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Geography 565
Lab Report 2 & 3
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Introduction:

Change detection is a crucial tool in studying an area. It can show you areas deforestation, afforestation, crop-land expansion, water loss, urban expansion, and more. The simple idea of seeing how an area has changed over time can get more complex once you realize the extent of the data and the critical calculations that must be made to accurately assess change. The goal here is to detect change areas from unchanged areas in a chosen area of Egypt. The main questions we are looking to answer is what type of change is occurring, how is this change occurring, and why might areas of no change be staying the same. By combining several methods for detecting change, including unsupervised classification, supervised classification, band stacking, and band differencing, these questions can be dissected and answered piece by piece.

Study Area:

The area of study that I am working on is an area of agricultural cropland in Egypt. The image contains three major landcover types; water, cropland, and barren land. I am using two images for this change detection, one from 1984, and one from 2003. The change in cropland between these two images is very apparent, however to develop an accurate map and achieve proper results, we must perform classification or band differencing on these images.

Methods:

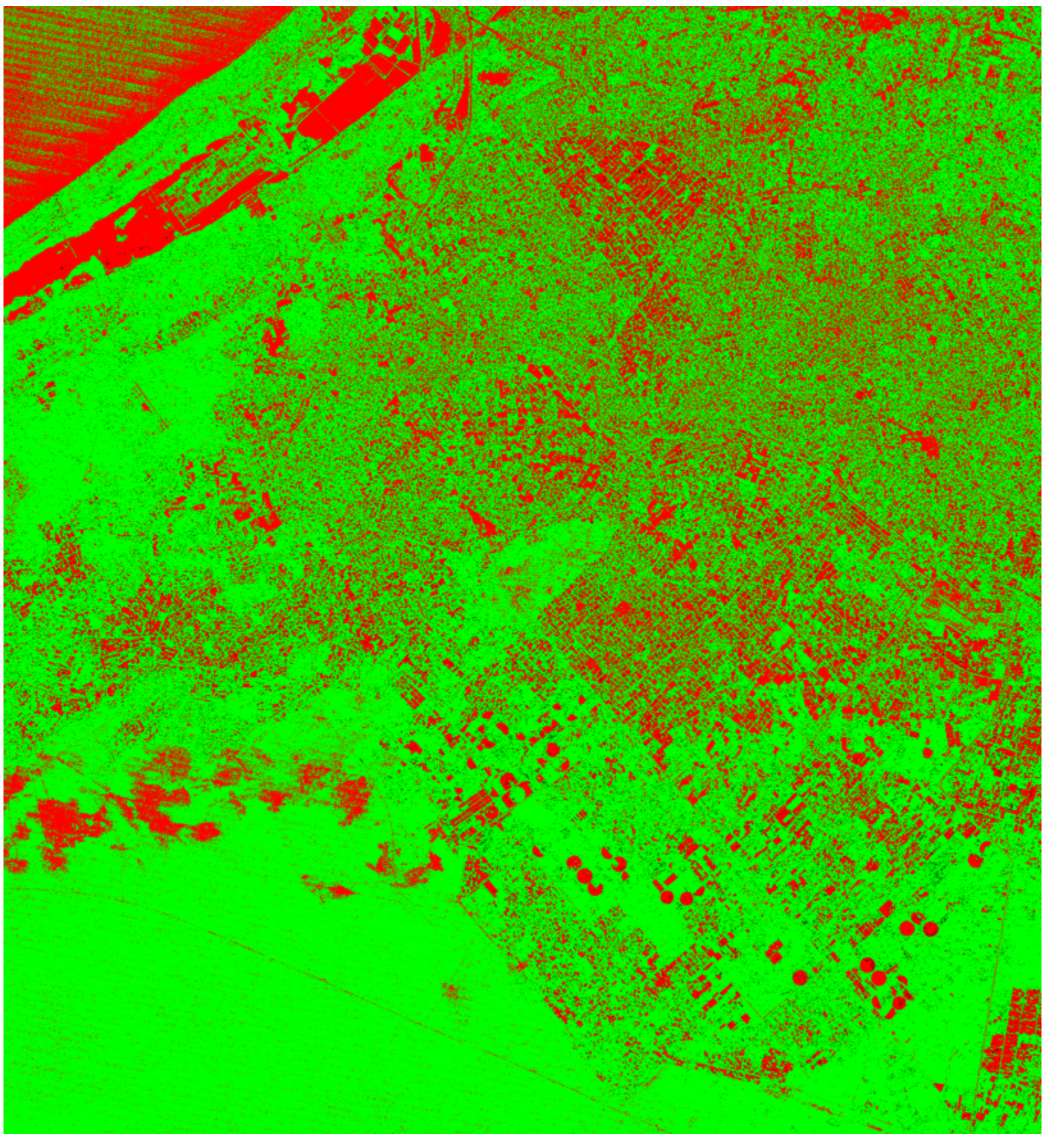
The first approach I used was band differencing. To perform the band differencing operation, I first created two NDVI images, one from the 1984 image and one from the 2003 image. Using NDVI I am better able to assess change in cropland from barren land. Once the NDVI images were made, I then performed band math by subtracting float values from the NDVI date image from 2003 minus the NDVI date image from 1984. Once this band difference image is made, we must then use density slicing to create our thresholds and classes. To create the classes, we must assess the NDVI images and interpret were we think change is occurring. By observing these images, taking note of the pixel values, and then creating thresholds and classes based on these values, we can make a map showing areas of change and no change.

The second approach I used was multi-date unsupervised classification. To begin the unsupervised classification, I must first create a multi-date image stack. This new image stack contains 12-bands. From this 12-band image, I then perform a K-means unsupervised classification on the image, in which I generated 100 distinct spectral classes. To produce the change detection map from these classes, I then analyze the imagery separately from 1984 and 2003, and label each class accordingly as change or no change.

The third approach I used was multi-date supervised classification. I used the same multi-date image stack that was used for the unsupervised classification. To do the supervised classification, I create regions of interest in certain categories such as water, change, and no change. These areas are then put through a support vector machine, which determines the best likely spectral assignment based on the regions of interest that I created.

Results:

Below is the band differencing change detection map. The red areas on the map indicate change, and the green areas on the map indicate no change. As you can see from the image, the band differencing map did not perform particularly well, with not much change detection in the center left area of the image where most of the change from barren to cropland actually occurred.



Band Differencing Image: Red indicates change, green indicates unchanged.

Overall Accuracy = 62.38%	Kappa Coefficient = .086		
Class	Change	No Change	Total
Unclassified	6.45%	1.43%	2.97%
No Change	25.81%	20%	21.78%
Change	67.74%	78.57%	75.25%
Total	100	100	100
Class	Commission	Omission	
No Change	63.64%	74.19%	
Change	27.63%	21.43%	
Class	Producers Accuracy	Users Accuracy	
No Change	25.81%	36.36%	
Change	78.57%	72.37%	

Confusion Matrix for band differencing change detection

Below is the multi-date unsupervised classification change detection map. This method performed much better with the heavies change in the center left, and following the ridge wrapping around the central bottom portion of the image. The purple areas in the map indicates areas of change while the green areas indicate areas of no change.

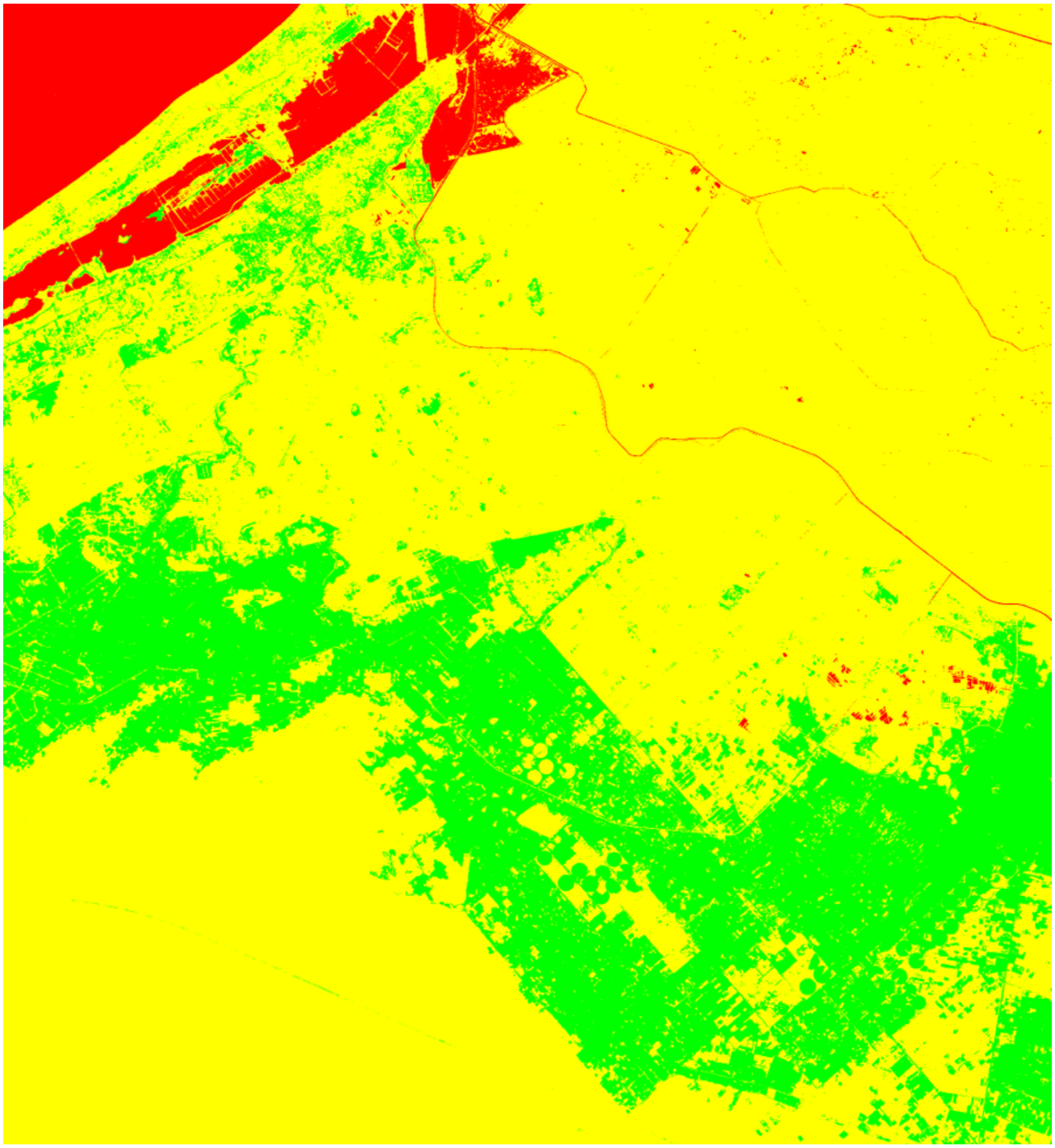
Multi-date unsupervised classification map; purple indicates change areas, green indicates unchanged areas.

Below is the confusion matrix for the unsupervised classification, and performed much better with an overall accuracy of about 86%.

Overall Accuracy = 86.1386%	**Kappa Coefficient = .6682**		
Class	No Change	Change	Total
Unclassified	0%	0%	0%
No Change Master Merged	91.43%	25.81%	71.29%
Changed Master Merge	8.57%	74.19%	28.71%
Total	100%	100%	100%
Class	Commission	Omission	
No Change Master Merged	11.11%	8.57%	
Changed Master Merge	20.69%	25.81%	
Class	Producers Accuracy	Users Accuracy	
No Change Master Merged	91.43%	88.89%	
Changed Master Merged	74.19%	79.31%	

Confusion Matrix for unsupervised classification change detection.

Below is the multi-date supervised change detection map I believe that this method produced that best result, with areas of true change depicted in green, areas of no change depicted in yellow, and water bodies depicted in red. The true change areas are all on the front push of the agricultural expansion, while there is not much change in the previous crop-land. The rivers that show up in the image are very apparent.



Multi-date supervised classification change detection; green areas indicate change, yellow areas indicate no change, and red areas indicate water bodies.

Below is the confusion matrix for the supervised classification. This approach performed similarly to the unsupervised classification matrix, however I believe that the final map result is a much better product.

Overall Accuracy = 87.91%	Kappa Coefficient = .7082		
Class	Change	No Change	Total
Unclassified	0%	0%	0%
Change Master Merge	72.41%	4.84%	26.37%
No Change Master Merge	27.59%	95.16%	73.63%
Total	100%	100%	100%
Class	Commission	Omission	
Change Master Merge	12.50%	27.59%	
No Change Master Merge	11.94%	4.84%	
Class	Producers Accuracy	Users Accuracy	
Change Master Merge	72.41%	87.50%	
No Change Master Merge	95.16%	88.06%	

Confusion Matrix for supervised classification change detection.

Discussion:

For the band differencing change detection map, the change areas all over the place, and not consolidated in the major barren to cropland change areas of the central left and bottom of the image. Instead, it picked up many different changes in crop field brightnesses. This is partly due in fault to the thresholds that I set in coming up with these classes. The overall accuracy of this approach was very low at 62.38%. Both no change and change classes did not perform particularly well, and may have been swapped. The producers and users accuracy for the change class is so high because almost every field that changed in specularity at all seemed to be classed as change, which is not what we want.

For the unsupervised change detection map, the change areas were better consolidated than the band differencing map, however there are still values inside of the already cultivated area that are just increases of brightness and not changing from barren land to crop-land. The no change class did particularly well with at 91.43%, and the no change class also had a high users and producers accuracy, however the changed area was somewhat lacking, and must be due to the way I had merged the 100 unsupervised spectral classes in the end.

For the supplied changed detection map, the change areas I feel where the best represented. The change areas from barren to crop-land show up on this map in a particularly cluster area, wrapped around the already cultivated land. I also added a separate class for water, as I felt it better represented the area. This approach did not classify as much the areas that were already cultivated and simply had a higher reflectance that year than the year before. I believe that this is because I had great freedom in choosing my own regions of interest, which helped the support vector machine to achieve the highest accuracy and truth. An overall accuracy of 87.91% is the best overall accuracy of the three approaches, with the no change area doing exceptionally well at 95.16%. The users and producers accuracy were adequate for both the no change and change areas as well.

Conclusion:

The goal of this exercise was to use three different change detection methods, band differencing, multi-date unsupervised classification, and multi-date supervised classification to produce a change detection map of an area of Egypt. By assessing each individual map and their confusion matrices, and by comparing those results with the NDVI and true-color images from 1984 and 2003, I have come to the conclusion that the multi-variate supervised classification approach is the best approach based on the map result classes and the overall accuracy. I believe that the supervised classification is the best approach because it gives the most freedom in choosing classes, and you can rely on more than just spectral signatures to come up with regions of interest. The support vector machine process is also a very great tool that is likely part of the high accuracy of this approach.