Stepwise Image Processing for Mapping Fire Scars in Fire-Adapted Vegetation at NASA Kennedy Space Center, Florida, USA

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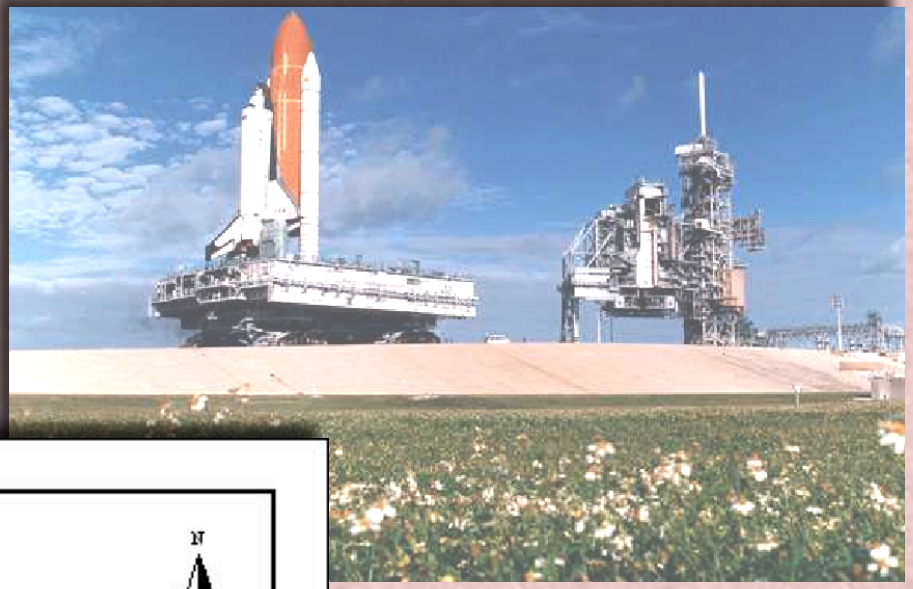
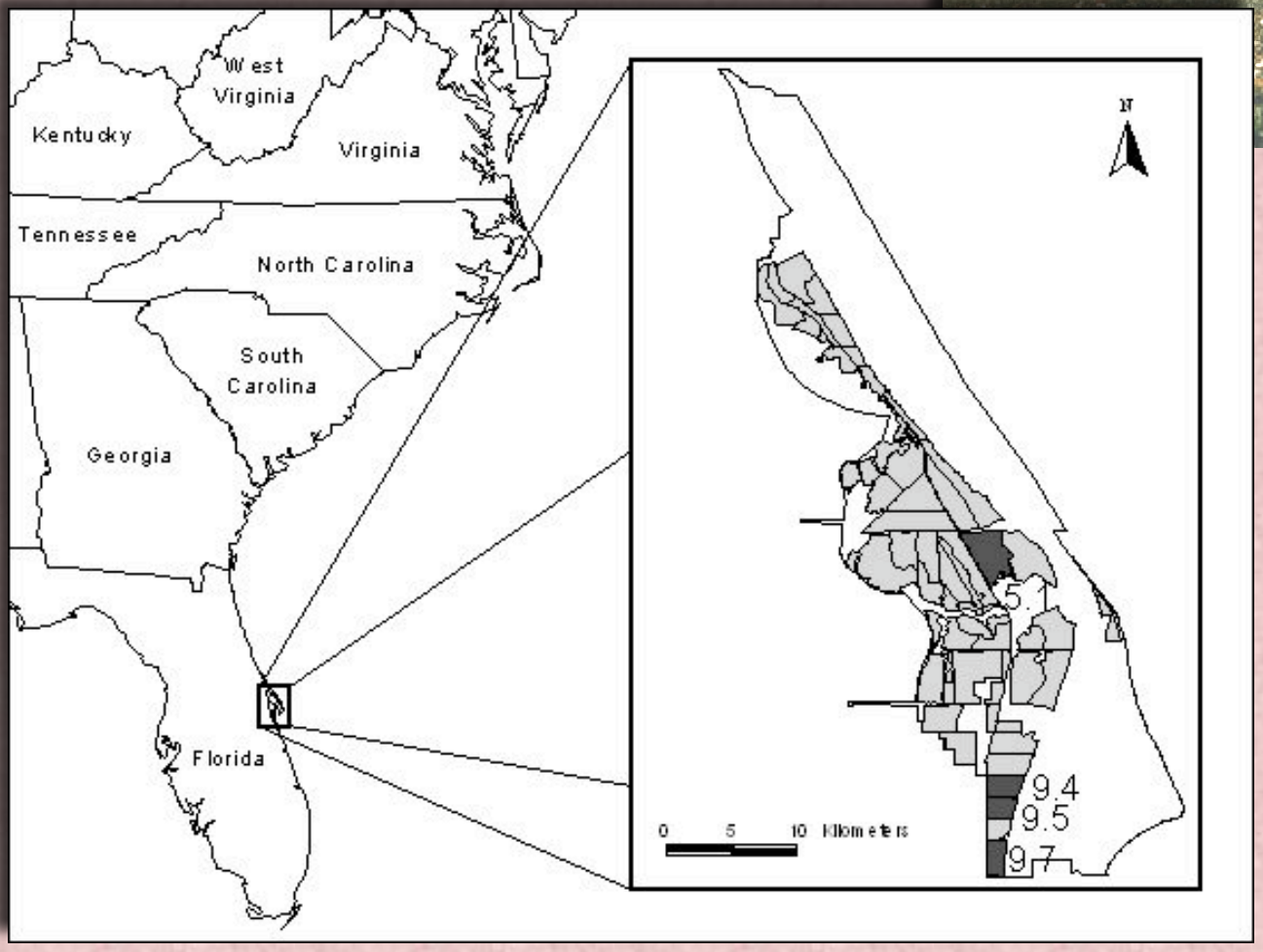
- Scientists at DYNAMAC Corporation (Brean Duncan, Dave Breininger, Paul Schmalzer, Ron Schaub, Carlton Hall, Ross Hinkle)
- NASA Colleagues: Eduardo Lopez Del Castillo and Lori Jones

Where?





Kennedy Space Center

Why?

- Fire is ecologically important in SE US.
- Frequent fires helped form open spaces dominated by oak scrub – unique habitat for many plant and animal species.
- Mapping fire scars in the past is helpful for better understanding the relationships between landscape structure and fires.
- The updated knowledge is useful for applying adaptive management at KSC.

Picture by Brean Dnocun

Florida Scrub-Jay

- Florida Scrub-Jay (*Aphelocoma coerulescens*) is a federally threatened species and an indicator of suitable habitat for many other species.
- Florida Scrub-Jay builds their nests in oak shrubs more successful than built in other vegetation (Bowman and Woolfenden 2002).
- Since 1960s, the population of Florida Scrub-Jay has experienced a dramatic decline (Breininger et al. 1996). Restorations of the native vegetation became a major task for natural resource managers at KSC.
- Continued controlled burning is the #1 priority for land management at KSC (Duncan and Schmalzer 2004).

Landscape-Scale Fire Scar Remote Sensing

- Pereira and Setzer (1993) found that TM channel 4 was the best to identify fire scars, followed by channel 5, 3, and 7;
- Pu and Gong (2004) suggested that original TM4 and TM7 and NDNI1 (TM4, TM7) and NDVI2 (TM4, TM3) exhibit the highest discrimination between burned scars and unburned vegetation areas;
- Hudak and Brockett (2004) compared the Tasseled Cap (TC) and Principal Components (PC) Transformations in mapping 22 annual fire scars and found that PC helped differentiate the spectral signal of fire scars in each image.
- Patterson and Yool (1998) pointed out that TC produced 17% higher overall classification accuracies than PC.

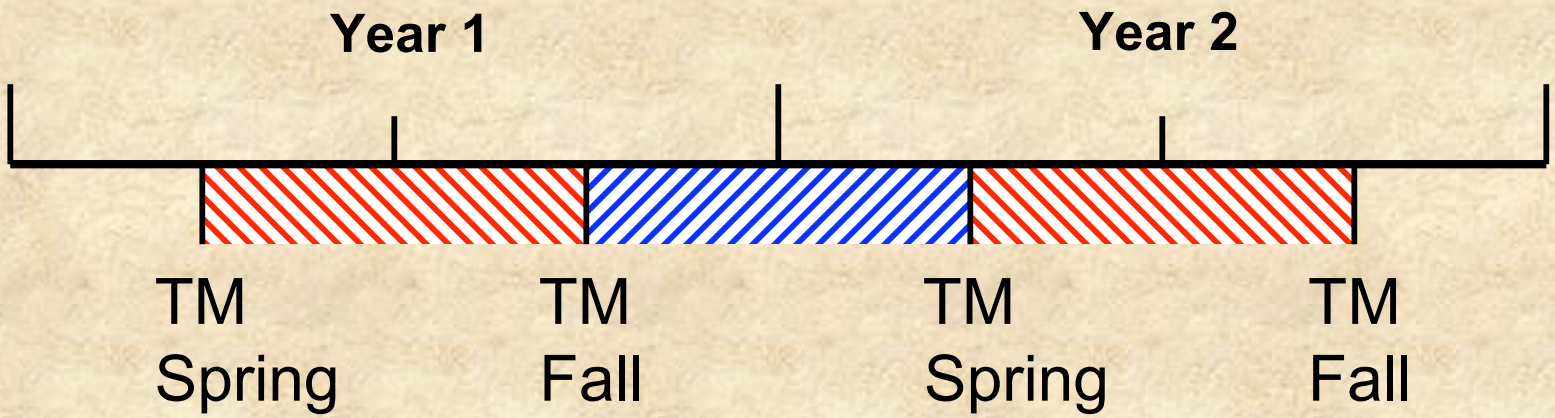
Picture by Brean Dnocun

Challenges

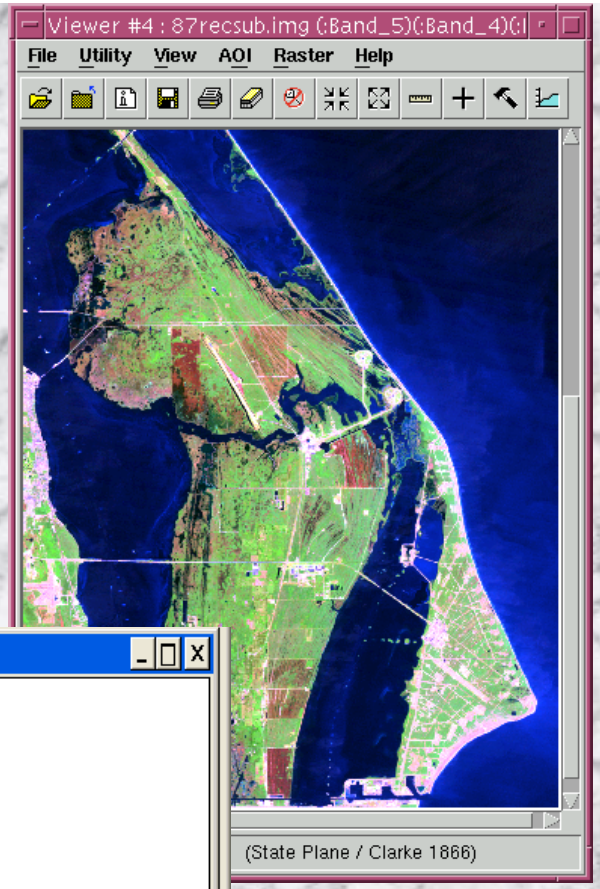
- Rapid succession after fires (Breininger et al. 2002).

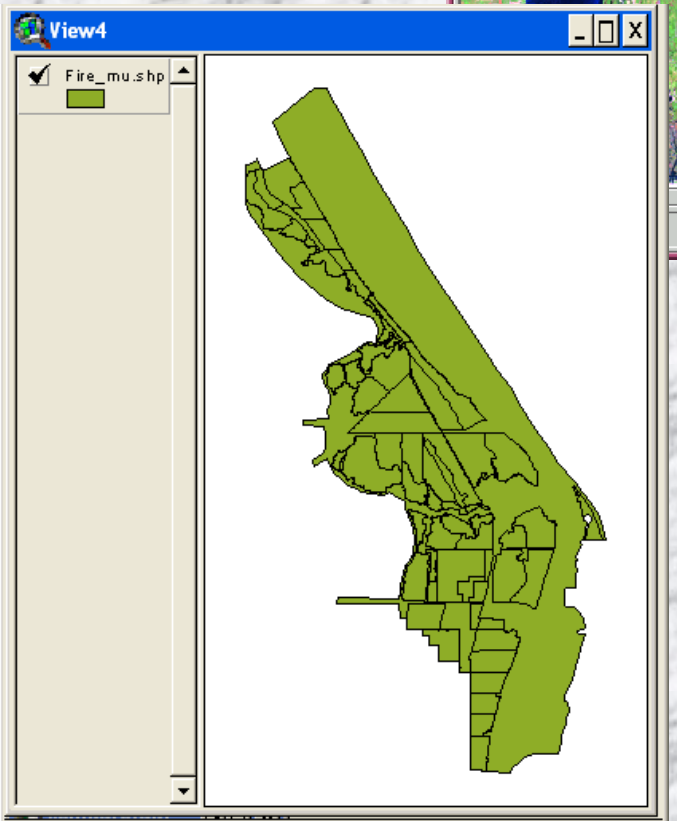
- Prescribed fires were applied frequently and burned patches were relatively small in area and had different patterns each time (Schmalzer 2003).

Strategy for Mapping Fire-Scar Time Series



Data



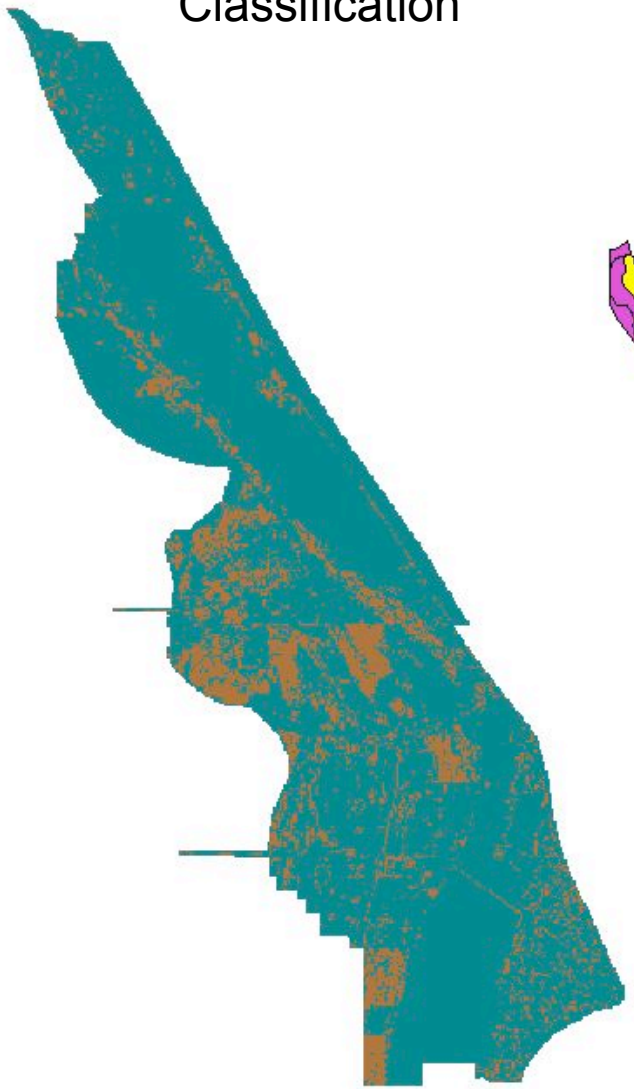


- Landsat TM Data, April 21, 1987
- Fire Scar Data Layer for Tel4 (FMU9.4) in 1987, by Breininger et al. (2002)
- Fire Management Units (FMUs)
- Fire Records by Management Units

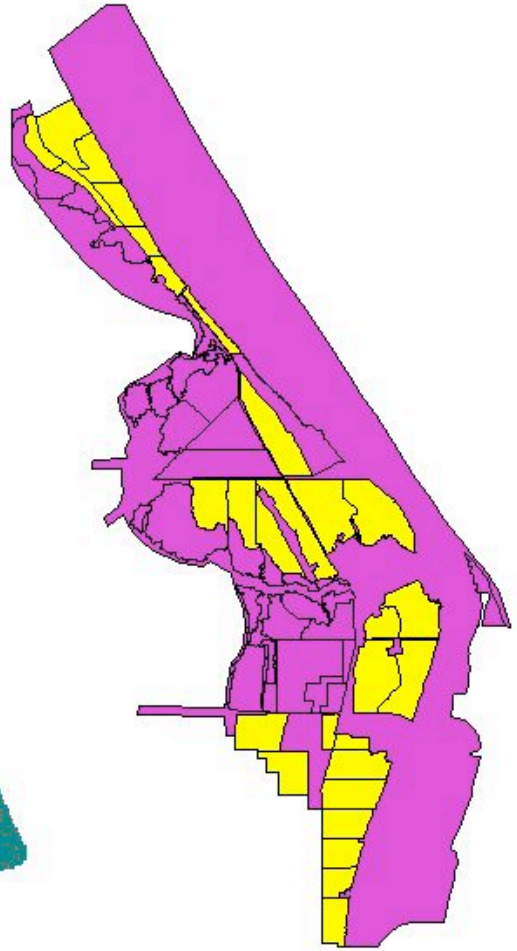
A Preliminary Comparison

TM5,4,2

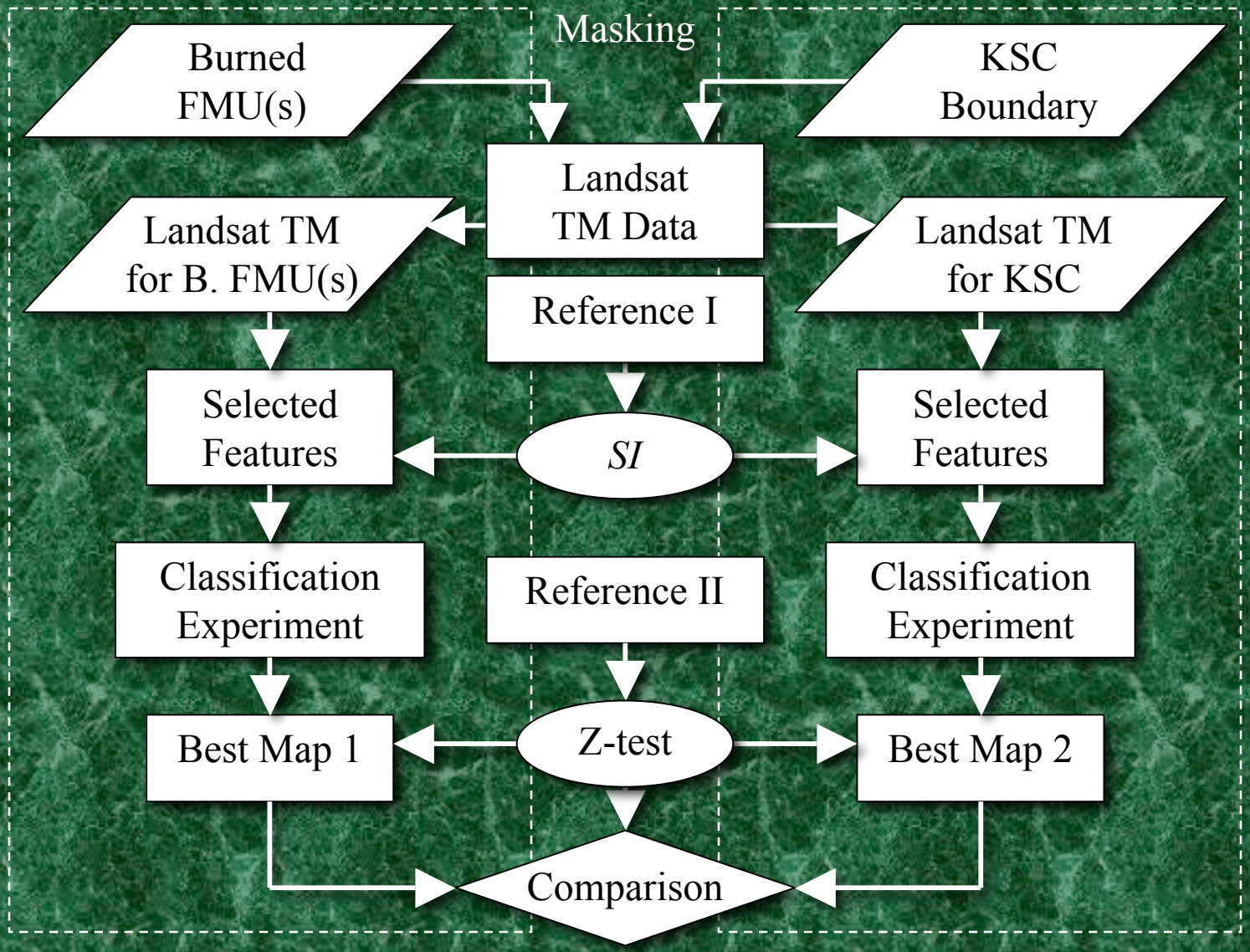
Classification



Fire Records



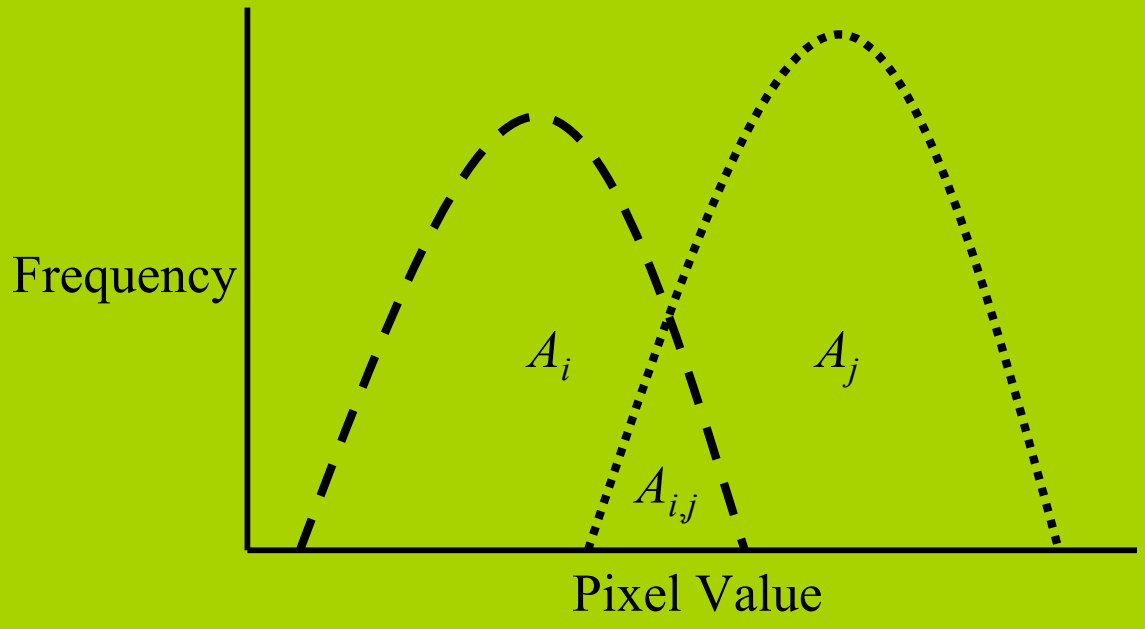
Experiment of Stepwise Image Processing



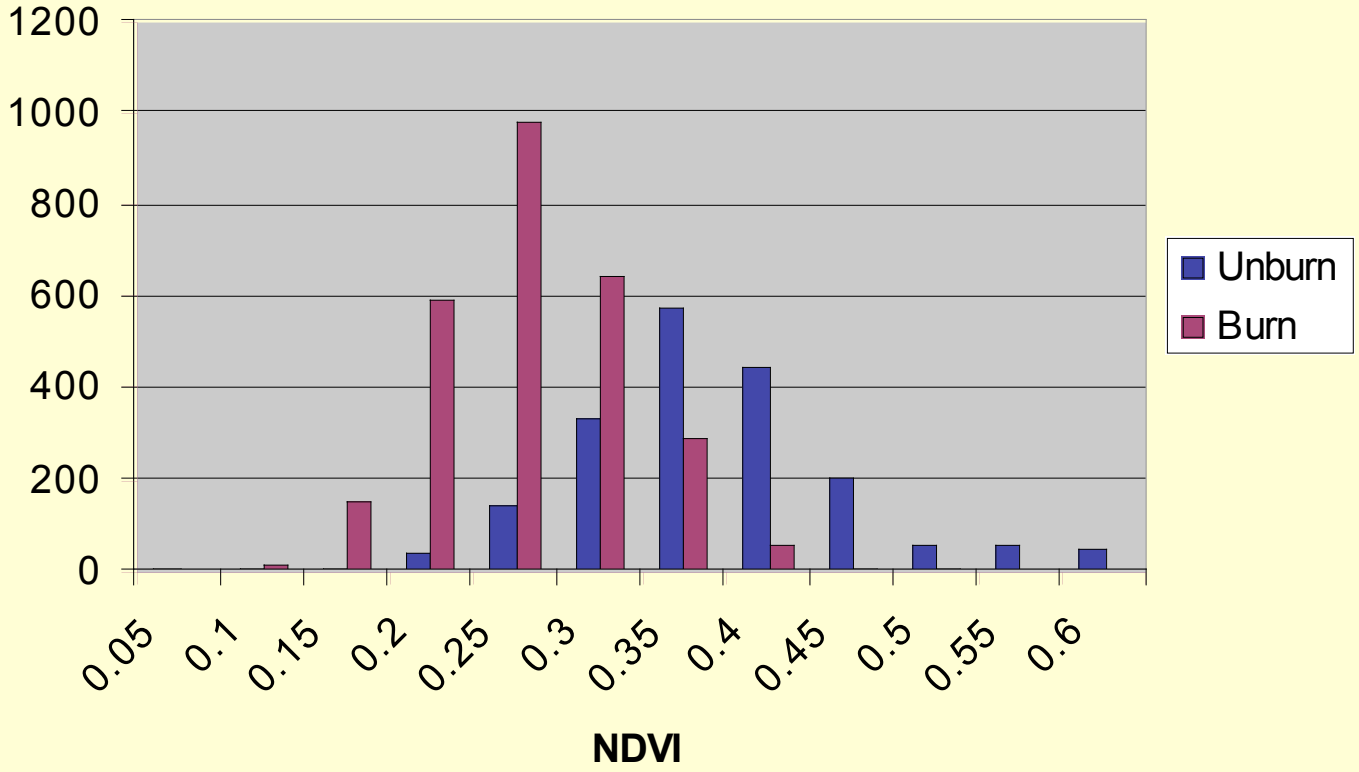
Separation Index (*SI*)

$$SI_{i,j} = 1 - \frac{A_{i,j}}{\mathrm{Min}(A_i, A_j)}$$

where, $SI_{i,j}$ is separation index between cover types i and j ($0 \leq SI_{i,j} \leq 1$), $A_{i,j}$ is the overlap areas between cover types i and j, and A_i or A_j is area for cover type i or j.

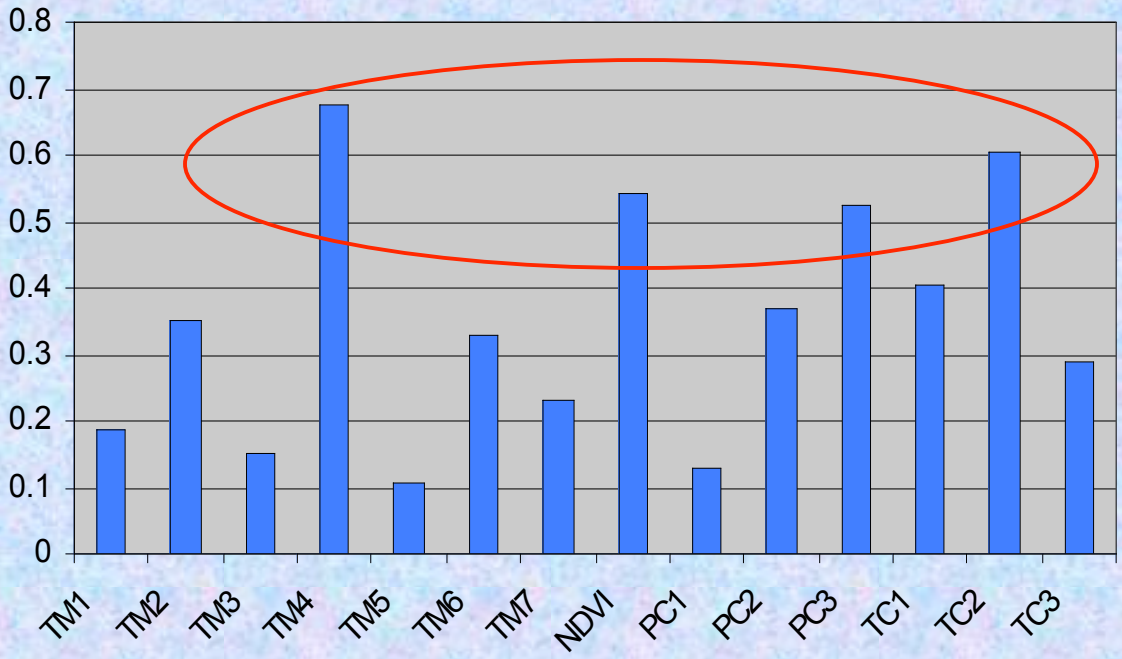


An Example

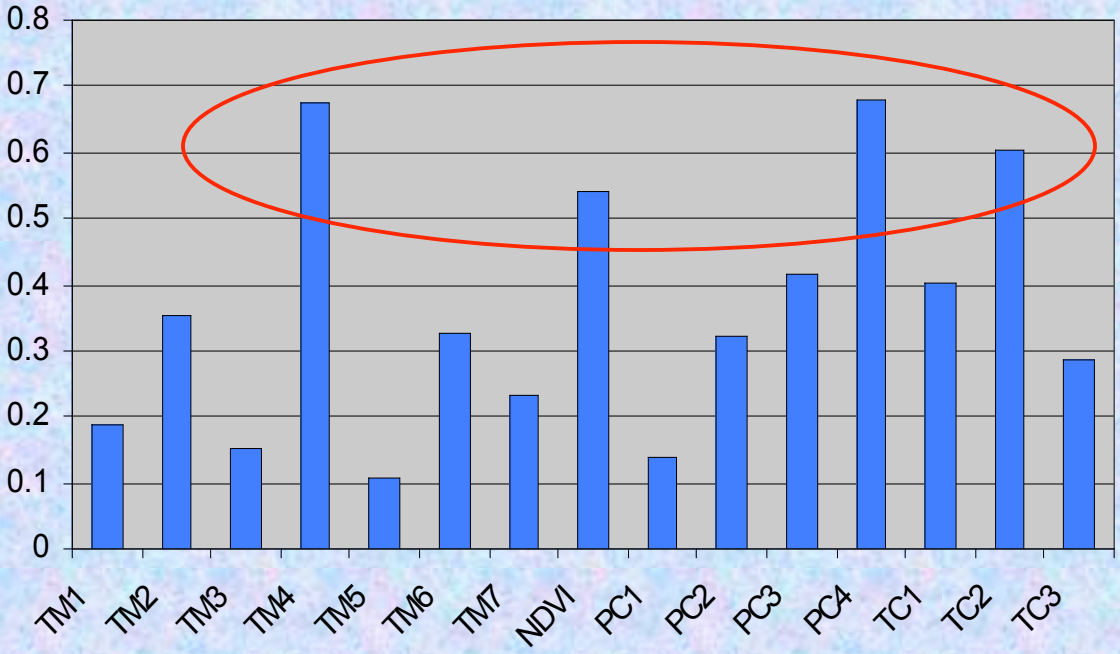


$$SI_{i,j} = 1 - \frac{A_{i,j}}{\mathrm{Min}(A_i, A_j)} = 1 - \frac{887}{1928} = 0.54$$

Result - SI



Burned-FMU TM Data



KSC TM Data

Accuracy Assessment

Error Matrix:

Classification \ Reference			
	f_{11}	f_{12}	f_{1+}
	f_{21}	f_{22}	f_{2+}
	f_{+1}	f_{+2}	N

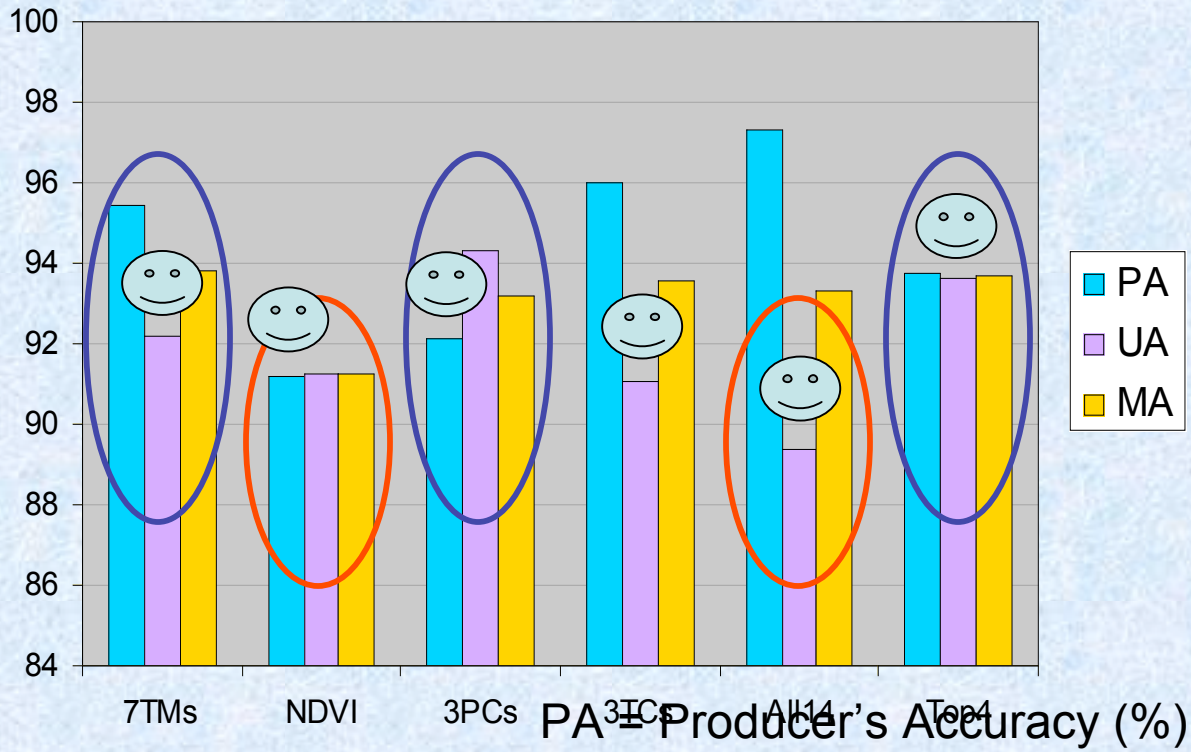
User's Accuracy (UA_1) = f_{11} / f_{1+}
Producer's Accuracy (PA_1) = f_{11} / f_{+1}

Mean Accuracy (MA_1) = (UA_1 and PA_1) / 2

Z-test: quantitatively compare two maps

Result – Classification Accuracy

Burned-FMU TM Data



PA = Producer's Accuracy (%)
UA = User's Accuracy (%)
MA = Mean of PA and UA (%)

Z-test

	NDVI	3 PC	3 TC	All 14	Top 4
7 TM	9.13*	0.78	2.72*	6.66*	1.85
NDVI		10.09*	6.33*	2.26	11.10*
3 PC			3.54*	7.54*	1.11
3 TC				3.94*	4.59*
All 14					8.54*

*** indicates significant difference at a 99% confidence level**

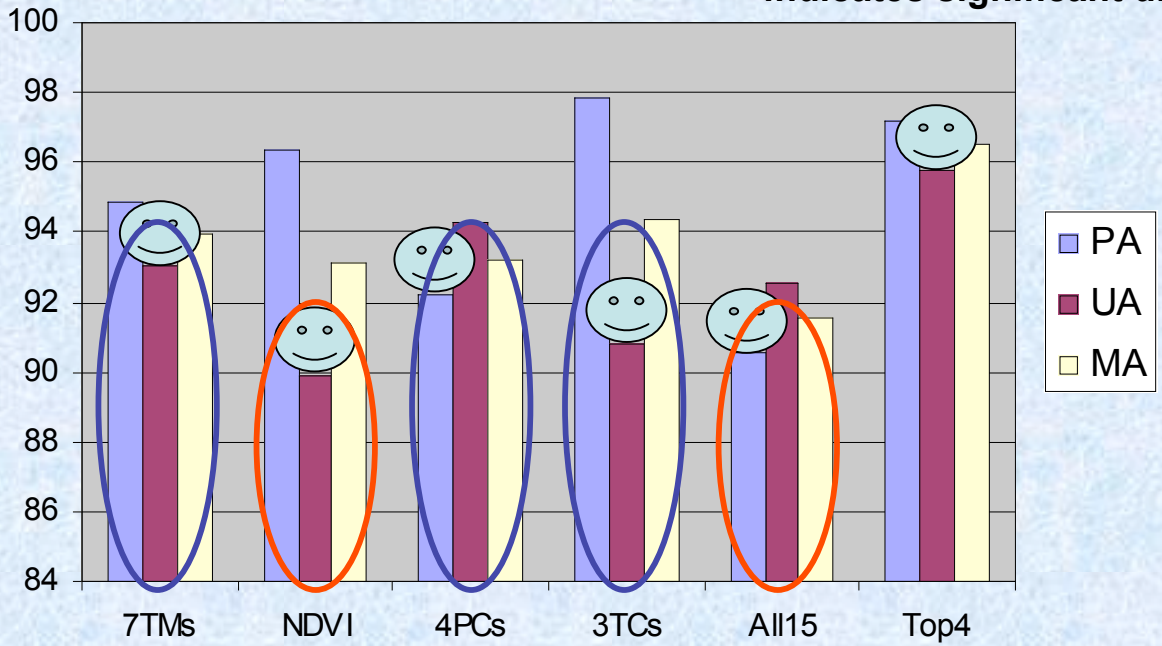
Result – Classification Accuracy

Z-test

KSC TM Data

	NDVI	4 PC	3 TC	All 15	Top 4
7 TM	7.21*	1.08	2.02	8.86*	15.03*
NDVI		6.24*	5.12	1.39	21.88*
4 PC			0.98	16.38*	7.87*
3 TC				6.67*	16.73*
All 15					24.15*

*** indicates significant difference at a 99% confidence level**



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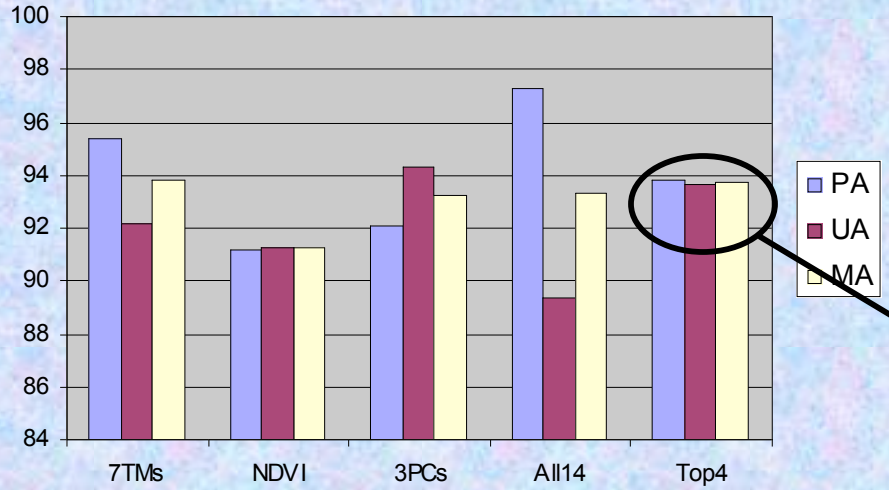
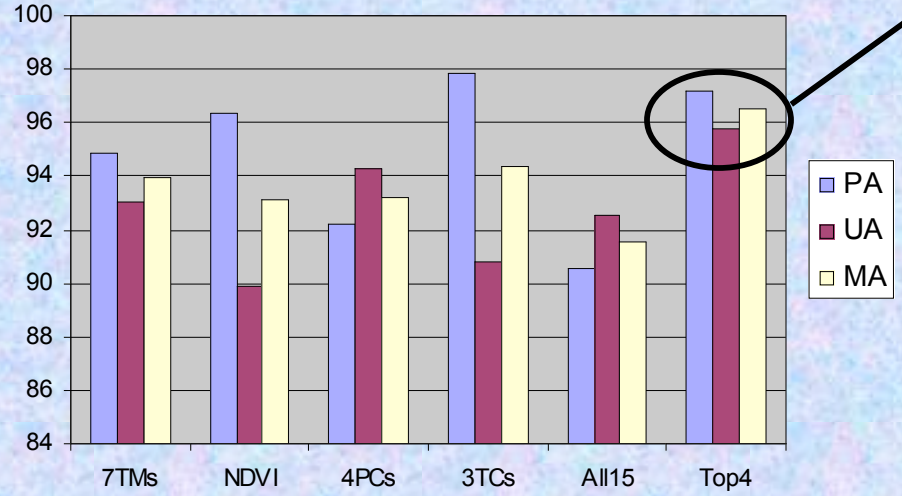
FMUs vs. KSC

Burned-FMU TM Data

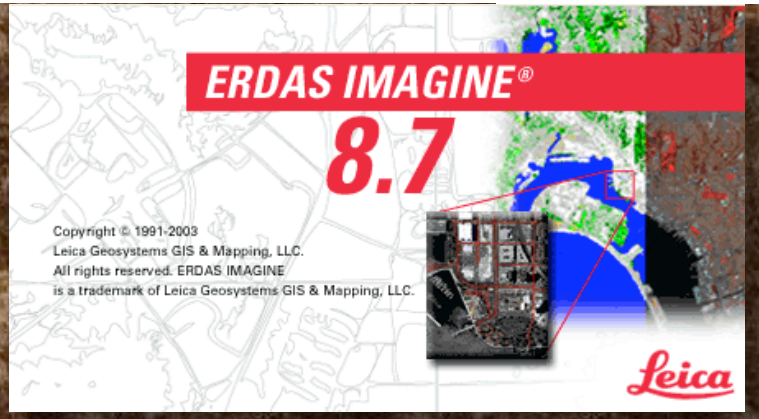


Z-value = 15.83

KSC TM Data



Application Procedure



Landsat TM Data Covering KSC Area at Time *T*

Feature Evaluations with *SI*

Best Features

Composite a New Image

Classification

Fire Scar Map at *T*

Fire Records between *T* and *T*-1

Burned FMU Data Layer

Filtering

Fire Scars between Oct. 1986 and April 1987

Technical Summary

- The 1st step is to use the separation index (*SI*) to evaluate each individual feature on its potential capability in discriminating unburned and burned areas. By comparing and sorting all the features of interest, it is possible to select reliable features for image data classification.
- The 2nd step is to compare classifications with selected feature groups derived from Landsat TM data. This is helpful to determine the best feature combinations for discriminating unburned and burned areas.
- The 3rd step is to filter the best classification map with the burned FMUs data layer for removing all the noises outside the burned FMUs.

What We Learned

The burned FMUs are so small in area that the local variability of the TM data cannot represent the global variability of typical land cover types. The limitation of the local variability was reflected with both PCA and image data classifications. Zoom-in analysis is not always the best choice.

Conclusions

- Too few, too many, or too ordinary features cannot improve classification accuracy.
- The combination of the best features derived from Landsat TM data covering entire KSC area are more reliable.
- Post-classification filtering with GIS helps control the continuous fire scar mapping.


Thanks