Using Remote Sensing Techniques to Quantify Forestation Changes in Southern New England from 1986-2000

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Data Sources: USGS Earth Explorer

Purpose:

With an ever-increasing global population that does not seem to be slowing down anytime soon, more habitable space needs to be created constantly. This usually results in the destruction of our forests, which are also used for energy needs and paper products. Our high demand for deforestation has its consequences since vegetation is important for our survival in many ways- including the role it plays in sequestering carbon. Carbon dioxide is a greenhouse gas that is capable of trapping radiation that reflects from the earth and leads to a net warming effect. This study set out to look at how the forests in southern New England, focusing mostly on mid to eastern Massachusetts (including parts of Connecticut and Rhode Island) changed from 1986-2000 using change detection remote sensing techniques. It also looked to see if there was any correlation between the change and thermal differences in the area.

Methods:

Images

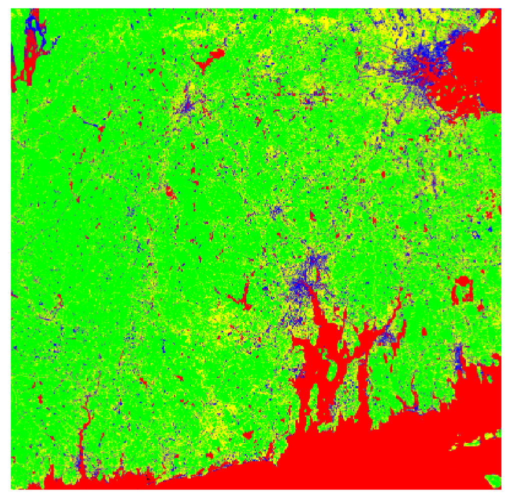
- Study area: Massachusetts from Quabbin Reservoir to the city of Boston, Rhode Island, and Eastern Connecticut.
- Images from USGS Earth Explorer using Bands 1-5 and 7 for each image
- Data was resized so images contained matching regions of focus
- Image 1: June 9, 1986 using Landsat TM 4-5 with 0% cloud cover, sun elevation of 59.75, sun azimuth of 119.6
- Image 2: September 27, 2000 using Landsat L7- SLC on with 0.01% cloud cover, sun elevation of 42.8, sun azimuth of 152.65

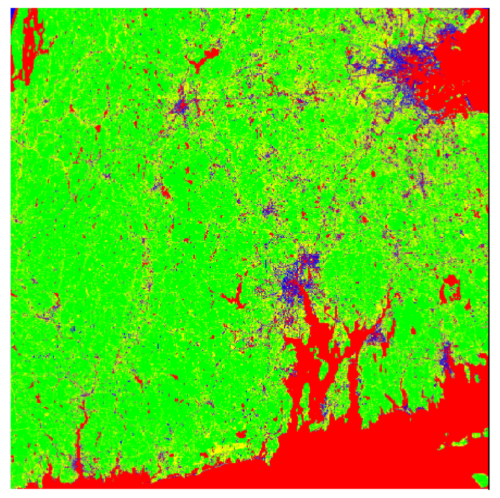

06/09/1986


09/27/2000

Classifying Land Cover

To extract vegetation information from the images, it is possible to use NDVI, which estimates net primary production, followed by the density slicing function to show which vegetation was healthy or unhealthy. Density slicing categorized the vegetation into four categories: no, low, moderate, and high vegetation. Another method is to use principal component analysis (PCA), to reduce data redundancy and prepare the image for change detection, coupled with unsupervised classification to classify the land use cover. Both were preformed for comparison; however, PCA was chosen for this project since it appeared to select out the forest more accurately.

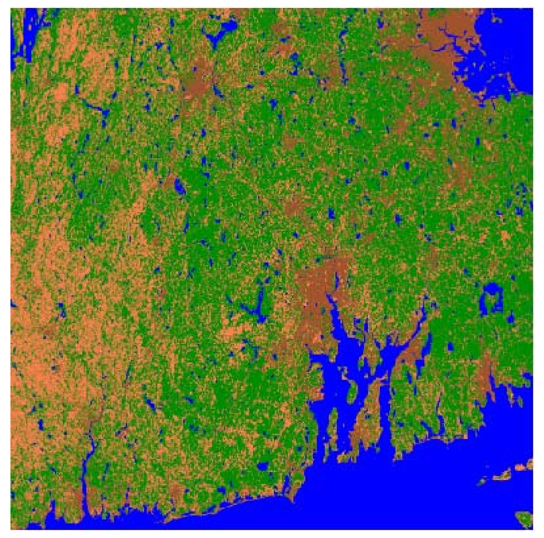

1986

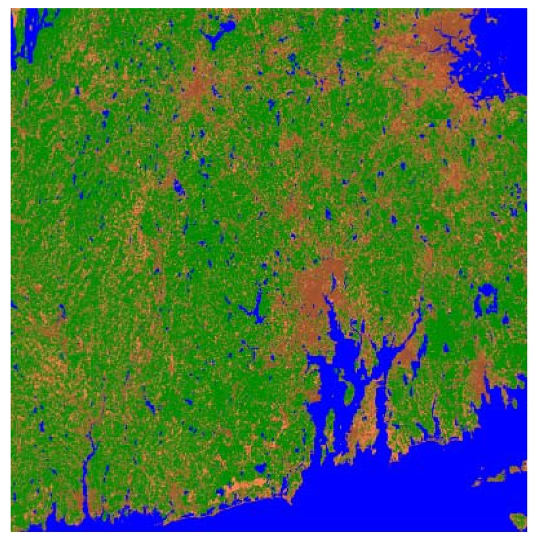

2000

NDVI: Density Slicing Images
No vegetation | Low vegetation | Moderate vegetation | High vegetation

PCA

For PCA, a Minimum Noise Fraction Rotation was performed. With this processed image, the unsupervised classification K-means was used to distinguish land cover. It ran 10 iterations to produce 10 classes that consisted of field, grass, forest (2), scattered trees, sand, urban, roads, buildings, and water. These classes were then combined to grass/fields (field, grass, and sand), urban (urban, roads, and buildings), forest (forest and trees), and water since the interest was in forested area and land cover that affects it. The changes were made permanent through class color mapping and post-classification (combine classes). In the 1986 image, there was a large cloud across the top that was coming up as the urban class. To correct this problem, the two combined K-means images were again resized by cropping them across the top.

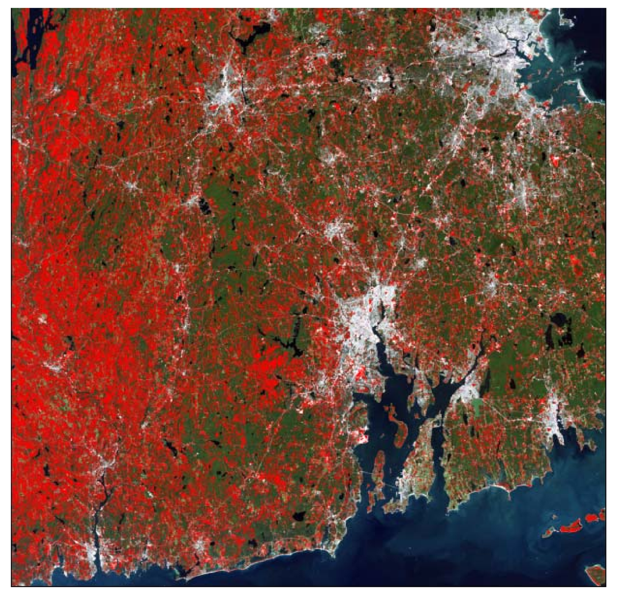

1986

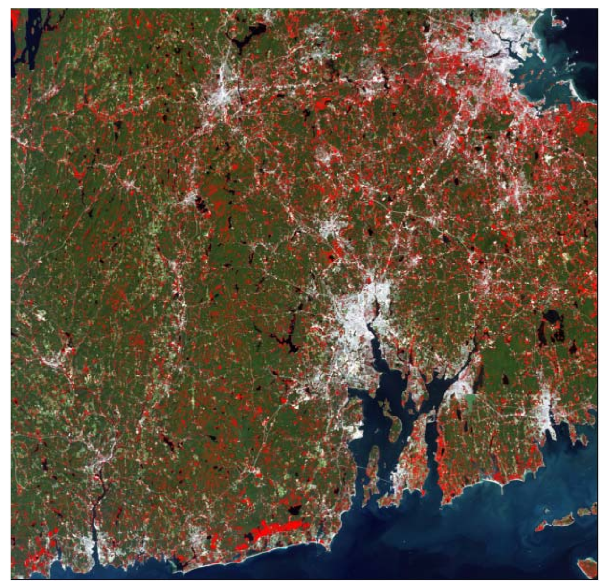

2000

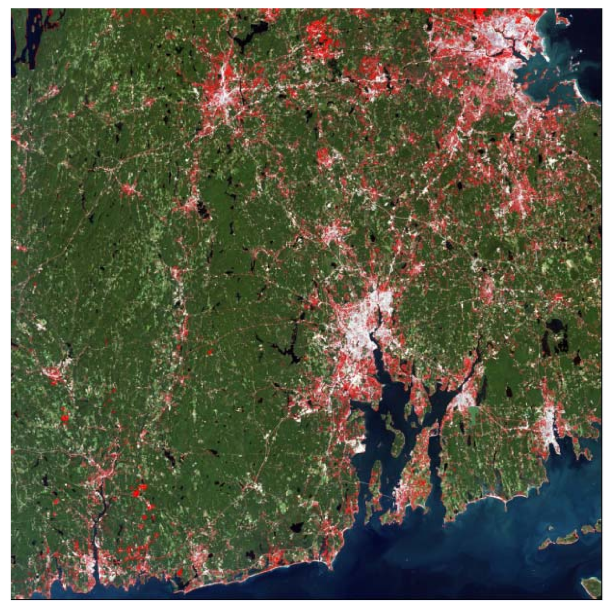
PCA: K-means Combined Images
Water | Grass/field | Urban | Forest

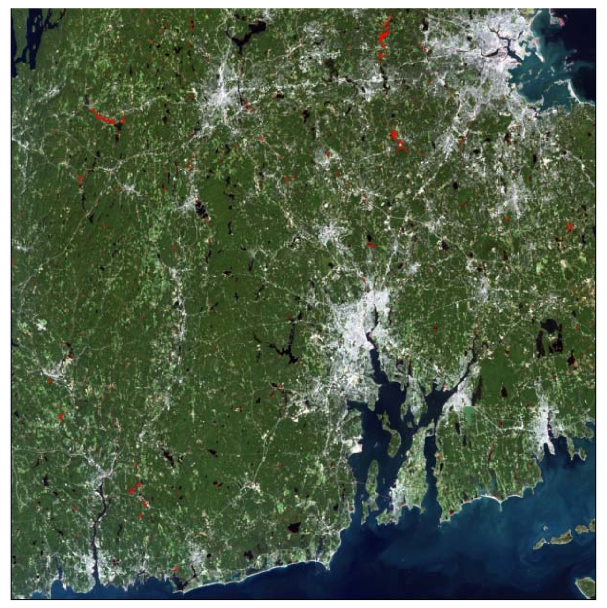
Change Detection

In order to compare the two images, post-classification comparison change detection was needed to identify differences in features over time. The 'Initial State' image was 1986 and the 'Final State' image was 2000. Similar classes in the two images were matched in the 'define equivalent classes' dialog box, and results were output in the form of images and a table.


Area where grass/fields were lost from 1986-2000 in red


Area where forest was lost from 1986-2000 in red


Area where urban was lost from 1986-2000 in red


Area where water was lost from 1986-2000 in red

Change Detection Results (Percentages)

		Initial State			
		Grass/ Field	Forest	Urban	Water
Final State	Grass/Field	32.60	13.37	26.74	0.70
	Forest	49.76	82.53	12.76	1.00
	Urban	17.52	3.69	59.29	0.63
	Water	0.12	0.41	1.21	97.67
	Change in Class	-32.70	14.15	19.95	-0.29

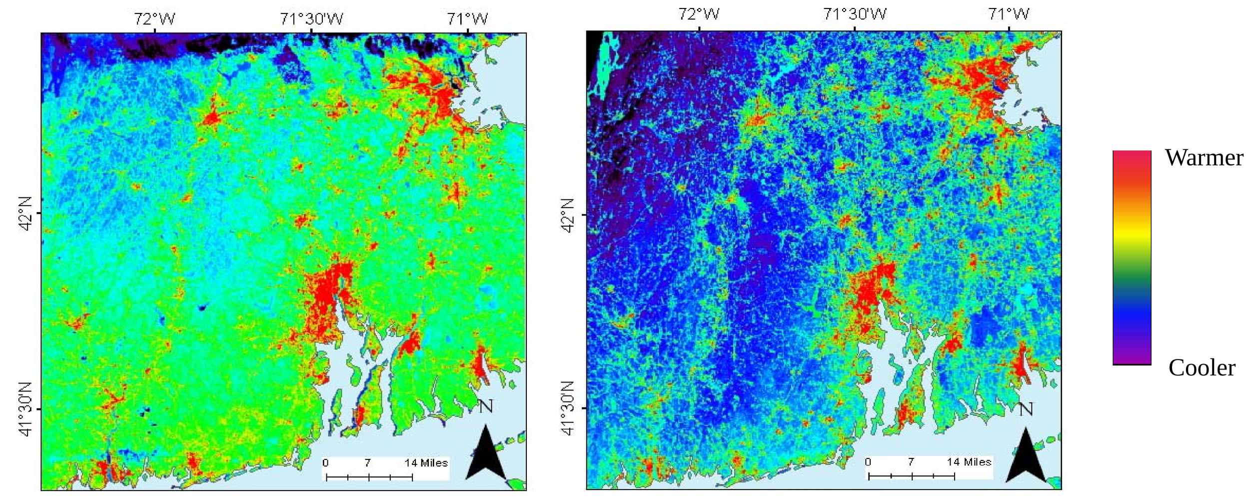
Results:

From the Change Detection images and table, changes in the classes can be tracked. What the study was concerned with was the change in forestation. It was found that 82.53% of the forest in 2000, as compared to 1986, remained forest while 13.37% became grass/field, 3.69% became urban, and 0.41% became water. The change in forest was +14.15%. This means there was no deforestation over this 14 year span, but reforestation occurred instead, with a gain of 1.05×10^9 m^2. Most of the red area in the Change Detection image showing the loss in the grass/field class, is land that became forests. The data states that 49.76% of the grass class became forests. In addition, 12.76% of the urban class and 1% of the water class became forested.

Using a confusion matrix to determine the accuracy of the classification, it was found that overall accuracy was 95% for the 1986 image and 94.6% for the 2000 image. Eighty percent is generally regarded as acceptable. However, it does not give information about individual classes. The producer accuracy for 1986 was greater than 80% for all but forests, which was 69.18% . The user accuracy was greater than 80% for all but grass, which was 67.81%. For the 2000 image, user accuracy was greater than 80% for all classes, and producer accuracy was greater than 80% for all but the grass/field, which was 71.43%.

Thermal Data:

- Used thermal band (band 6) for each image and resized data
- Used a low-pass filter for image enhancement
- ENVI Color Tables: RAINBOW



1986 2000

Thermal Results:

1986: Overall area was warm with urban areas as hottest spots. Coolest area across top was cloud cover.

2000: Overall area was much cooler with urban areas still being the hottest, although appearing to be smaller in area.

Conclusion:

The area of forested land increased over this time period by 1.05×10^9 m^2. Most of the forests were lost to grass/fields, yet these were also the areas most likely to turn into forests. The urban area increased as well, while grass and water decreased. However, grass and forest producer and user accuracies were lower than desired so the class changes may not be very accurate. The thermal data shows an overall cooling in the more forested 2000 image, which could be due to differences in the seasons since the 1986 image was taken in June, and the 2000 image was from September. A change of this extent does not seem to be a result of forest change. Being able to compare changes in area through time is an extremely useful application of remote sensing.