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Estimating Land Cover Change using Image Pre-processing of *Landsat* images

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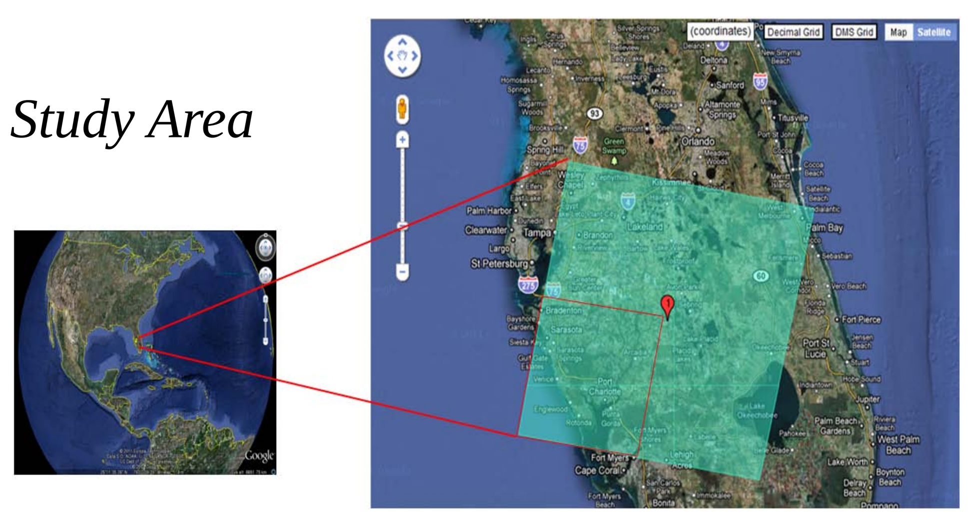
ABSTRACT:

It is not too much to say that image pre-processing is one of the most important steps in remote sensing analysis. Image pre-processing should be performed in advance of every analysis and therefore there are numerous methods developed for image pre-processing. At this time, I would like to introduce one of the methods of image pre-processing of cloud removal that I have developed. Cloud cover in the image affects the radiometric value of some pixels across the image. To remove the reflectance effects of cloud cover and restore the pixels under the cloud, I secured two backup images which were taken within a similar time period as original image (subset 2, subset 3) that could be used to replace the cloudy region in the base image. For this pixel replacement, image rectifications to identical projection including defining sub-images for all images are done in advance of any processing. Histogram adjustment to match the spectral value was performed to subset 2 and subset 3 and then correlation of each class (urban, swamp, forest, farm, shallow water, deep water) was calculated to support the appropriateness of the replacing pixels. Finally, some of the pixels from the overlapping region in subset 4 (adjacent image) were used to assess the precision by comparing pixels at the region under cloud in base image which has been replaced by pixels to recover surface data from subset 2 or subset 3 and the same region in subset 4 which is not covered by clouds. I estimated a 18-year Land Cover Change around Peace River Mouth in Florida with Landsat images through this method; however this method could be applied to other places in the world and have more precise analysis by sensors with higher temporal resolution (e.g., MODIS, SPOT, etc.).

INTRODUCTION

- Study Area



Peace River mouth region in Florida, USGS EE

- Satellite Imagery

Subset #	Image Date	Clipped from Scene ID.	Path	Row	Sensor (#)	Cloud (%)
Subset 1	1984-07-01	LT50160411984183XXX09	16	41	TM (5)	0
Subset 2	1984-08-18	LT50160411984231AAA03	16	41	TM (5)	10
Subset 3	1984-08-02	LT50160411984215AAA04	16	41	TM (5)	25
Subset 4	1984-07-08	LT50170411984190XXX06	17	41	TM (5)	10
Subset 1	2002-08-20	LT50160412002232LGS01	16	41	TM (5)	0
Subset 2	2002-07-03	LT50160412002184LGS01	16	41	TM (5)	10
Subset 3	2002-07-27	LE70160412002208EDC00	16	41	ETM+ (7)	10
Subset 4	2002-07-26	LT50170412002207LGS01	16	42	TM (5)	0

Why p16 r42 ?

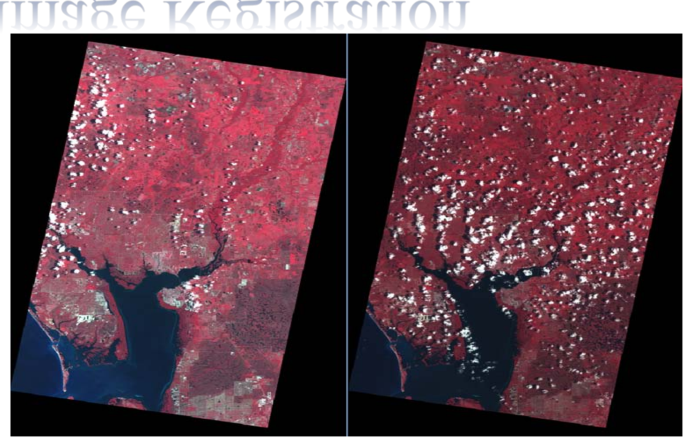
Use Overlapping Region !

METHOD

- Overview Flowchart

Georeference → **Atmospheric Correction** → Classification → Visualize

Image Registration



Topographic & geometric correction done

GIS data layer from Department of Transportation, Government of Florida

7/1 1984, TM5 *8/18 1984, TM5*

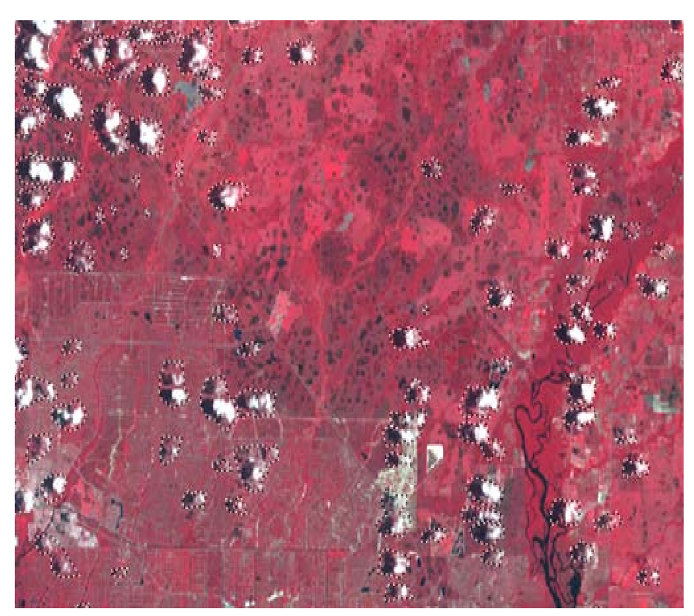
Removing Clouds

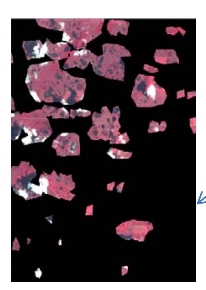
by *Model Builder* in ERDAS Imagine

Good :
Became possible to get data under clouds!
Bad:
- Uncertain & complicated boundary!
- Shade!

Make AOI for every cloud (and shade) & Replace them!

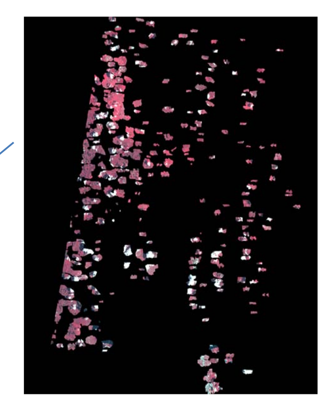
OR





Still some clouds

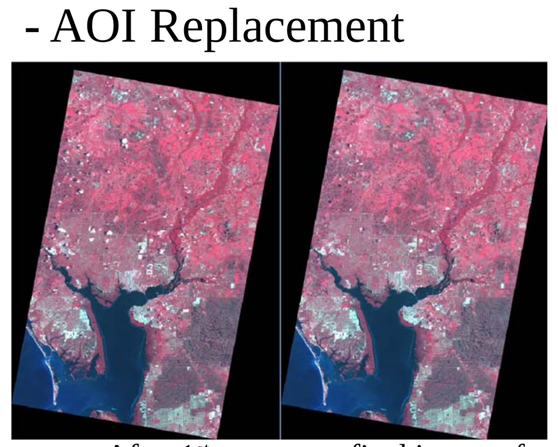
Zoomed in



AOI clipped on the image that will replace with.

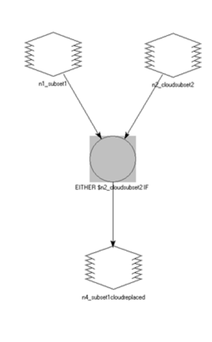
lots of clouds removed!!
Do once more?
Third image!

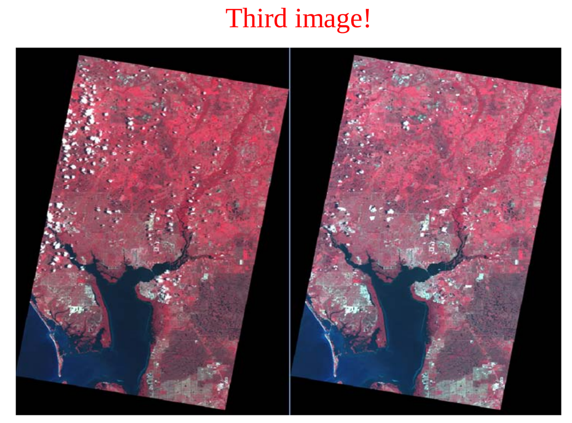
- AOI Replacement



After 1st replacement

final image after 2nd replacement





7/1 1984, TM5 *After 1st Replacement*

“ EITHER $n2_cloudsubset2 IF [$n2_cloudsubset2>0] OR $n1_subset1 OTHERWISE ”

it is easy to see that most dramatic change occurs between first and third column (1st replacement), while much less change occurs between third and fifth column (2nd replacement).

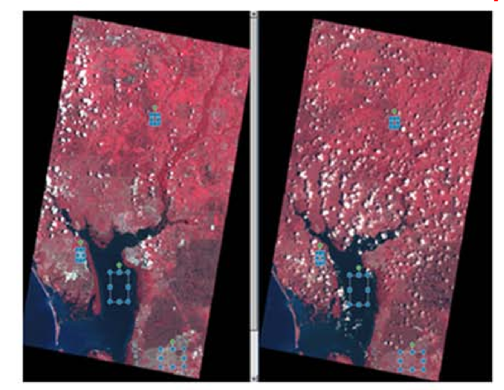
		Subset 1	Subset 2 histogram matched to subset 1	Subset 1 cloudy pixels replaced from subset 2	Subset 3 histogram matched to subset 1	Subset 1 cloudy pixels replaced from subset 2 and subset 3
Band 2	Mean	28.082	28.166	26.935	26.927	26.702
	Std.dev.	22.685	22.717	19.346	19.150	18.677
	Median	33	33	33	34	33
Band 3	Mean	24.559	24.546	23.216	23.174	22.934
	Std.dev.	23.025	23.008	18.864	18.794	17.998
	Median	26	26	26	26	26
Band 4	Mean	52.961	52.929	52.546	52.519	52.431
	Std.dev.	44.529	44.462	43.349	43.253	43.072
	Median	65	65	66	66	66

Precision Estimation

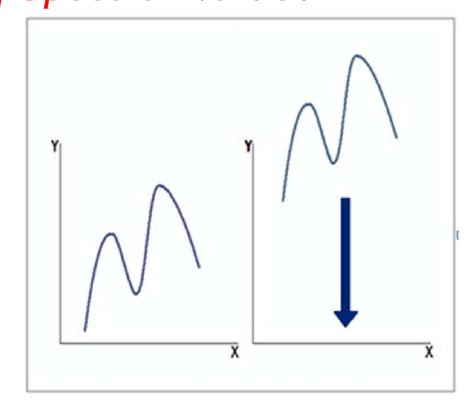
Subset 4 is the clipped region from Landsat TM scene path 17 and row 41 that shares some of the part between base images. This part of the image is used as a source for estimating the relevance of replaced pixels from backup images. The procedure is to see whether the replaced pixels from the backup images under the cloud in subset 1 are comparable to the pixels in cloud free region in subset 4 at the same geographic region. Figure 8 clearly shows the same AOI put over subset 1, subset 4, and final image after replacements. AOI was designed by randomly picking regions (farm or forest) that clouds have been removed.. Then I matched histograms to equalize the spectral values, and calculated the correlation. Median was a little bit higher (about 4 in 8 bit scale) than the AOI from the original image because subset 4 had more clouds leading more path radiance to the sensor. The correlation was 0.98 (band 4). Through this procedure, I proved my methods of cloud removing to be relevant. Mean and standard deviation are shown in table 3. At first, I planned to use the scene from path 16 row 42 and I secured one scene taken at the same date as subset 1. Later, I found out the image from next row in a same day is useless since the atmospheric condition is almost same because of the small time gap between the adjacent images.

*-**Relevant** to Use Pixels from Other Image in terms of Spectral Value?*

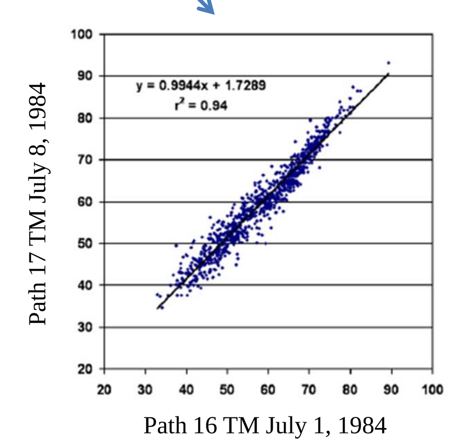
Only overlapping area displayed between subset 1



Training sites selection for correlation calculation

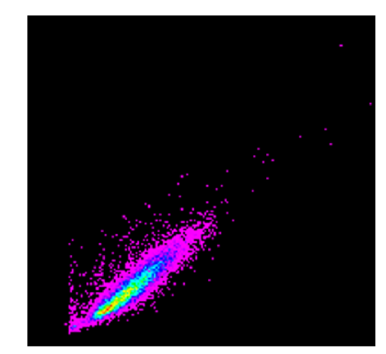


Histogram adjustment of highly correlated object



COR is…
0.9844664711640759 !
- Through model maker

Same Procedure,
COR for agriculture is…
0.9462737123944146 !!



Feature Space Plot for agriculture

Merged two subset.
Even though we could see BVs for subset image 1 is little bit higher.

		AOI within Subset 4	AOI within Final Image
Band 2	Mean	19.250	18.636
	Std.dev.	22.530	16.325
Band 3	Mean	17.250	15.939
	Std.dev.	20.123	14.013
Band 4	Mean	31.750	36.017
	Std.dev.	36.845	33.176

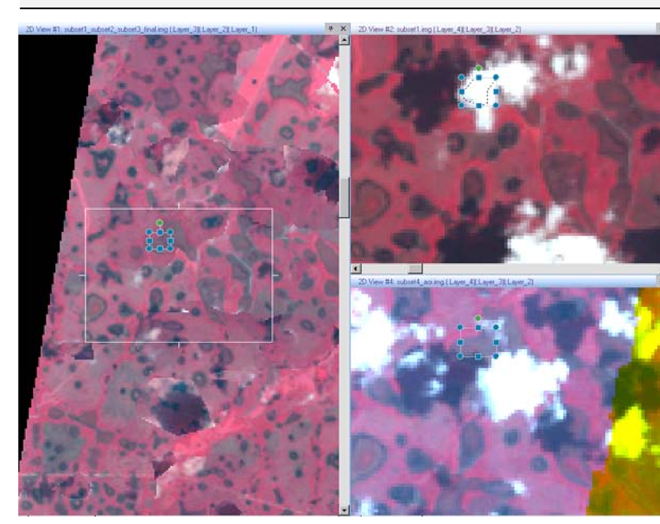


Figure 8. pixels under cloud in subset 1, cloud free pixels in subset 4, and pixels those became cloud free after two replacements (in clockwise order starting from upper-right).

AOI was designed by randomly picking regions (farm or forest) that clouds have been removed. Matching histograms to equalize the spectral values, and calculation of correlation were performed. Median was a little bit higher (about 4 in 8 bit scale) than the AOI from the original image because subset 4 had more clouds leading more path radiance to the sensor.

Classification

- Supervised classification (Maximum Likelihood)
- Six classes: shallow water, deep water, farm, forest, swamp, urban
- 10 training sites for each class, several MSS images as reference
- No gap between classes

- Residual Analysis

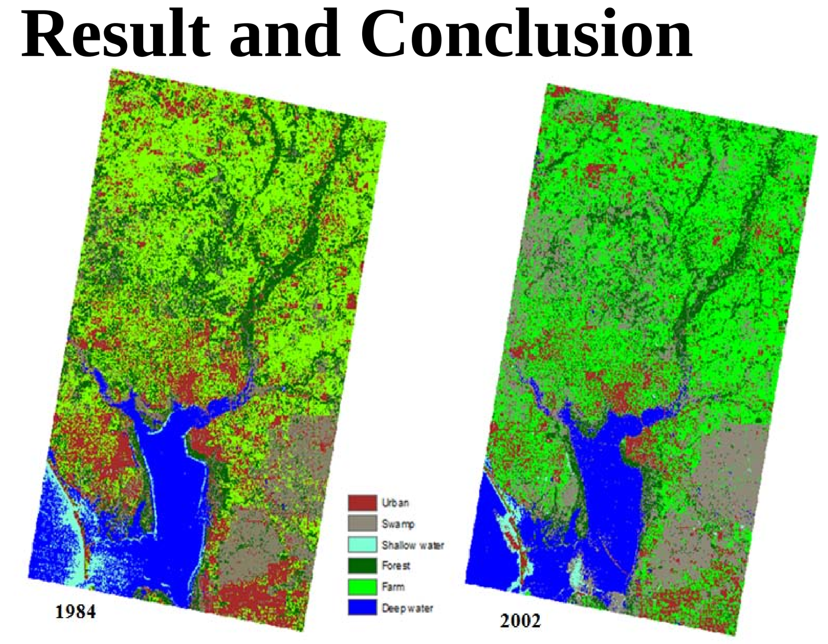
Same procedure applied to the 2002 images

From left subset 1, subset 1 after 1st replacement, final image for 2002.

		Subset 1	Subset 2 histogram matched to subset 1	Subset 1 cloudy pixels replaced from subset 2	Subset 3 histogram matched to subset 1	Subset 1 cloudy pixels replaced from subset 2 and subset 3
Band 2	Mean	21.824	21.875	21.282	21.084	21.257
	Std.dev.	16.876	16.831	15.262	14.679	15.235
	Median	26	27	26	26	26
Band 3	Mean	19.577	19.548	18.884	18.652	18.859
	Std.dev.	17.603	17.084	15.217	14.261	15.186
	Median	21	21	21	21	21
Band 4	Mean	46.801	46.790	46.649	46.656	46.625
	Std.dev.	39.260	39.228	38.729	38.718	38.710
	Median	59	60	60	59	60

Change of the central tendency for each subset while two replacement processes was in progress.

Result and Conclusion



Some notable changes

- Disappearance of river stream in upper right (IFOV issue)
- Loss of forest and increase of farmland size
- Shallow water portion greatly decrease

References
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-United States Geological Survey (2009). Landsat Thematic Mapper (TM) Level 1 Data Format Control Book (DFCB).
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