MULTI-TEMPORAL IMAGE ANALYSIS OF THE COASTAL WATERSHED, NH

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ABSTRACT

Given the recent no-cost availability of Landsat imagery through the United States Geological Survey (USGS), a more detailed examination of the changes in habitat and reflectance from this imagery is now possible. The Coastal Watershed in New Hampshire is an area covering 990 square miles of varied habitat, from areas that are well developed, to large tidal bays and managed forests. The watershed is also home to around 155 species of rare plants, 18 rare species of animals, and 35 different rare natural communities and ecosystems. However, due to pressure from rapid development, fragmentation, invasive species, water quality degradation, and climate change, many of these habitats are disappearing faster than ever. A detailed look at one complete year of Landsat imagery of this area can serve as a better indicator of land cover change in the Coastal Watershed, as well as a baseline for monitoring vegetation response to climate change. For this study, a multi-temporal analysis of six usable dates of Landsat imagery for a single year was performed, including an examination of various derivative bands such as the normalized difference vegetation index (NDVI) and tasseled cap indices. The analysis performed in this study will serve as a point of reference for future studies monitoring the Coastal Watershed, both for historical and future change analyses.

INTRODUCTION

The coastal region of New Hampshire contains some of the most valuable habitat in the state, however it is also one of the regions with the highest population growth rates and is identified by The Nature Conservancy as a 'crisis ecoregion' where habitat is at high risk of suffering irreversible losses. The Coastal Watershed encompasses around 9% of the total area of the state as well as to one of the more unique tidal bays, Great Bay. The unique features of the watershed have also lead to the almost 40% growth in population from 1984 to 2008. Therefore, monitoring how the habitat of the Watershed has changed from the mid 1980's to today can be an indicator for how vegetation is reacting to both human pressures through expansion, as well as to aspects of climate change.

The recent policy change to free availability of the Landsat imagery by the United States Geological Survey (USGS) has allowed us to quantify habitat change in the Costal Watershed using land cover change over time. However, using those data reemphasizes the importance of preprocessing when completing multi-temporal analyses of Landsat TM images. Each of the images was taken at a different time of year, which means that the atmospheric conditions in which the images were taken were very different. The effects from the atmosphere can make it very difficult to do change detection between several dates, since some of the change could be attributed to changes in the atmosphere rather than land cover changes. Several methods have been proposed to convert satellite digital number (DN) values to surface reflectance, including both image based correction techniques or models that need either *in-situ* field measurements or modeled values of atmospheric parameters (Chavez, 1996, Song et al., 2001, Lu et al., 2002, Paolini et al., 2006, Schroeder et al., 2006, Mahiny and Turner, 2007). The methods that require atmospheric parameters generally are quite accurate, as long as the parameters are correct, which is often the limiting factor. However, many have found that some of the image-based models can do almost as well as the models using atmospheric inputs (Lu et al., 2002, Schroeder et al., 2006, Mahiny and Turner, 2007). One of these models is the dark object subtraction (DOS) model, and modifications of DOS. Although fairly simple, the DOS models produce good results with low root mean square error (RMSE) as an absolute atmospheric correction technique. One of the modifications of the DOS atmospheric correction technique is the cosine of the solar zenith angle (COST) method presented by Chavez (1996).

Therefore, the objective of this study was to atmospherically correct one year of available Landsat imagery using the COST model. The at-surface reflectance values for each of the dates could then be compared for the entire year, giving a good baseline model for how the Coastal Watershed changes throughout the growing season. Future work can be done to compare these values with current reflectance changes and determine how the watershed is changing due to human and climate pressures.

METHODS AND RESULTS

For our study area, all of the Landsat TM5 images with 10% or less cloud cover were acquired for 1991 and then atmospherically corrected using the cosine of the solar zenith angle (COST) method (Chavez, 1996). The COST model employs similar methods as the DOS method, but instead uses the cosine of the sun zenith angle ($\cos(\theta)$) to approximate effects of absorption and Rayleigh scattering of the reflectance signal in the atmosphere. The COST model first converts the minimum DN values, representing dark objects on the image, to at-satellite radiance using the Markham and Barker (1986) equation:

$$L_{\lambda min} = L_{\lambda MIN} + DN_{\lambda min} * {(L_{\lambda MAX} - L_{\lambda MIN})}/{DN_{\lambda max}} \tag{1}$$

where $L_{\lambda min}$ is the minimum at-satellite spectral radiance values for the dark objects, $L_{\lambda MAX}$ and $L_{\lambda MIN}$ are constants given in table 2 of Markham and Barker (1986), $DN_{\lambda min}$ is the minimum DN values acquired for each band, and $DN_{\lambda range}$ is 255, the maximum DN value possible for the bands. For this study, the lowest DN value in each band with at least 1000 pixels was taken to be the $DN_{\lambda min}$ for that band. The theoretical radiance of a dark object is then computed, under the assumption that dark objects have 1% or smaller reflectance (Chavez, 1996, Song et al., 2001):

$$L_{\lambda,1\%} = 0.01 * d^2 * {\cos^2\theta}/{(\pi * Esun_\lambda)} \tag{2}$$

where $L_{\lambda,1\%}$ is the dark object at-satellite radiance, d is the sun-earth distance for the acquisition location and time, θ is the solar zenith angle, and $Esun_\lambda$ is the mean solar exoatmospheric spectral irradiance given in table 4 of Markham and Barker (1986). The haze correction value is then computed by taking the difference of the minimum at-satellite spectral radiance and the dark object at-satellite radiance:

$$L_{\lambda haze} = L_{\lambda min} - L_{\lambda 1\%} \tag{3}$$

Through the computation of $L_{\lambda haze}$ the COST method is mathematically the same as the DOS method, however, where the methods differ is in the conversion of the at-satellite radiance to surface reflectance (Lu et al., 2002):

$$\rho = \pi * d^2 * {(L_{\lambda sat} - L_{\lambda haze})}/{(TAU_v * Esun_\lambda * \cos\theta * TAU_z)} \tag{4}$$

where ρ is the computed surface reflectance, TAU_v and TAU_z are atmospheric multiplicative transmittance components, and $L_{\lambda sat}$ is the at-satellite reflectance computed using equation (1) for each DN value on the image rather than the $DN_{\lambda min}$. While both TAU values approximate atmospheric transmittance, TAU_v is a measure of transmittance along the path from the ground to the sensor, and TAU_z is a measure of transmittance from the sun to the ground (Chavez, 1996). In the DOS model, TAU_v and TAU_z were approximated by 1, meaning the model ignores any atmospheric transmittance. However, the COST model assumes that the sensor is taking vertical images, therefore TAU_v should be 1, and TAU_z can be approximated by $\cos(\theta)$ (Chavez, 1996). Therefore, the surface reflectance equation becomes:

$$\rho = \pi * d^2 * {(L_{\lambda sat} - L_{\lambda haze})}/{(Esun_\lambda * \cos^2\theta)} \tag{5}$$

Using the COST method in ERDAS Imagine's Model Maker, six dates of Landsat TM5 from 1991 were converted from DN values to surface reflectance. The six dates used for this study include: April 4th, June 7th, July

9th, August 26th, September 27th, and October 29th, all collected in Landsat path 12, row 30. Prior to any correction, each of the Landsat images was georeferenced and cut to the size of the Coastal Watershed using ERDAS Imagine. Once the correction was implemented, the images were visually inspected (Figure 1).

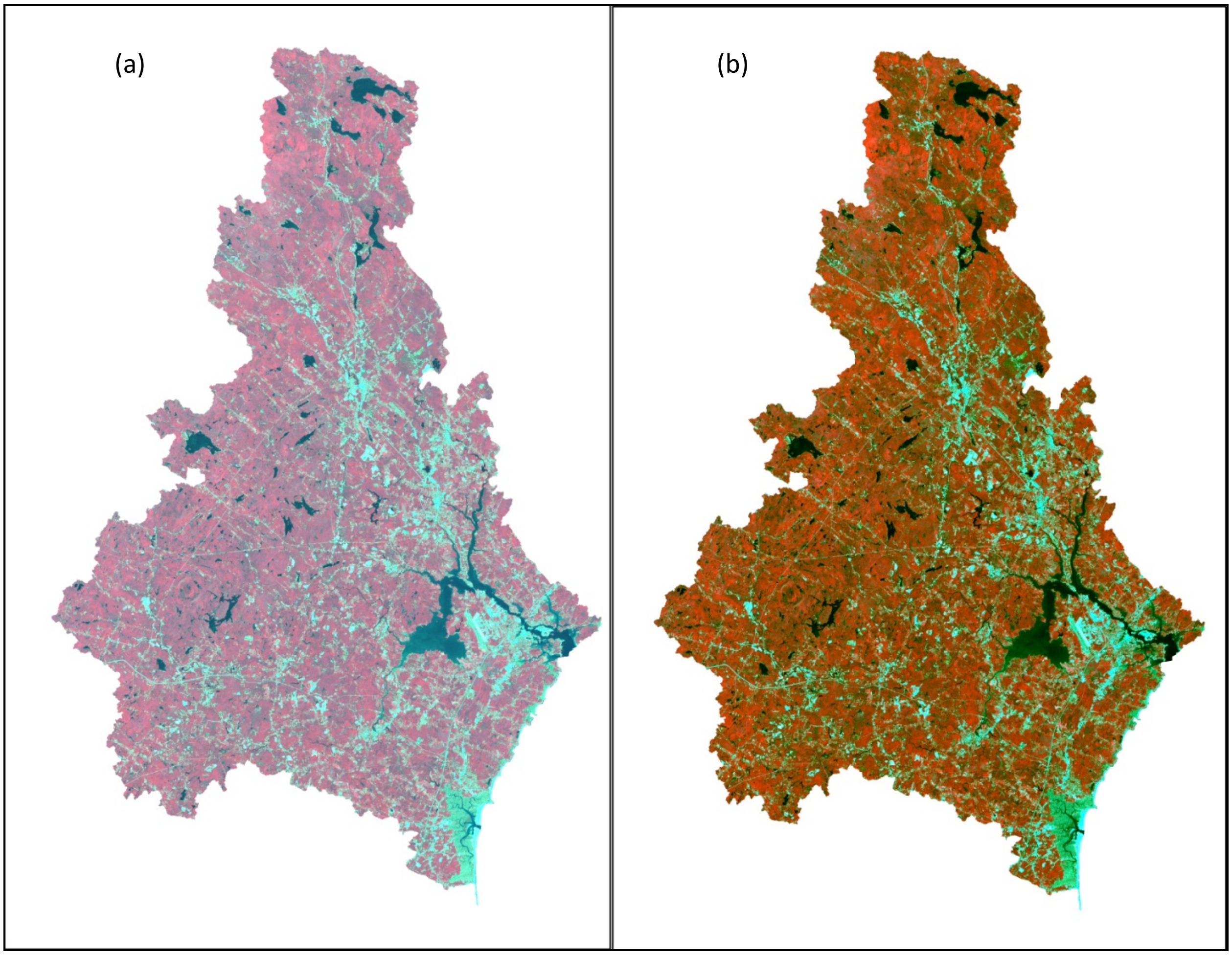


Figure 1. The Landsat TM5 CIR images of the Costal Watershed before (a) and after (b) COST atmospheric correction was performed on the 06/07/1991 image.

When looking at the average reflectance values for the first four bands of the corrected Landsat images, it is obvious that the reflectance values change throughout the growing season (Figure 2). However, it is hard to make a conclusion whether these changes form a pattern over longer time periods, or if there is no predictable change in these values.

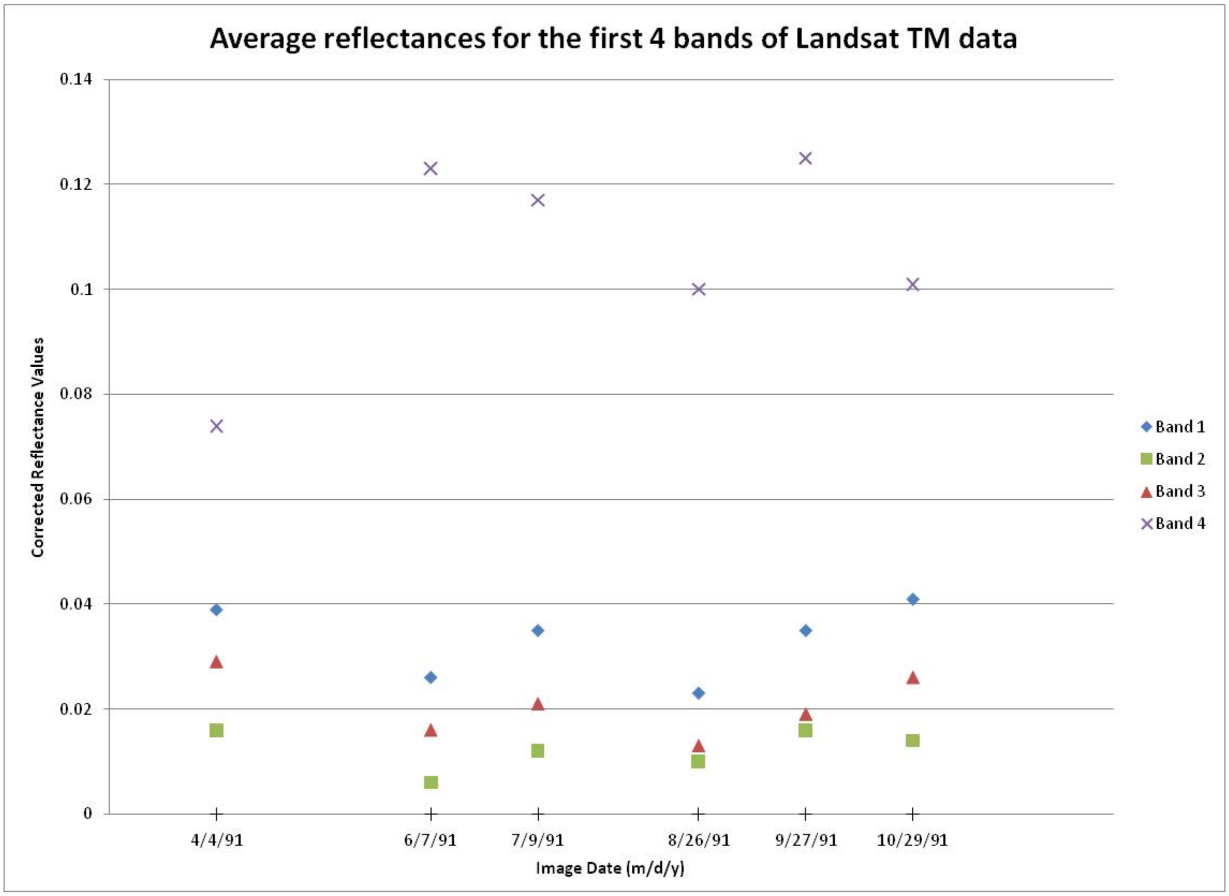


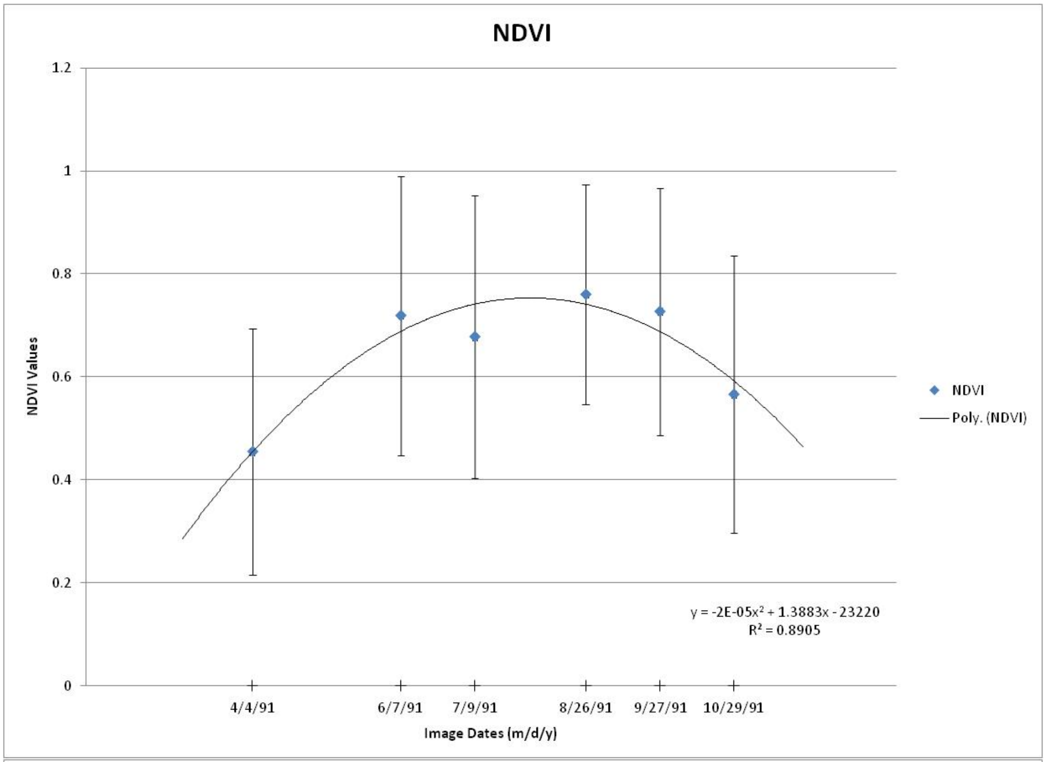
Figure 2. The average reflectance of each of the first four Landsat TM5 bands for each date of imagery.

Along with inspecting the average reflectance of each of the Landsat bands, several derivative bands were created in order to look at the trends in vegetation reflectance values throughout the growing season. The first derivative band that was generated was the Normalized Difference Vegetation Index (NDVI) using:

$$NDVI = \frac{(Band\ 4 - Band\ 3)}{(Band\ 4 + Band\ 3)} \tag{6}$$

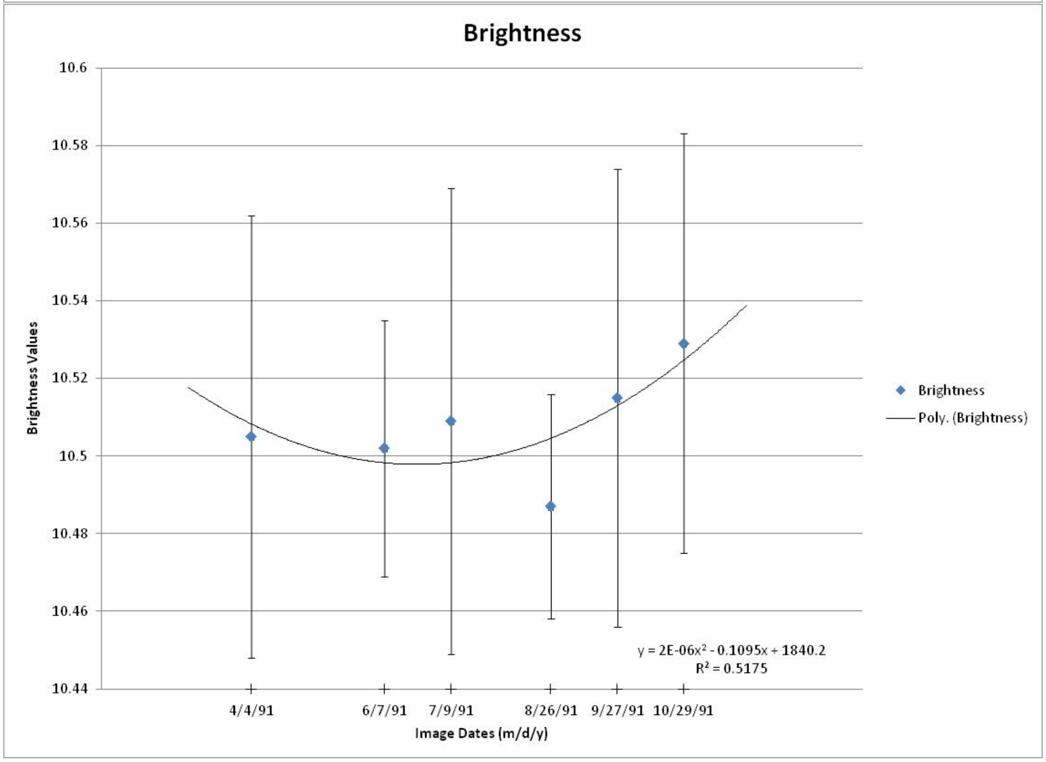
The other derivative bands were the brightness, greenness, and wetness bands using the Tasseled Cap Transformation in ERDAS Imagine (ERDAS, 2008). The average values of each of the derivative bands for each of the images were compared and a polynomial trend was fitted to each of the bands (Figure 3). The polynomial trend line for the NDVI band had the best fit to the data (R^2=0.8905).

(a)



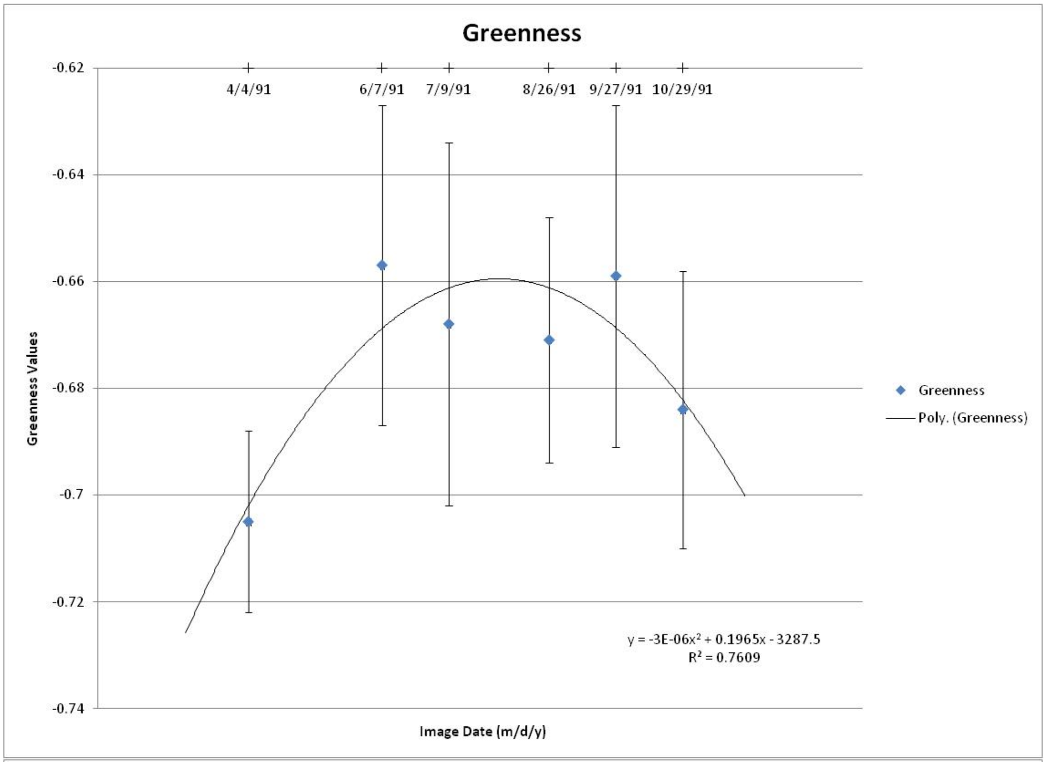
NDVI
1.2
1
0.8
0.6
0.4
0.2
0
NDVI Values
4/4/91
6/7/91
7/9/91
8/26/91
9/27/91
10/29/91
Image Dates (m/d/y)
NDVI
Poly. (NDVI)
y = -2E-05x² + 1.3883x - 23220
R² = 0.8905

(b)



Brightness
10.6
10.58
10.56
10.54
10.52
10.5
10.48
10.46
10.44
Brightness Values
4/4/91
6/7/91
7/9/91
8/26/91
9/27/91
10/29/91
Image Dates (m/d/y)
Brightness
Poly. (Brightness)
y = 2E-06x² - 0.1095x + 1840.2
R² = 0.5175

(c)



(d)

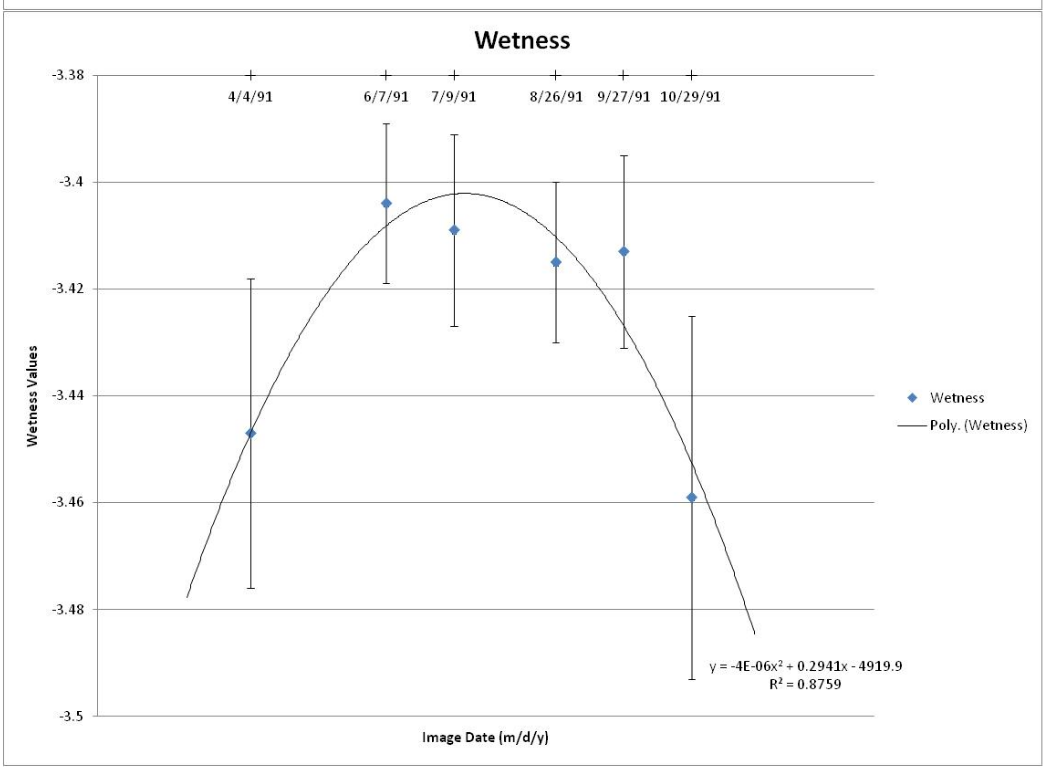


Figure 3. The average values for each of the derivative band: (a) NDVI, (b) Brightness, (c) Greenness, and (d) Wetness. The standard deviations of each of the averages and polynomial trend lines are also shown on these graphs.

CONCLUSIONS

The COST method, introduced by Chavez (1996), was sufficient at atmospherically correcting images to surface reflectance for one year of Landsat TM5 imagery. However, the absolute correction technique was relatively time consuming to do for each individual image. For future studies, which will compare the trends seen in this year of data to trends in images from 1985 through 2008, a combination of absolute and relative atmospheric corrections may be used. Some studies have indicated that correcting a "reference image" using an absolute atmospheric correction technique, such as COST, and then using a relative atmospheric correction technique to correct the other images to the reference image can cut down on the preprocessing time of the images and give just as good results as individually correcting each of the images (Schroeder et al., 2006).

The observed changes in the NDVI derivative band matched the prediction that it should increase in the middle of the growing season and tend to decrease at the beginning and end of the summer months, which indicates that the COST method did not disproportionately correct any of the images. However, one year of data on its own does not tell us very much about how vegetation may be responding to human and climate pressures, so these data will be useful in comparing to other growing season years. Once other years' NDVI values have been produced for the growing season, the polynomial trends of each of the years can be compared, and beginnings, ends, and intensities of the growing season can be approximated and compared.

This study provided the groundwork for continued research on how the Costal Watershed of New Hampshire has responded to intense development and climate change factors over the past 25 years. Future studies will reveal exactly how these changes can be detected using Landsat TM5 images and their derivative bands.

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