56/5375	71/5390
Forest	0.26	5.32	40/15462	867/16289
Grassland	1.39	0.44	80/5752	25/5697
Water	0	0.09	0/55980	49/56029
Wetlands	34.72	2.37	876/2523	40/1687

3.1.3.3 Producers and Users Accuracies

The producers accuracies had a high level of accuracy with the lowest being forest with a level of 94.68% of accuracy. Wetlands on the other hand had the lowest level of user accuracy of 65.28% level of accuracy. This was one of the lowest level of accuracy ever recorded in the all the satellite images that were classified.

Table 3.12: Producer and user accuracies

Class	Prod. Acc. (Percent)	User Acc. (Percent)	Prod. Acc. (Pixels)	User Acc. (Pixels)
Built Up Area	98.68	98.96	5319/5390	5319/5375
Forest	94.68	99.74	15422/16289	15422/15462
Grassland	99.56	98.61	5672/5697	5672/5752
Water	99.91	100	55980/56029	55980/55980
Wetlands	97.63	65.28	1647/1687	1647/2523

3.1.4 2008 Image Classification

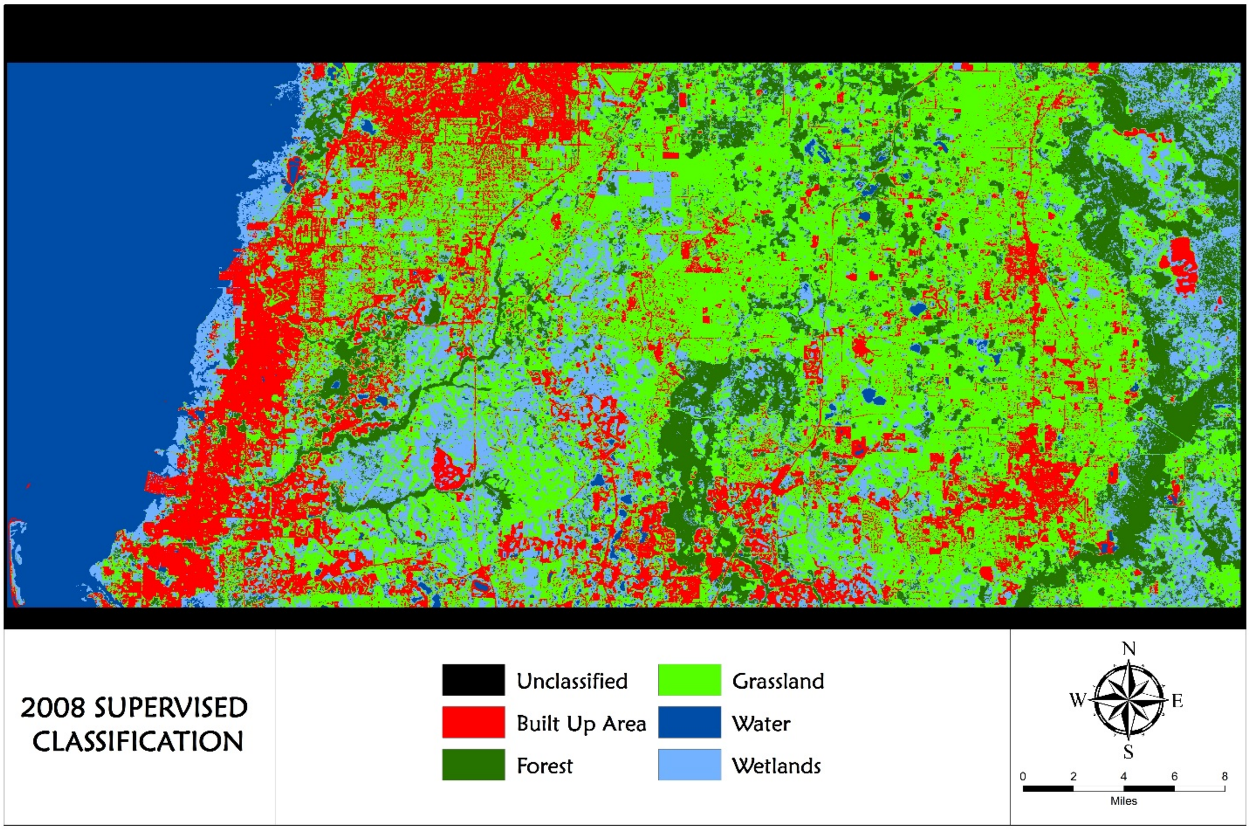

Fig: 3.7: 2008 Classified Image of Pasco County

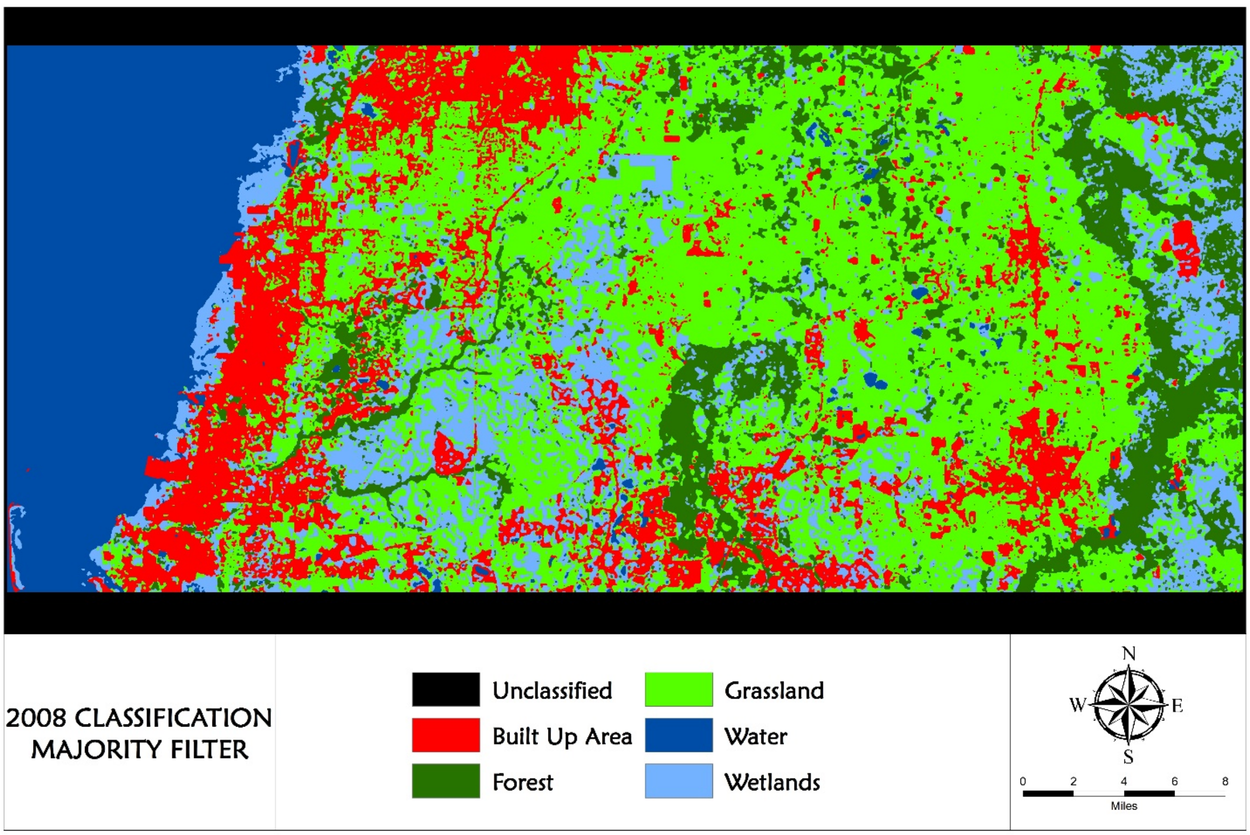

Fig. 3.8: 2008 Majority Filtered Classification of Pasco County

3.1.4.1 Confusion Matrix

The confusion matrix calculation of the 2008 land use and land cover classification showed that the overall accuracy of the classification was 98.7% and the kappa coefficient was 0.9778. This showed that the classification of the 2008 satellite image was very accurate. Tables 4.13 and 4.14 shows the breakdown of accuracies of the land use classes used for this classification. From the tables below, it can be observed that none of the land use classes accuracy level fell below 95%.

Table 3.13: Ground truth pixels

Class	Built Up Area	Forest	Grassland	Water	Wetlands	Total
Built Up Area	6988	0	10	7	0	**7005**
Forest	0	28648	0	6	24	**28678**
Grassland	4	100	4302	37	1	**4444**
Water	0	0	0	55917	0	**55917**
Wetlands	0	1023	10	62	1662	**2757**
Total	**6992**	**29771**	**4322**	**56029**	**1687**	**98801**

Table 3.14: Ground truth percentages

Class	Built Up Area	Forest	Grassland	Water	Wetlands	Total
Built Up Area	99.94	0	0.23	0.01	0	**7.09**
Forest	0	96.23	0	0.01	1.42	**29.03**
Grassland	0.06	0.34	99.54	0.07	0.06	**4.5**
Water	0	0	0	99.8	0	**56.6**
Wetlands	0	3.44	0.23	0.11	98.52	**2.79**
Total	**100**	**100**	**100**	**100**	**100**	**100**

3.1.4.2 Errors of Omission and Commission

The errors o commission showed that wetland had the highest level of error of 39.72%. This indicates that almost 40% of the pixels selected in the land use class belonged to another class, most likely forest and grassland. Water had the lowest level of error with no error of commission. The errors of omission were all pretty low. All errors of omission for the 2008 image classification did not go above the 5% mark with forest having the highest level of error and built-up area as having the lowest.

Table 3.15: Errors of commission and omission

Class	Commission (Percent)	Omission (Percent)	Commission (Pixels)	Omission (Pixels)
Built Up Area	0.24	0.06	17/7005	4/6992
Forest	0.1	3.77	30/28678	1123/29771
Grassland	3.2	0.46	142/4444	20/4322
Water	0	0.2	0/55917	112/56029
Wetlands	39.72	1.48	1095/2757	25/1687

3.1.4.3 Producers and Users Accuracies

The producers accuracy recorded a high level of probability no less that 95%. This indicated that all land use classes were properly classed. In the users accuracy however, wetlands had a low probability of 60.28% that the pixels selected for that class actually belonged to that class. All the other classes had a much higher probability rate.

Table 3.16: Producer and user accuracies

Class	Prod. Acc.(Percent)	User Acc.(Percent)	Prod. Acc.(Pixels)	User Acc.(Pixels)
Built Up Area	99.94	99.76	6988/6992	6988/7005
Forest	96.23	99.9	28648/29771	28648/28678
Grassland	99.54	96.8	4302/4322	4302/4444
Water	99.8	100	55917/56029	55917/55917
Wetlands	98.52	60.28	1662/1687	1662/2757

3.1.5 2013 Image Classification

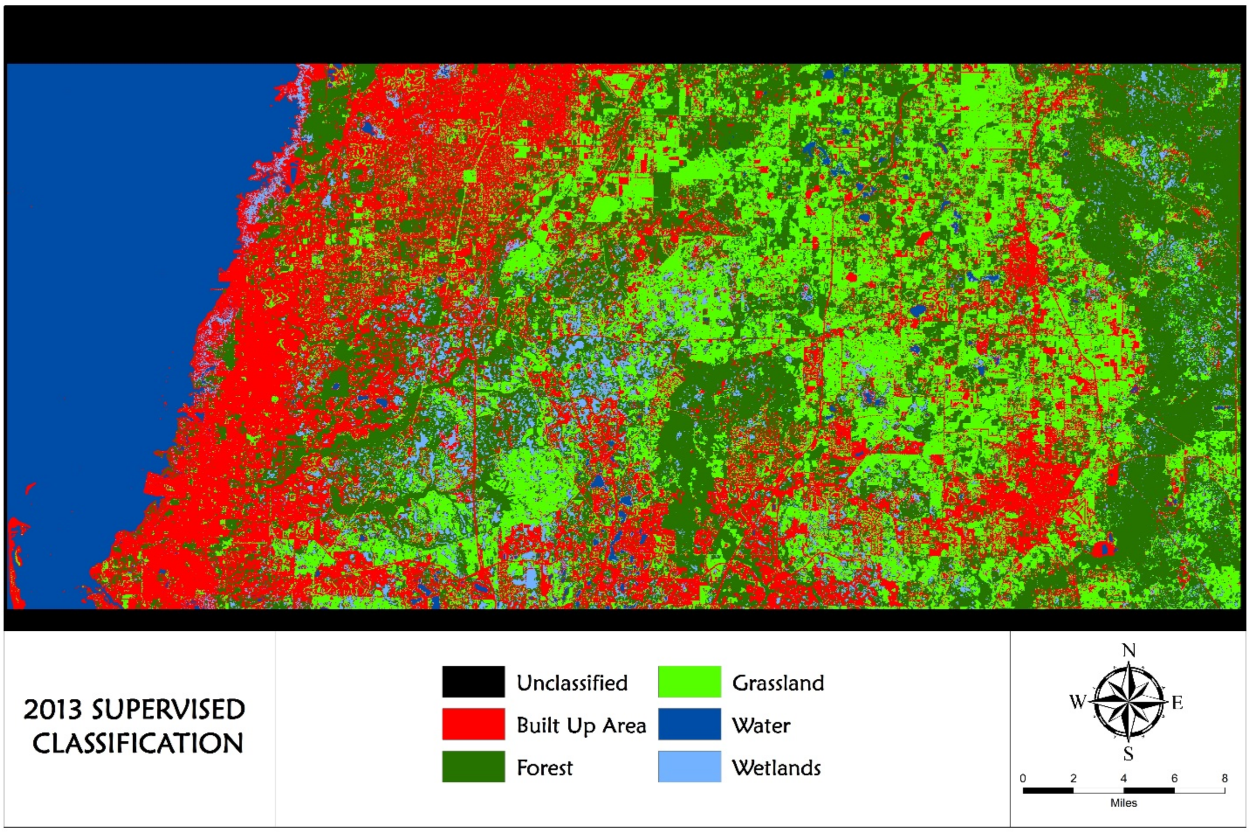

Fig: 3.9: 2013 Classified Image of Pasco County

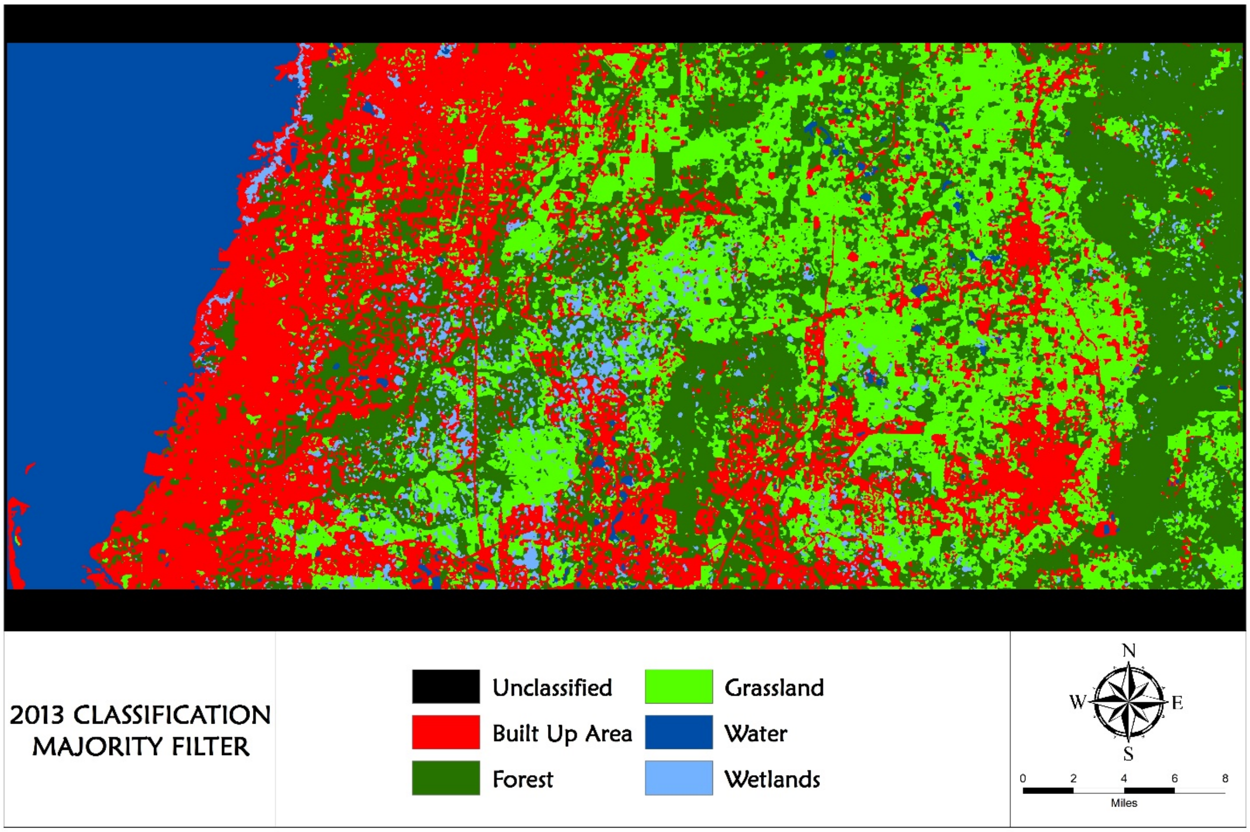

Fig.3.10: 2013 Majority Filtered Classification of Pasco County

3.1.5.1 Confusion Matrix

The confusion matrix calculation for the 2013 classified image showed an overall accuracy of 99.6% and a kappa coefficient of 0.9905. The breakdown of the accuracies of each land use classes and their percentages are shown in tables 4.17 and 4.18

Table 3.17: Ground truth pixels

Class	Built Up Area	Forest	Grassland	Water	Wetlands	Total
Built Up Area	7831	216	39	9	2	8097
Forest	0	19921	9	31	13	19974
Grassland	7	49	4404	0	2	4462
Water	0	0	0	112934	0	112934
Wetlands	0	123	0	30	897	1050
Total	**7838**	**20309**	**4452**	**113004**	**914**	**146517**

Table 4.18: Ground truth percentages

Class	Built Up Area	Forest	Grassland	Water	Wetlands	Total
Built Up Area	99.91	1.06	0.88	0.01	0.22	5.53
Forest	0	98.09	0.2	0.03	1.42	13.63
Grassland	0.09	0.24	98.92	0	0.22	3.05
Water	0	0	0	99.94	0	77.08
Wetlands	0	0.61	0	0.03	98.14	0.72

Total	100	100	100	100	100	100

3.1.5.2 Errors of Omission and Commission

The table below shows that the errors of omission and commission all recorded low numbers of errors except for wetlands which recorded a level of 14.57% in errors of commission. This indicated that about 15% of the total pixels selected for this land use class belonged to another class.

Table 3.19: Errors of commission and omission

Class	Commission (Percent)	Omission (Percent)	Commission (Pixels)	Omission (Pixels)
Built Up Area	3.29	0.09	266/8097	7/7838
Forest	0.27	1.91	53/19974	388/20309
Grassland	1.3	1.08	58/4462	48/4452
Water	0	0.06	0/112934	70/113004
Wetlands	14.57	1.86	153/1050	17/914

3.1.5.3 Producers and Users Accuracies

The producers and users accuracies all recorded a high level of probability that the pixels selected belonged to the right group. All except wetlands in the user accuracy were in the high 90s.

Table 3.20: Producer and user accuracies

Class	Prod. Acc. (Percent)	User Acc. (Percent)	Prod. Acc. (Pixels)	User Acc. (Pixels)
Built Up Area	99.91	96.71	7831/7838	7831/8097
Forest	98.09	99.73	19921/20309	19921/19974
Grassland	98.92	98.7	4404/4452	4404/4462
Water	99.94	100	112934/113004	112934/112934
Wetlands	98.14	85.43	897/914	897/1050

3.2 Change Detection

The figures and tables below shows the changes in the land use and land cover over a 5 year interval for the past 20 years. This gives a clear description as to what land cover changed and to what it changed into. The change detections are measured in square miles and percentages. With this analysis we can begin to see the various levels of change that occurred as the years progressed.

3.2.1 1993-1998 Change

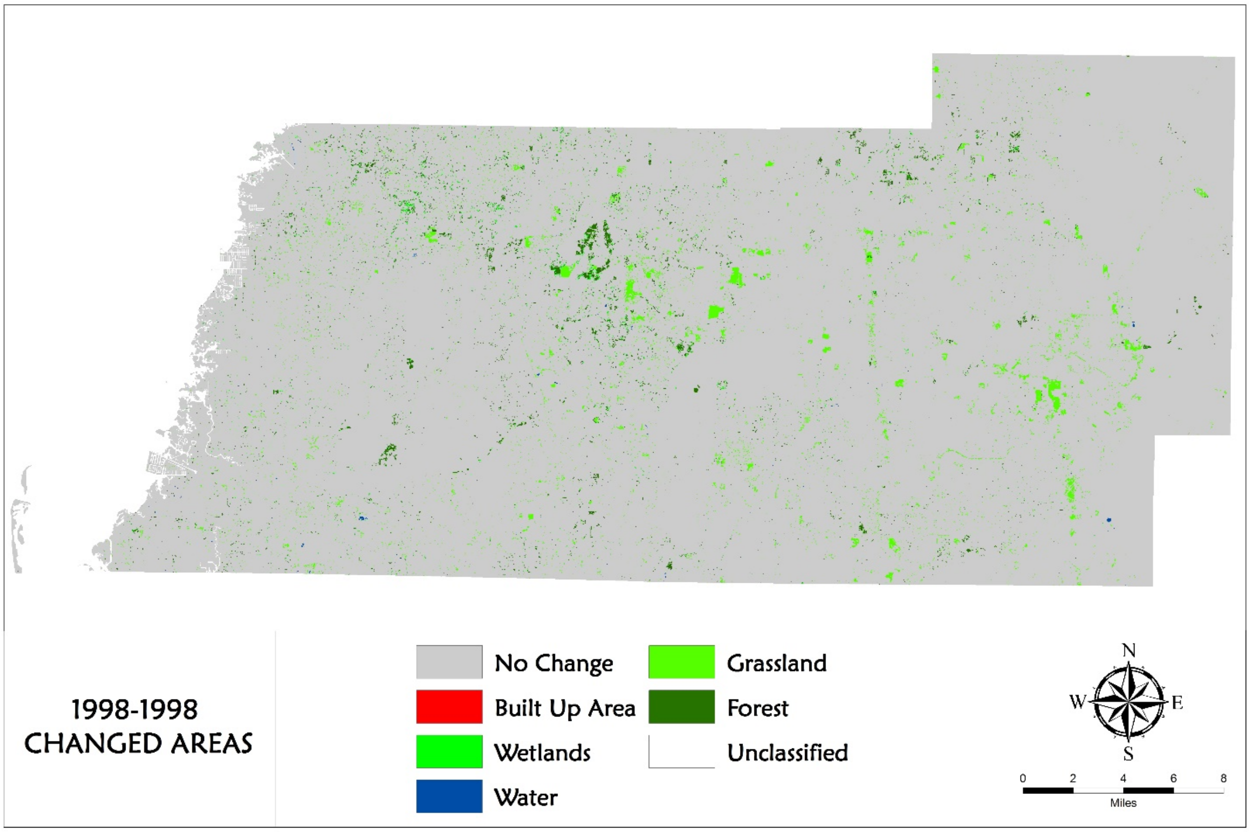

Fig. 3.11: 1993 – 1998 Changed Areas

Figure 4.11 shows the section within the county that changed in terms of land cover between 1993 and 1998. The sections with the gray color are those with no change. It can be observed that moves of the change occurred around forest and grassland areas.

From the table below it can be observed that of the five land cover classes built up area had the largest net gain with a total of 143.05 sq. miles. This was an 88 percent gain from its original size. All the other land cover classes all had net losses of various sizes in sq. miles and percentages. These results can be seem in tables 4.21 and 4.22

Table 3.21: Area Change of Land Use Type from 1993 to 1998

Area (Sq. Miles)	Built Up Area	Wetlands	Water	Grassland	Forest	Row Total	Class Total
Built Up Area	135.99	35.45	5.04	87.73	40.07	304.28	304.28
Wetlands	2.46	70.57	0.04	3.67	27.88	104.63	104.63
Water	0.29	2.39	166.62	0.09	0.02	169.41	169.41
Grassland	14.59	3.85	0	210.1	4.16	232.7	232.7
Forest	7.9	34.53	0	14.31	186.92	243.67	243.67
Class Total	161.23	146.8	171.7	315.9	259.05	0	0
Class Changes	25.24	76.23	5.08	105.8	72.13	0	0
Image Difference	143.05	-42.17	-2.29	-83.2	-15.38	0	0

Table 3.22: Percentage Change of Land Use Type from 1993 to 1998

Percentages	Built Up Area	Wetlands	Water	Grassland	Forest	Row Total	Class Total
Built Up Area	**84.344**	24.151	2.933	27.772	15.468	100	100
Wetlands	1.527	**48.075**	0.022	1.163	10.763	100	100
Water	0.183	1.626	**97.042**	0.028	0.008	100	100
Grassland	9.046	2.625	0	**66.509**	1.605	100	100
Forest	4.901	23.522	0.003	4.529	**72.157**	100	100
Class Total	**100**	**100**	**100**	**100**	**100**	**0**	**0**
Class Changes	**15.656**	**51.925**	**2.958**	**33.491**	**27.843**	**0**	**0**
Image Difference	**88.72**	**-28.727**	**-1.333**	**-26.338**	**-5.939**	**0**	**0**

3.2.2 1998-2003 Change

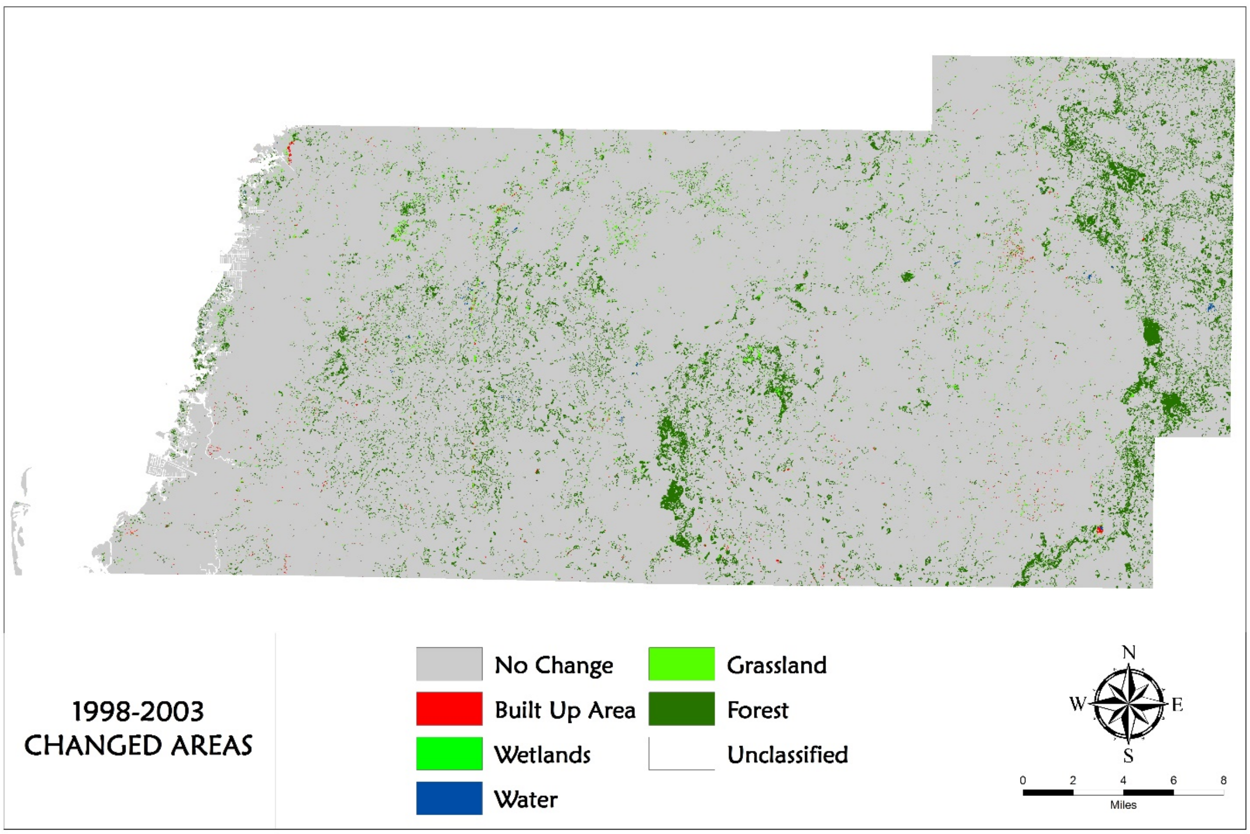

Fig .3.12: 1998 – 2003 Changed Areas

From the figure above it can be observed that a large area of the county had changed from other land use classes in to mainly grassland and forest. This can also be observed in the table below which shows that grassland and forest both had a positive gain and built up area and wetland both had negative changes. This means that the grassland and forest gain and built up area and wetlands lost.

Table 3.23: Area Change of Land Use Type from 1998-2003

Area (Sq. Miles)	Built Up Area	Wetlands	Water	Grassland	Forest	Row Total	Class Total
Built Up Area	**112.56**	1.41	0.14	14.34	6.07	134.51	134.51
Wetlands	15.37	**42.14**	2.21	1.8	5.47	67	67
Water	7.05	0.44	**166.88**	0.47	0.07	174.92	174.92
Grassland	111.32	5.65	0.03	**203.9**	28.57	349.48	349.48
Forest	57.98	54.99	0.15	12.18	**203.48**	328.78	328.78
Class Total	**304.28**	**104.63**	**169.41**	**232.7**	**243.67**	**0**	**0**
Class Changes	**191.72**	**62.49**	**2.52**	**28.79**	**40.19**	**0**	**0**
Image Difference	**-169.77**	**-37.63**	**5.51**	**116.78**	**85.11**	**0**	**0**

Table 3.24: Percentage Change of Land Use Type from 1998-2003

Percentages	Built Up Area	Wetlands	Water	Grassland	Forest	Row Total	Class Total
Built Up Area	**36.992**	1.346	0.081	6.161	2.491	100	100
Wetlands	5.05	**40.277**	1.306	0.775	2.246	100	100
Water	2.318	0.421	**98.51**	0.202	0.029	100	100
Grassland	36.584	5.399	0.017	**87.627**	11.727	100	100
Forest	19.056	52.556	0.086	5.235	**83.508**	100	100
Class Total	**100**	**100**	**100**	**100**	**100**	**0**	**0**
Class Changes	**63.008**	**59.723**	**1.49**	**12.373**	**16.492**	**0**	**0**
Image Difference	**-55.794**	**-35.967**	**3.252**	**50.186**	**34.93**	**0**	**0**

3.2.3 2003-2008 Change

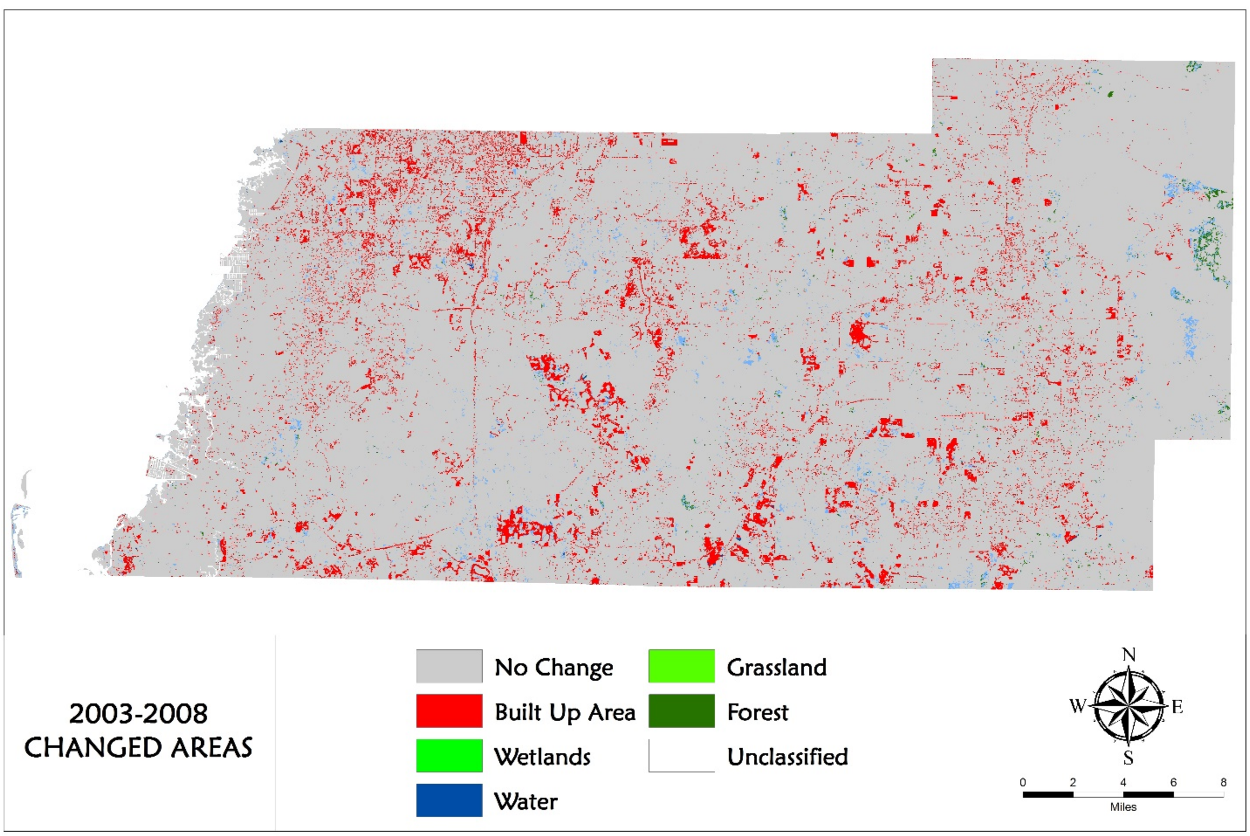

Fig.4.13: 2003 – 2008 Changed Areas

The figure above shows the areas and land use class where changes had taken place. This shows that most of the areas which experience change were areas previously recognized as mostly forests. This is further explained in tables 4.25 and 4.26. The tables below shows that all land use classes except for forest had positive gains. Forest on the other hand lost a total of 197.9 sq miles to other land use classes. This constitutes about 60% of the total forest cover in the county. One thing to note is that this may not be entirely correct as the classifier may have misclassified some forest areas as wetland and grassland. This may have occurred due to the time and date of the image capture. The full details of the land use change between 2003 and 2008 are shown in tables below.

Table 3.25: Area Change of Land Use Type from 2003-2008

Area (Sq. Miles)	Built Up Area	Wetlands	Water	Grassland	Forest	Row Total	Class Total
Built Up Area	**107.58**	2.42	0.36	54.12	17.46	181.95	181.95
Wetlands	3.26	**39.27**	2.34	10.11	107.36	162.33	162.33
Water	1.25	2.5	**171.35**	0.23	0.22	175.55	175.55
Grassland	22.24	6.96	0.82	**282.49**	91.46	403.97	403.97
Forest	0.19	15.85	0.05	2.51	**112.29**	130.88	130.88
Class Total	**134.51**	**67**	**174.92**	**349.48**	**328.78**	**0**	**0**
Class Changes	**26.93**	**27.73**	**3.57**	**66.98**	**216.49**	**0**	**0**
Image Difference	**47.44**	**95.34**	**0.63**	**54.5**	**-197.9**	**0**	**0**

Table 3.26: Percentage Change of Land Use Type from 2003-2008

Percentages	Built Up Area	Wetlands	Water	Grassland	Forest	Row Total	Class Total
Built Up Area	**79.981**	3.61	0.205	15.487	5.311	100	100
Wetlands	2.421	**58.615**	1.336	2.894	32.653	100	100
Water	0.926	3.732	**97.961**	0.066	0.067	100	100
Grassland	16.531	10.39	0.472	**80.834**	27.817	100	100
Forest	0.141	23.654	0.026	0.719	**34.152**	100	100
Class Total	**100**	**100**	**100**	**100**	**100**	**0**	**0**
Class Changes	**20.019**	**41.385**	**2.039**	**19.166**	**65.848**	**0**	**0**
Image Difference	**35.266**	**142.303**	**0.36**	**15.593**	**-60.192**	**0**	**0**

3.2.4 2008-2013 Change

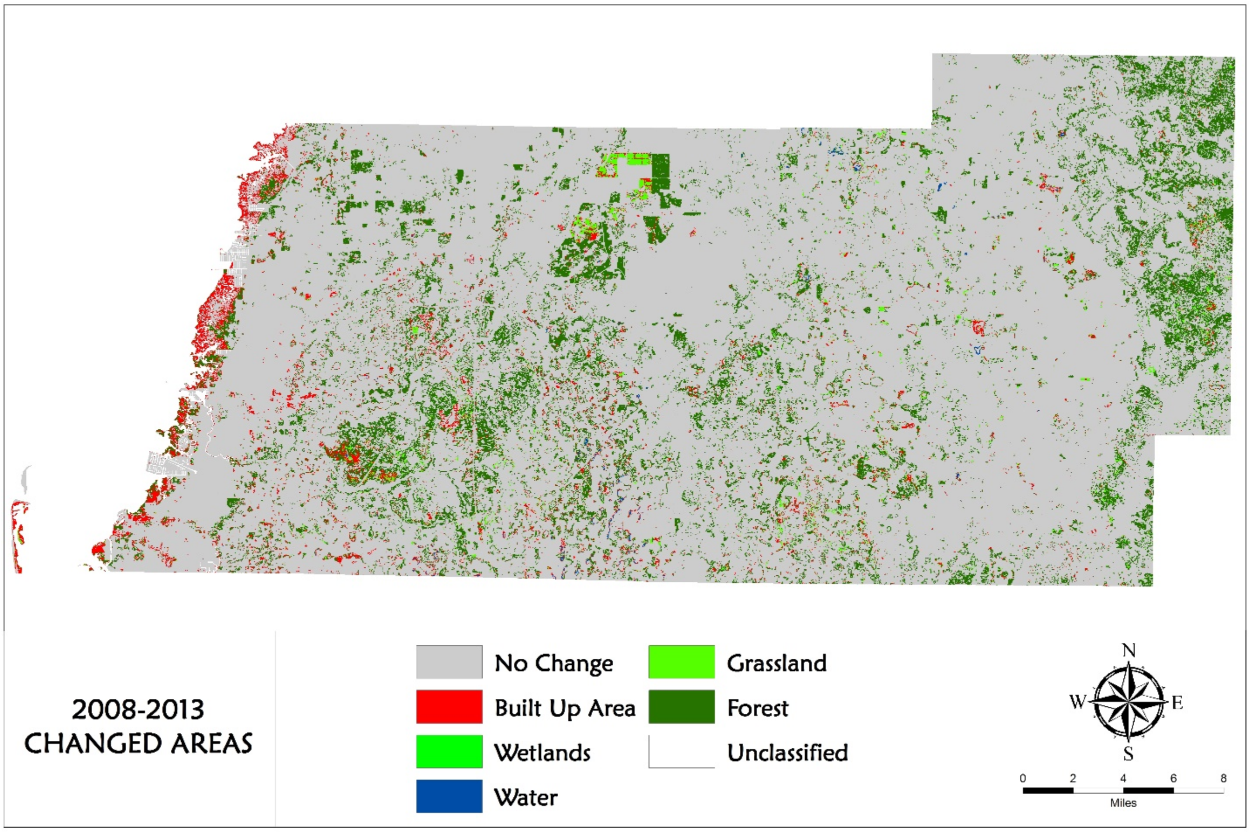

Fig .3.12: 2008 – 2013 Changed Areas

The figure above shows the sections and land use classes that changed and where the change took place. From the figure above it can the seen that the most dominant change ws between built up area and forest land use classes. This can further be seen in tables 3.27 and 3.28. from the tables, it can be observed that built up area and forest had positive changes with 88.68 sq. Miles and 182.39 sq.miles being added to these land use classes respectively. Wetland, water and grassland had net losses with grassland losing the biggest chunk of it all (-153.14 sq. miles).Grassland in particular lost most of its class to built-up area and forest. One attribution to this is the sudden expansion of houses, both residential and commercial, after the recession.

Table 3.27: Percentage Change of Land Use Type from 2008-2013

Area (Sq. Miles)	Built Up Area	Wetlands	Water	Grassland	Forest	Row Total	Class Total
Built Up Area	150.13	22.5	4.28	91.68	2.04	270.63	270.63
Wetlands	2.91	33.56	0.9	8.27	2.53	48.17	48.17
Water	0.18	1.06	170.07	0.45	0.01	171.77	171.77
Grassland	19.21	9.04	0.02	220.57	1.99	250.83	250.83
Forest	9.52	96.17	0.28	83	124.3	313.27	313.27
Class Total	**181.95**	**162.33**	**175.55**	**403.97**	**130.88**	**0**	**0**
Class Changes	**31.81**	**128.77**	**5.48**	**183.4**	**6.58**	**0**	**0**
Image Difference	**88.68**	**-114.16**	**-3.77**	**-153.14**	**182.39**	**0**	**0**

Table 3.28: Percentage Change of Land Use Type from 2008-2013

Percentages	Built Up Area	Wetlands	Water	Grassland	Forest	Row Total	Class Total
Built Up Area	82.515	13.862	2.437	22.694	1.56	100	100
Wetlands	1.599	20.676	0.512	2.046	1.934	100	100
Water	0.1	0.653	96.878	0.112	0.011	100	100
Grassland	10.555	5.568	0.012	54.602	1.523	100	100
Forest	5.231	59.241	0.161	20.546	94.971	100	100
Class Total	**100**	**100**	**100**	**100**	**100**	**0**	**0**
Class Changes	**17.485**	**79.324**	**3.122**	**45.398**	**5.029**	**0**	**0**
Image Difference	**48.742**	**-70.326**	**-2.15**	**-37.908**	**139.356**	**0**	**0**

4 Conclusion

This project examined the land cover change of Pasco County, Florida over a 20 year period (1993-2013). Five satellite images were classified using a 1993, 1998, 2003, and 2008 TM Landsat satellite, and a 2013 OLI/TIRS Landsat Image. The classification accuracy of all five classified image was assessed by comparing the result of the classes with images obtained from Google Earth high resolution images. The overall accuracies for both images was above 90 percent while the Kappa Coefficient for both images were above 0.9, which indicates that the classification was highly accurate. The results from the confusion matrix, errors of omission and commission, and Producers and users accuracies also proved that the classification was also very high.

Using the change detection analysis, it was observed that there were different levels of change over the 20 year period. All land cover types/classes at one point or the other gained from other land use types and at other points lost to other classes.

This land cover data would provide detailed information for the county administrators on how much the county land cover has changed and by how much it has changed. It will also assist conservationist on what kind of land cover to concentrate on and how to manage these resources so they don't get depleted and save it for future generations.

References

Calculate Confusion Matrices (Using ENVI) | Exelis VIS Docs Center. (n.d.). Retrieved August 4, 2015, from http://www.exelisvis.com/docs/CalculatingConfusionMatrices.html#UseROI

Chunhao Zhu, & Yingkui Li. (2013). High Temporal Resolution Land Use/Land Cover Change from 1984 to 2010 of the Little River Watershed, Tennessee, Investigated Using Landsat and Google Earth Images. *Southeastern Geographer*, *53*(3), 250–266.

Clark, M. L., & Aide, T. M. (2011). Virtual Interpretation of Earth Web-Interface Tool (VIEW-IT) for Collecting Land-Use/Land-Cover Reference Data. *Remote Sensing*, *3*(12), 601–620. http://doi.org/10.3390/rs3030601

End to End Remote Sensing Tutorial Page 1-17. (n.d.). Retrieved August 4, 2015, from http://fas.org/irp/imint/docs/rst/Sect1/Sect1_17.html

Pasco County, Florida. (2015, March 5). In *Wikipedia, the free encyclopedia*. Retrieved from http://en.wikipedia.org/w/index.php?title=Pasco_County,_Florida&oldid=650037306