

# Operational Monitoring of Alteration in Regional Forest Cover Using Multitemporal Remote Sensing Data (2000-2003)

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# **General Objectives of the Study**

- **This research will apply remote sensing techniques to map changes in forest cover in California to examine LCLUC over several 5-year time periods**
- **The scope of this research will be the testing and improvement of an operational FS-CDF forest change monitoring program**

# **Specific Objectives of the Study**

## **Research Objective 1**

**Establish an operational forest cover change monitoring program based on the following project efficiency indicators:**

- Change-map accuracy assessment**
- Flexibility of implementation**
- Interpretability of methods and results**
- Consistency across phenologically diverse areas**

# **Specific Objectives of the Study**

## **Research Objective 1: Related research questions**

- 1. Which change detection techniques produce the most accurate, interpretable maps of forest cover change?**
- 2. How do the existing FS-CDF program methods compare to those generated by state-of-the-art techniques?**
- 3. How do results differ between southwest and northeast California study sites?**

# **Specific Objectives of the Study**

## **Research Objective 2**

**Implement the forest monitoring program established in Objective 1 to analyze the extant data sets (spanning 1985-2000)**

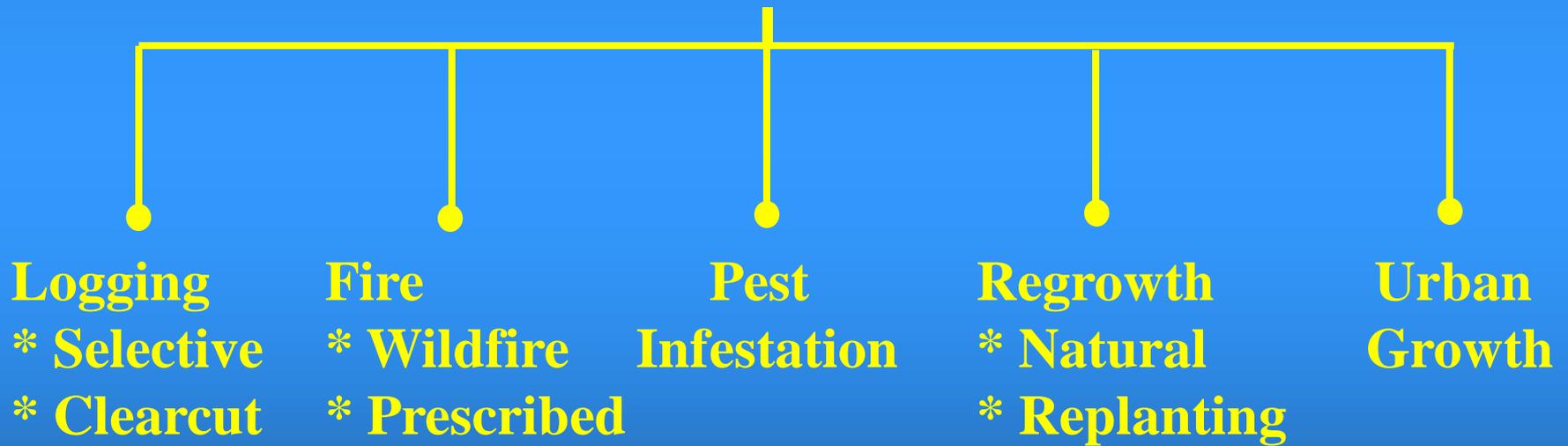
# **Specific Objectives of the Study**

**Research Objective 2: Related research questions for the following time periods- 1985-1990, 1990-1995, 1995-2000**

- 1. How is forest cover change manifested in terms of a) geographical extent, b) cause, c) rate?**
- 2. How does forest cover change affect landscape spatial patterns (e.g., habitat fragmentation)?**
- 3. How are changes in forest cover associated with mapped lifeform and species categories in the region?**

# Research Relevance

## LCLUC Disturbance Monitoring







**BREAKING NEWS**

**WILDFIRE IN S. CALIF.**

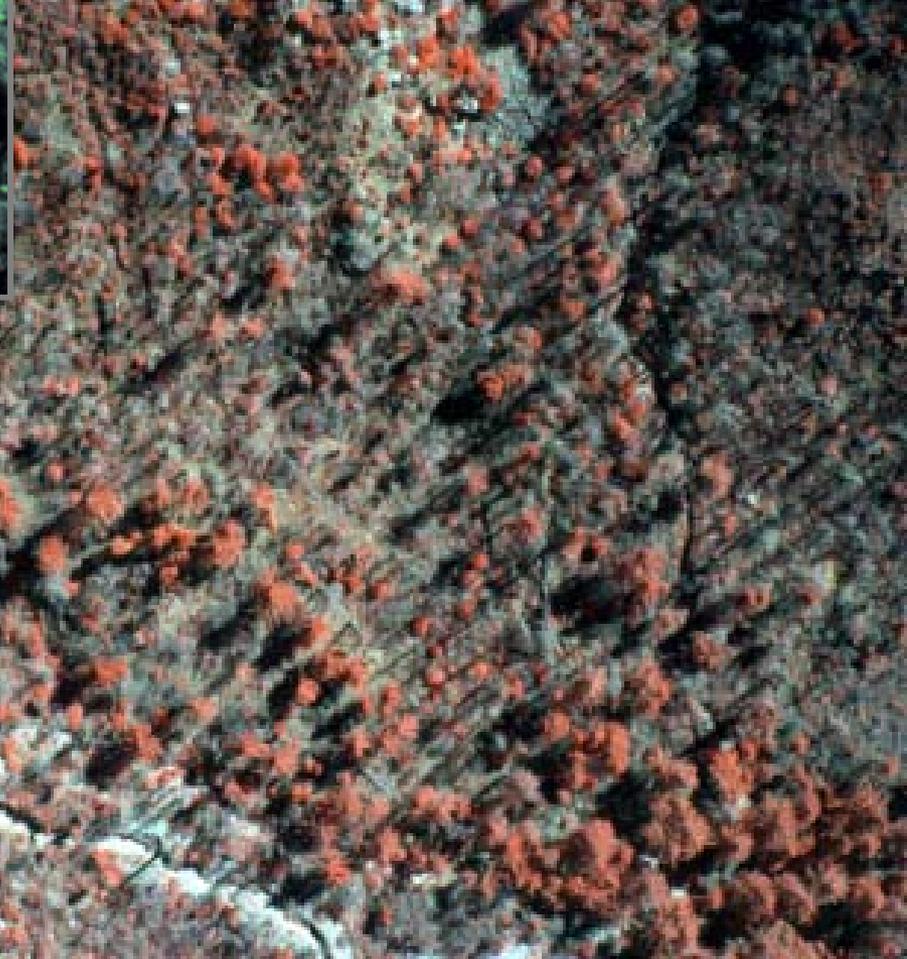
KGTV/FLAMES NEAR ALPINE  
CLOSE INTERSTATE 8

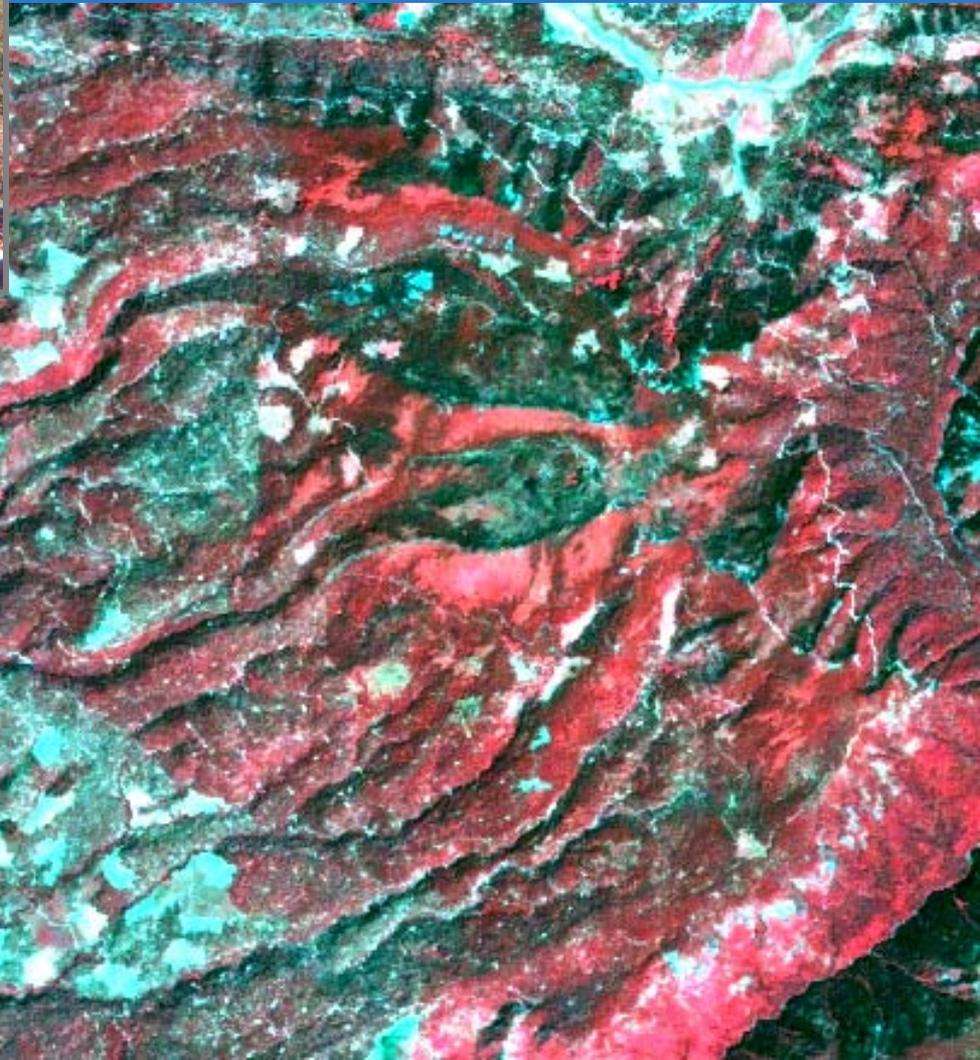
**CNN**

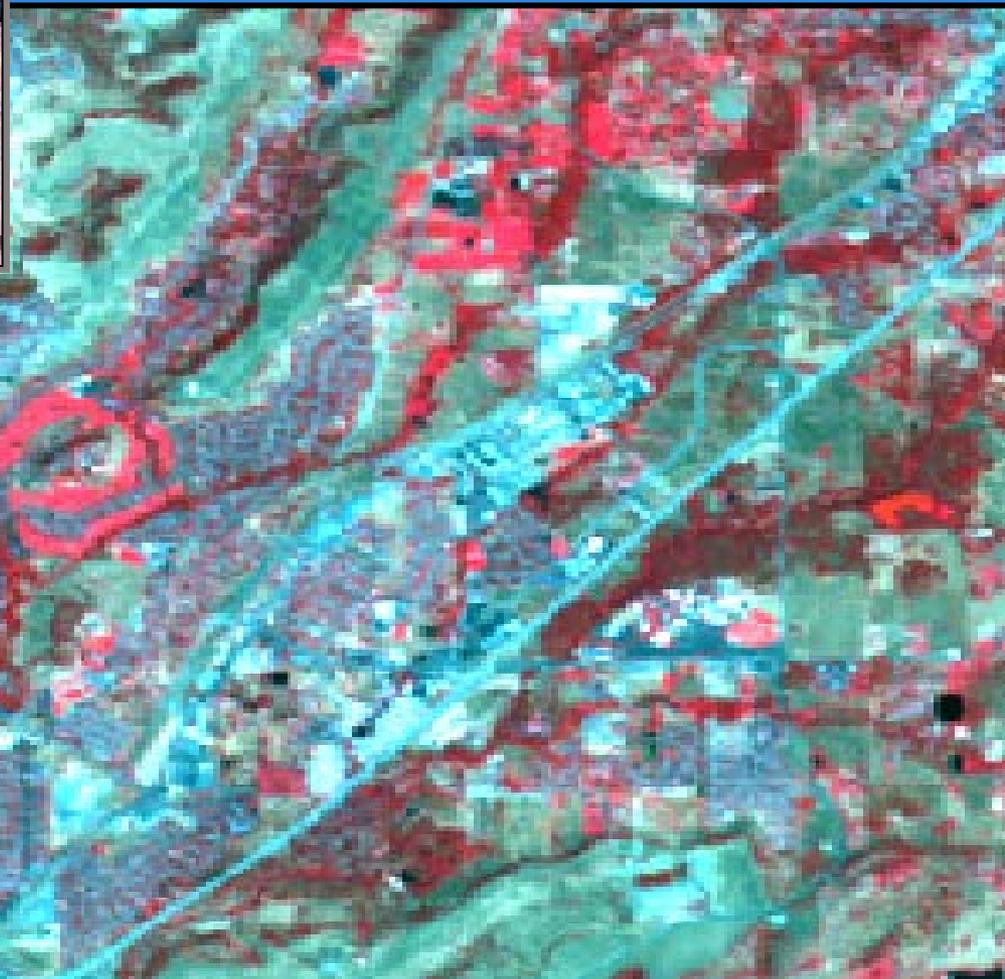
**LIVE**

9:47a ET



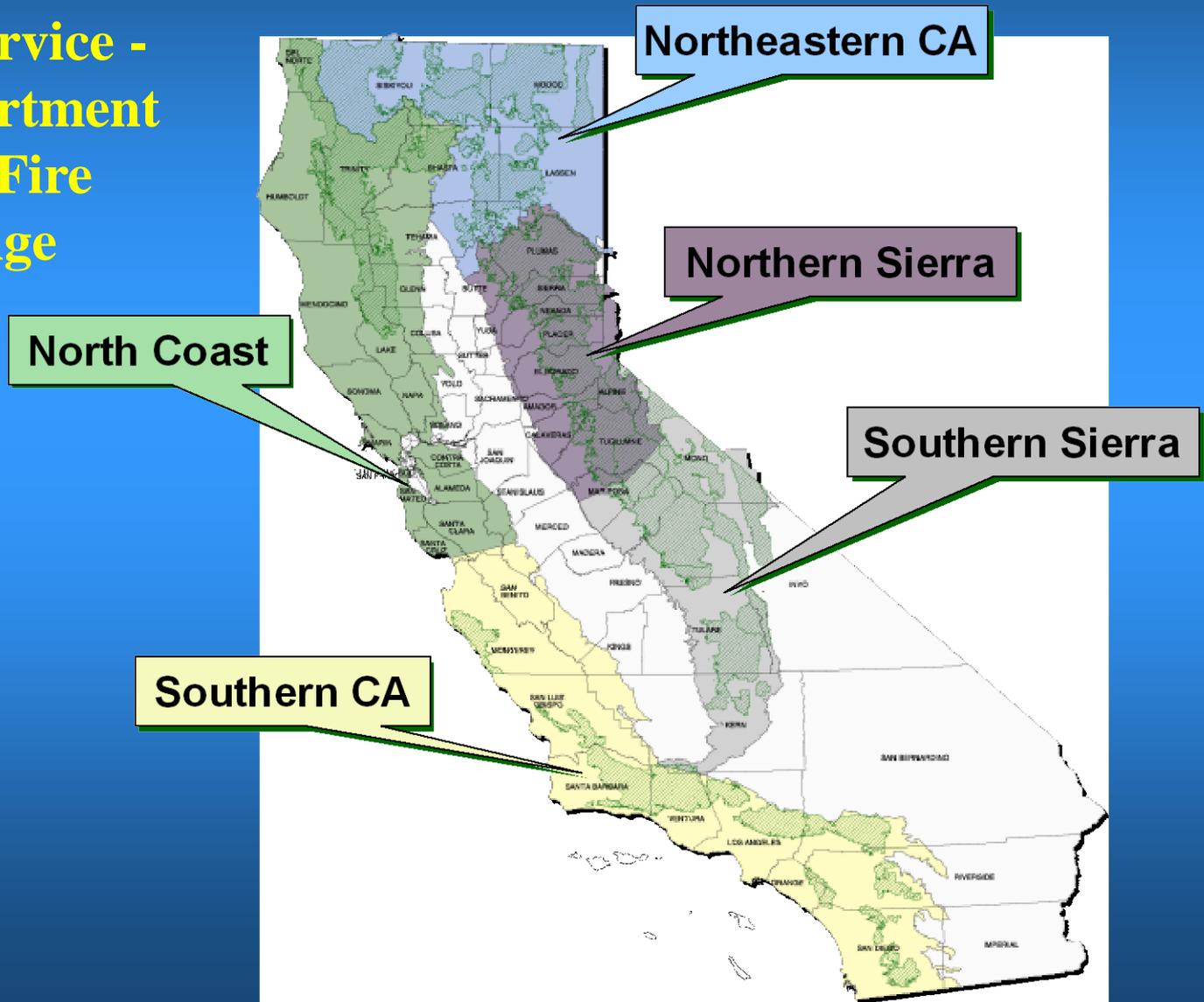






# Existing FS-CDF Program Methods

\*USDA Forest Service -  
California Department  
of Forestry and Fire  
Protection Change  
Monitoring  
Program



# Existing FS-CDF Program Methods

## Change Data

with accuracy assessment

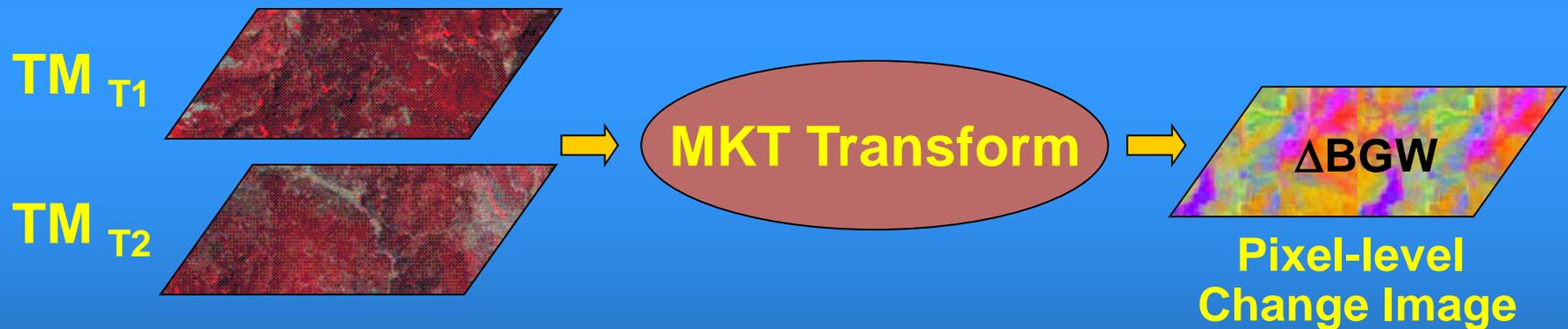
- - 70 to - 100% CC
- - 41 to - 70% CC
- - 16 to - 40% CC
- + 15 to - 15% CC
- + 16 to + 40% CC
- + 41 to + 100% CC
- Shrub/Grass Decrease > 15%
- Shrub/Grass Increase > 15%
- Change w/in Existing Urban Area
- Cloud or Cloud Shadow

## Cause Database

- Mortality
- Wildfire
- Harvest
- Regeneration
- Fuel Break
- Thinning
- Development
- Conversion
- Other
- Unknown

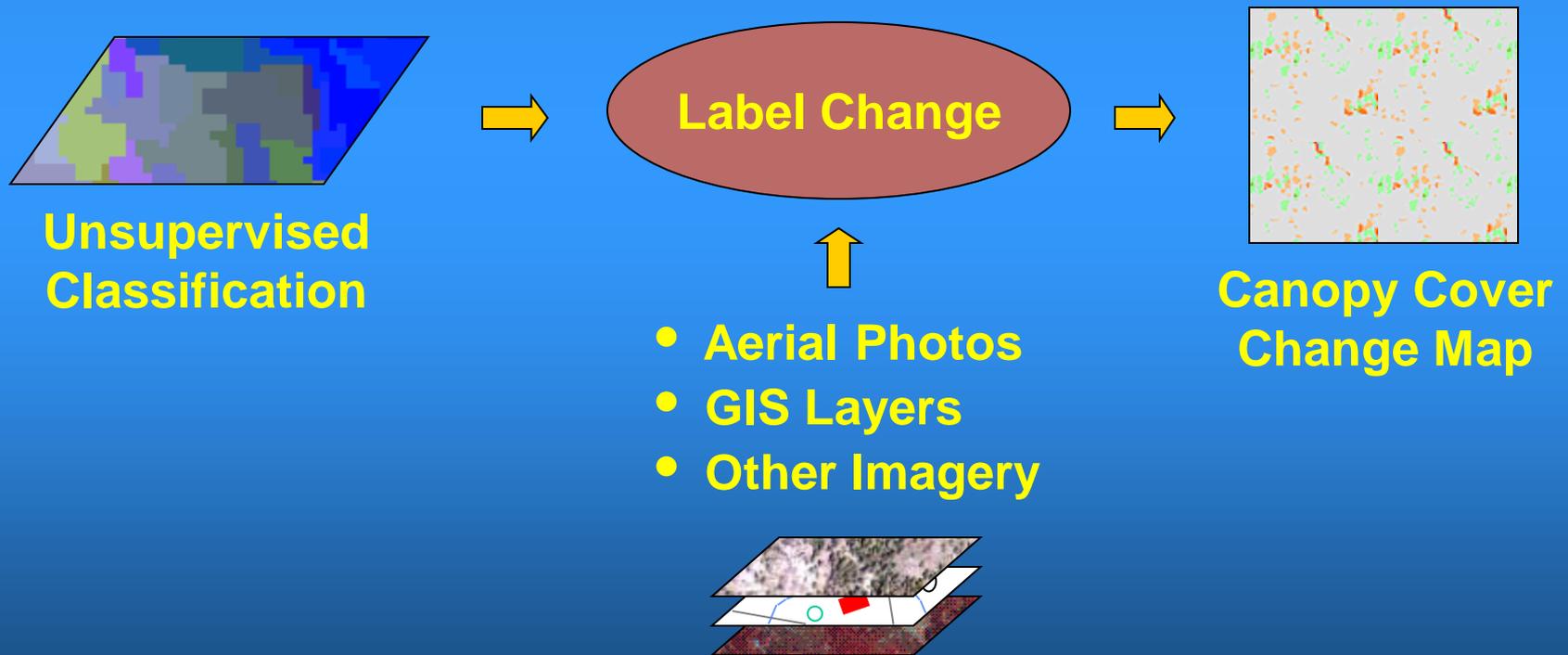
# Existing FS-CDF Program Methods

## Expert Program Methods - Phase I Image Processing



# Existing FS-CDF Program Methods

## Expert Program Methods - Phase II Classify and Label Change



# Study Sites



# Current Methods

The research proposed presents a comprehensive, multitemporal, multistage forest cover change monitoring strategy

## 1. Data sets:

- Landsat 5 and 7, Aerial Photos, ADAR, IKONOS
- Fire Perimeters, Pest Records, Logging Records
- Canopy cover measurements (densitometer and high spatial resolution resolution multispectral data)

# Canopy Cover Measurements



**IKONOS Data (4 meter)**



# Current Methods

## 2. Radiometric Normalization

## 3. Image Enhancement Techniques

- Spectral Mixture Analysis
- Change Vector Analysis
- Spatial Indices (Texture-Context)

## 4. Classification

- Classification Tree
- ANN-Fuzzy ARTMAP

## 5. Evaluation

- Error Matrix, Fuzzy Accuracy, Spatial Accuracy

# Scientific Results

- **Atmospheric Correction /Normalization**
- **Image Change Enhancement**
- **Image Classification**
- **Accuracy Assessment**

# **Atmospheric Correction/ Normalization**

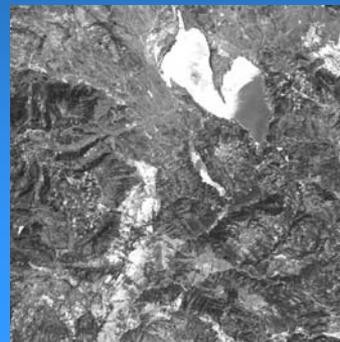
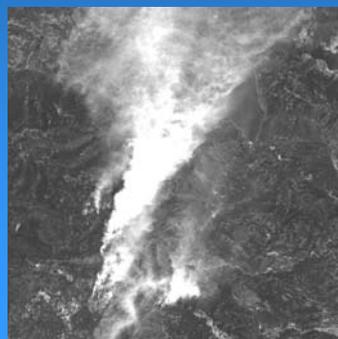
- **Space-varying haze correction (Carlotto, 1999)**
- **Spectral measurement space consists of two subspaces**
  - **Subspace 1 = bands affected by scattering (visible)**
  - **Subspace 2 = bands less affected by scattering (infrared)**
- **Correspondence between the two subspaces used to predict Subspace 1 as a function of Subspace 2 on a per-pixel basis**

# Spatially Varying Haze Correction

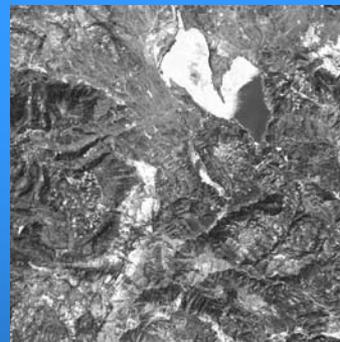
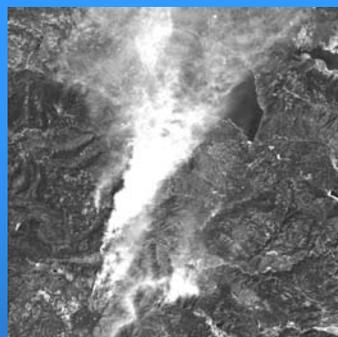
**Uncorrected**

**Corrected**

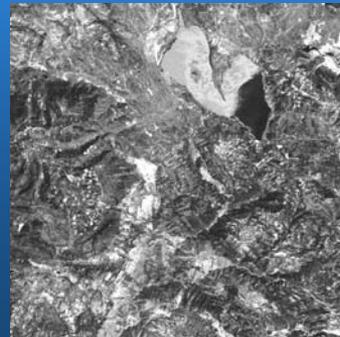
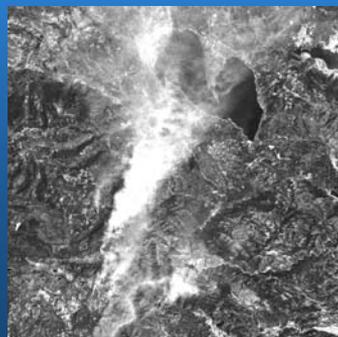
**Landsat 7  
ETM Band 1**



**Landsat 7  
ETM Band 2**



**Landsat 7  
ETM Band 3**



# Atmospheric Correction/ Normalization

- **Results (ANOVA between pre vs. post correction)**
  - **The algorithm removes the effects of smoke plumes without altering the pixel values of areas unaffected by haze**
  - **Areas that *have* changed between dates are readily detected, post-normalization**
  - **Reliable and easily implemented across varying topography and landcover types**

# Image Enhancement Comparisons

- **Study attempted to**
  - **Examine the potential of Multitemporal Spectral Mixture Analysis (MSMA) to map changes in forest cover over large areas**
  - **Compare the MSMA approach to that of MKT**
  - **Evaluation based on**
    - **Classification accuracy**
    - **Ease of use, flexibility of implementation, operational issues etc.**

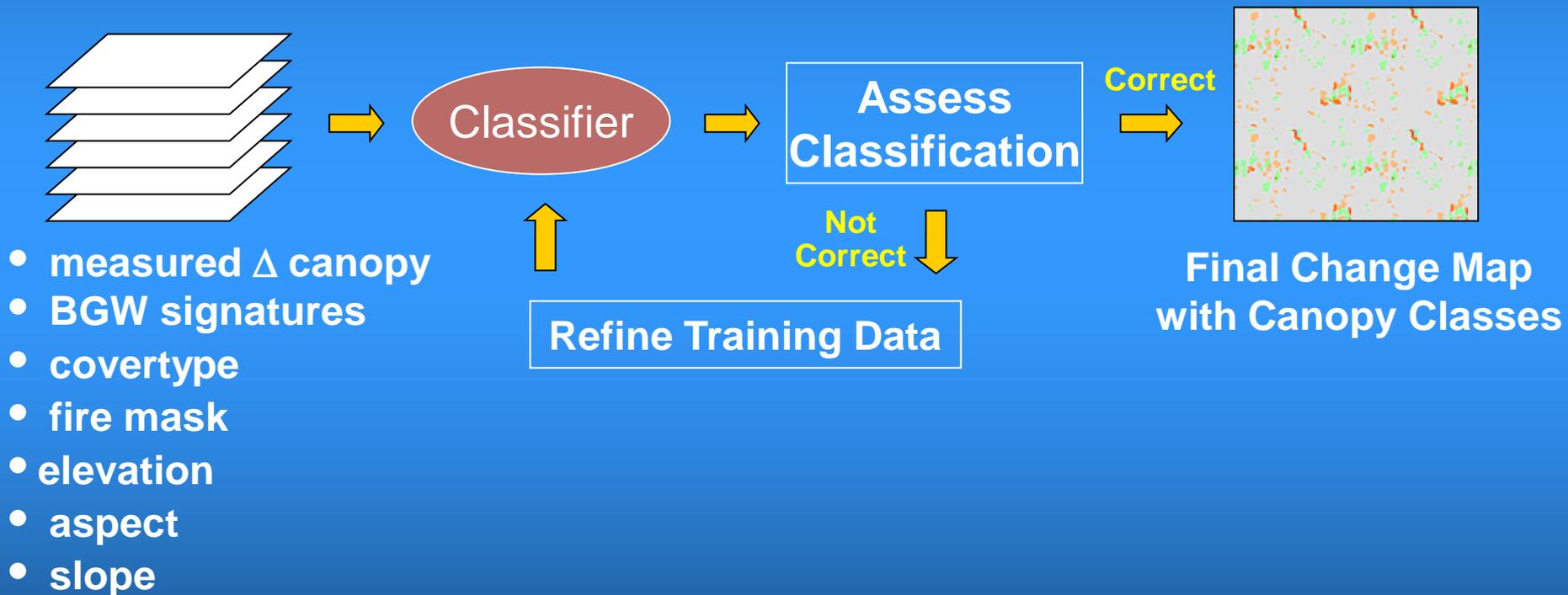
# Image Enhancement Comparisons

- **Results**
  - **MSMA produces four change fractions (i.e.,  $\Delta$  shade,  $\Delta$  green veg.,  $\Delta$  non-photosynthetic veg., and  $\Delta$  soil) using reference endmembers**
  - **MSMA  $\Delta$  fractions are biophysically robust and interpretable**
  - **MSMA  $\Delta$  classification using approach was repeatedly 5-10% more accurate than MKT in all investigations**
  - **However, MKT produces equally reliable  $\Delta$  features and is more easily implemented**

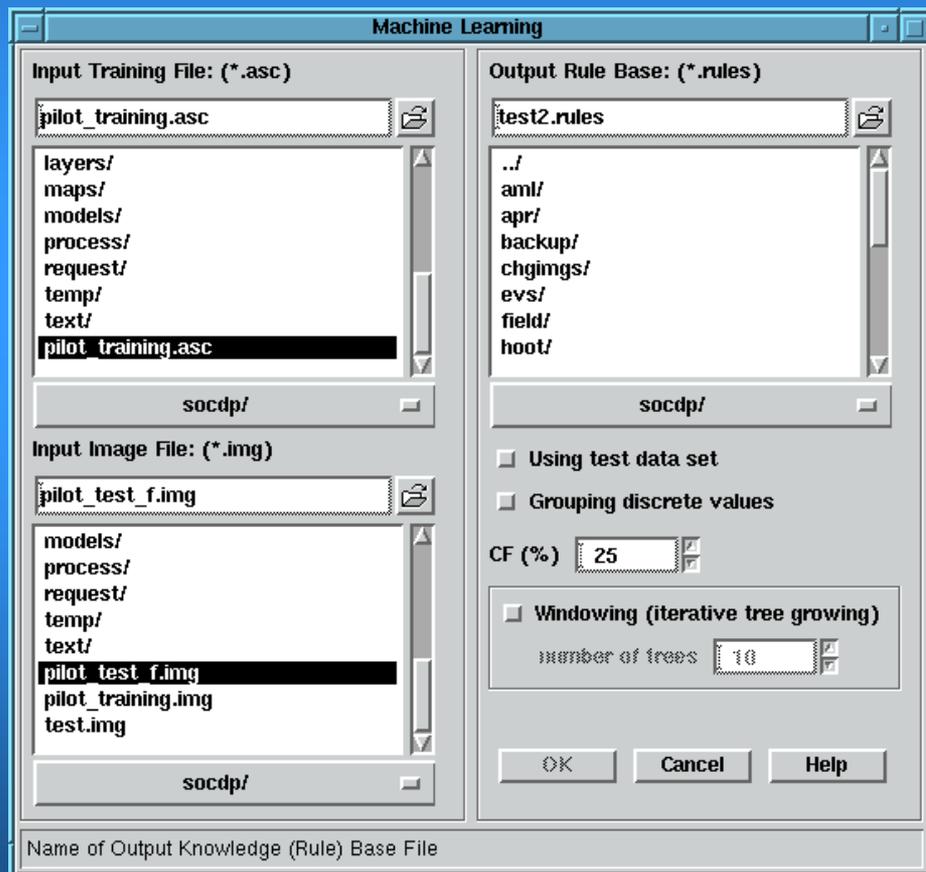
# Image Classification Comparisons I

- **Study attempted to**
  - **Examine the potential of a C4.5-based classification tree Machine Learning Classifier (MLC)**
  - **Compare the utility of the MLC approach to S-plus**
  - **Evaluation of MLC vs. S-plus based on**
    - **Classification accuracy**
    - **Ease of use, flexibility of implementation, operational issues etc.**

# Classification Approach

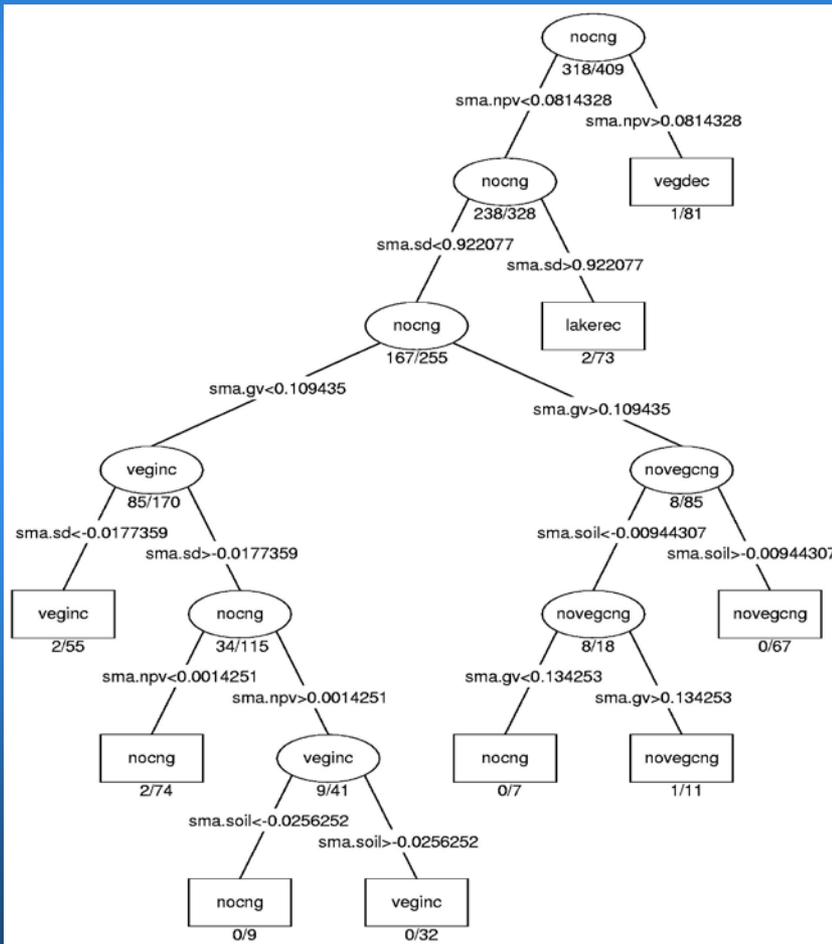


# Machine Learning Classifier



- Useful interface with Erdas
- Rules easily classified
- Deals with categorical data well
- Iterative tree growing negates the need for pruning
- Tendency to create large trees
- Rules determine that unclassified pixels receive value of largest category in the map
- Thematic output has been unreliable

# S-plus Classification Tree Approach



- No existing interface with Erdas
- Rules easily classified
- Difficulty with categorical data with layers having more than 31 classes
- Trees are manageable, through pruning, providing more control
- Thematic output is generally reliable

# S-Plus classification accuracy (Southern California)

		Reference class									
		1	2	3	4	5	6	7	8	9	Sites
Classified as	1	97	9	2				1			109
	2	4	47	1	1	1					54
	3	2		58		1					61
	4	9	4	9	74	4		8	10		118
	5				1	75			1	4	81
	6						25		2		27
	7	2	1	1				69			73
	8					2	1		65		68
	9									71	71
Sites		114	61	71	76	83	26	78	78	75	662

**Overall Accuracy = 88%**

Class	Class Description
1	-71 to -100% CC
2	-41 to -70% CC
3	-16 to -40% CC
4	+15 to -15% CC
5	+16 to +40% CC
6	+41 to +100% CC
7	Shrub/grass decrease > 15%
8	Shrub/grass increase > 15%
9	Change within existing developed areas

Producer's Accuracy	
Class	%
1	85
2	77
3	82
4	97
5	90
6	96
7	88
8	83
9	95

User's Accuracy	
Class	%
1	89
2	87
3	95
4	63
5	93
6	93
7	95
8	96
9	100

# MLC classification accuracy (Southern California)

		Reference class									
		1	2	3	4	5	6	7	8	9	Sites
Classified as	1	89	6	2							97
	2	2	37	2				1			42
	3	17	10	70	3	8	1	5	4	1	119
	4			1	70	1		2	3	1	78
	5	1			2	55			1		59
	6					2	21				23
	7	4		7	2			70			83
	8				1	4			74		79
	9		1							81	82
Sites		113	54	82	78	70	22	78	82	83	662

**Overall Accuracy = 86%**

Class	Class Description
1	-71 to -100% CC
2	-41 to -70% CC
3	-16 to -40% CC
4	+15 to -15% CC
5	+16 to +40% CC
6	+41 to +100% CC
7	Shrub/grass decrease > 15%
8	Shrub/grass increase > 15%
9	Change within existing developed areas

Producer's Accuracy	
Class	%
1	79
2	69
3	85
4	90
5	79
6	95
7	90
8	90
9	98

User's Accuracy	
Class	%
1	92
2	88
3	59
4	90
5	93
6	91
7	84
8	94
9	99

# Order of variables used at each split:

S = S-plus, M = MLC

<b>Variables</b>	<b>1</b>	<b>2-3</b>	<b>4-6</b>	<b>7-9</b>	<b>10-12</b>
<b>Fire</b>			S	M	
<b>Aspect</b>				M	
<b>Slope</b>				M	
<b>Elevation</b>		S M			
<b>Vegetation</b>		S M			
<b>MKT_1</b>			S M		
<b>MKT_2</b>	S M				
<b>MKT_3</b>			S		M
<b>MKT_4</b>			M		
<b>MKT_5</b>			M		
<b>MKT_6</b>				S	M

# Image Classification Comparisons I

- **Results**
  - **Both approaches produce canopy cover change maps of high classification accuracy (i.e., overall accuracy and individual class accuracies)**
  - **Due to large trees produced by C4.5, rules can tend to be less *generalizable* to larger areas**
  - **In general, S-plus classifies better at the pixel level and at the site level**
  - **S-plus can be easily implemented**

# Image Classification Comparisons II

- **Study attempted to**
  - **Examine the potential of Fuzzy ARTMAP**
  - **Compare the utility of the ARTMAP approach to S-plus**
  - **Evaluation of ARTMAP vs. S-plus based on**
    - **Classification accuracy**
    - **Ease of use, flexibility of implementation, operational issues etc.**

# ARTMAP classification accuracy (Southern California) (test site)

		Reference class									
		1	2	3	4	5	6	7	8	9	Sites
Classified as	1	17									17
	2		29	1							30
	3			23							23
	4				11						11
	5					27	1				28
	6						1				1
	7							10			10
	8								24		24
	9									15	15
Sites		17	29	24	11	27	2	10	24	15	159

**Overall Accuracy = 98.7%**

Class	Class Description
1	-71 to -100% CC
2	-41 to -70% CC
3	-16 to -40% CC
4	+15 to -15% CC
5	+16 to +40% CC
6	+41 to +100% CC
7	Shrub/grass decrease > 15%
8	Shrub/grass increase > 15%
9	Change within existing developed areas

Producer's Accuracy	
Class	%
1	100
2	100
3	96
4	100
5	100
6	50
7	100
8	100
9	100

User's Accuracy	
Class	%
1	100
2	97
3	100
4	100
5	96
6	100
7	100
8	100
9	100

# Accuracy Assessment

- **Approaches**
  - **Conventional error matrix (non-spatial)**
  - **Fuzzy accuracy (non-spatial)**
  - **Using misclassification probabilities (per class) to map spatial variation in error**

# Forest Canopy Cover Change Map



San Diego  
County

-  +15 to -15 % CC (Little or No Change)
-  +16 to +40 % CC
-  +41 to +100 % CC
-  -16 to -40 % CC
-  -41 to -70 % CC
-  -71 to -100 % CC
-  Change within Existing Urban Area
-  Shrub/Grass Decrease > 15 %
-  Shrub/Grass Increase > 15 %



# Change Map Error Matrix

Reference Class

Classified As	Reference Class										Sites
	1	2	3	4	5	6	7	8	9	15	
1	7										7
2		12									12
3			5	2							7
4			1	148	1		3	7	2		162
5					4						4
6						1					1
7				4			15		1		20
8				1	1			15			17
9				4					25		29
15										1	1
Sites	7	12	6	159	6	1	18	22	28	1	260

Class Description

Producer's Accuracy

User's Accuracy

Class	Class Description
1	-71 to -100% CC
2	-41 to -70% CC
3	-16 to -40% CC
4	+15 to -15% CC (Little or No Change)
5	+16 to +40% CC
6	+41 to +100% CC
7	Shrub/Grass Decrease > 15%
8	Shrub/Grass Increase > 15%
9	Change within Existing Developed Area
15	Cloud or Cloud Shadow

Class	Producer's Accuracy	Notes
1	= 7 / 7 = 100%	Tree Decr
2	= 12 / 12 = 100%	96%
3	= 5 / 6 = 83%	
4	= 148 / 159 = 93%	
5	= 4 / 6 = 67%	Tree Incr
6	= 1 / 1 = 100%	71%
7	= 15 / 18 = 83%	
8	= 15 / 22 = 68%	
9	= 25 / 28 = 89%	
15	= 1 / 1 = 100%	

Class	User's Accuracy	Notes
1	= 7 / 7 = 100%	Tree Decr
2	= 12 / 12 = 100%	92%
3	= 5 / 7 = 71%	
4	148 / 162 = 91%	
5	= 4 / 4 = 100%	Tree Incr
6	= 1 / 1 = 100%	100%
7	= 15 / 20 = 75%	
8	= 15 / 17 = 88%	
9	= 25 / 29 = 86%	
15	= 1 / 1 = 100%	

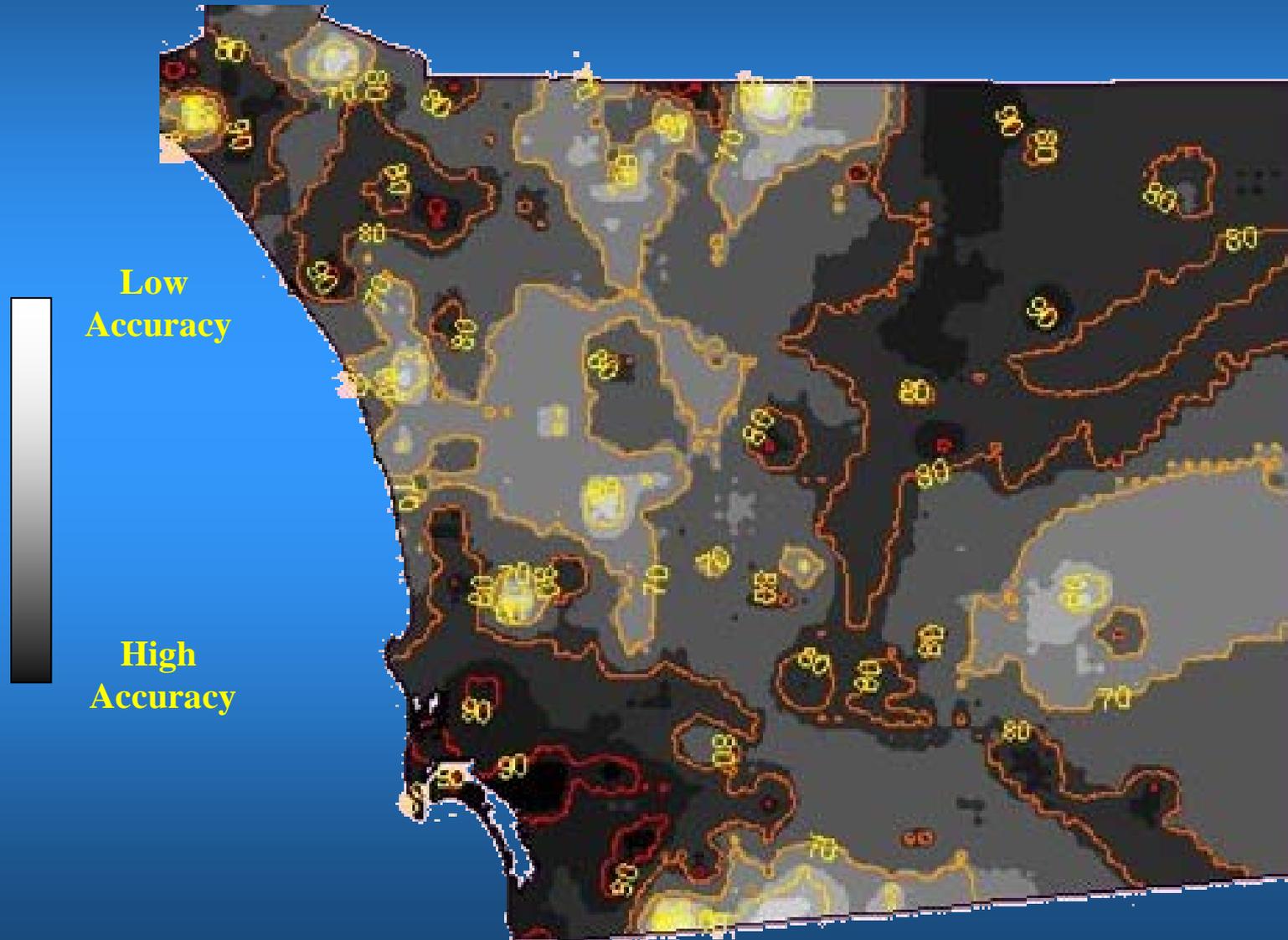
(inverse is error of omission)

(inverse is error of commission)

Training sites: 135 34%  
 AA sites: 260 66%  
 TOTAL sites: 395

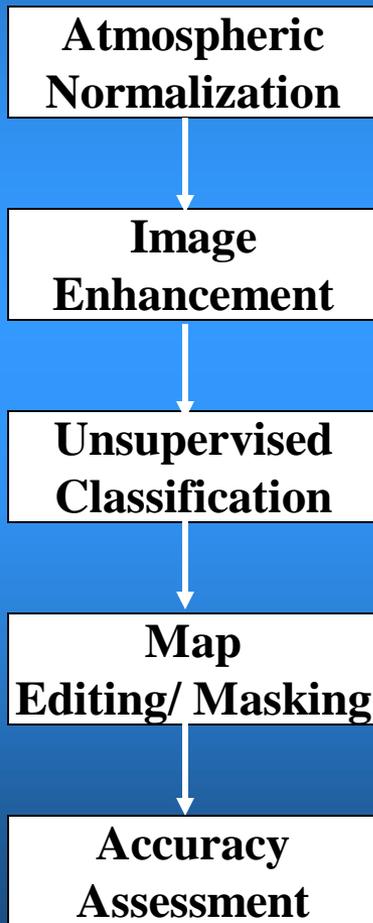
Overall Accuracy = 89.2%

# Estimated Accuracy Map



# Summary

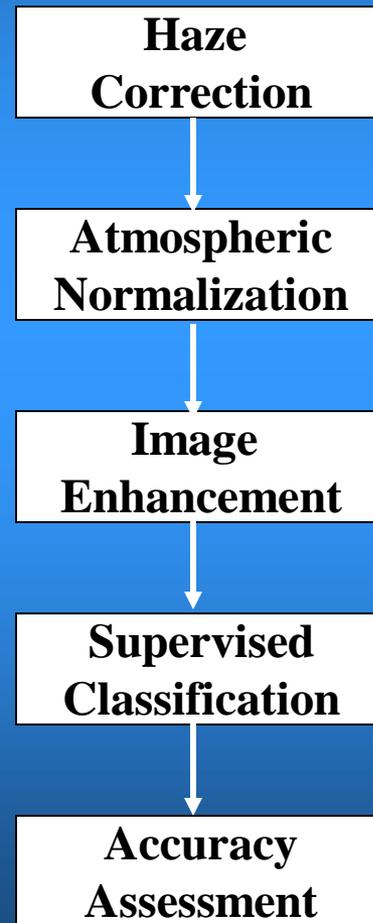
## Expert FS-CDF Approach



**Months of Work Involved**

3.0 -4.0      0.5-1.0

## Current SDSU Approach



# Future Steps

- **Atmospheric Correction /Normalization**
  - Compare DOS approaches with ATCOR3
- **Image Change Enhancement**
  - Examine the utility of Change Vector Analysis (CVA) vs. MKT (i.e, phenological increases)
- **Image Classification**
  - Compare S-plus Classification Tree approach to Fuzzy ARTMAP
- **Accuracy Assessment (spatial)**
  - Examine the use of ‘confidence’ images in conveying accuracy assessment

## **Most Significant Results/ Findings**

- **Spatially varying haze-correction algorithm should prove useful in fire-related studies**
- **Multitemporal Kauth Thomas is robust in enhancing change over large areas**
- **Classification Tree and or/ Fuzzy ARTMAP classifiers are better at mapping LCLUC because of their non-parametric nature, ability to incorporate non-image data and their generalizability**
- **Fuzzy approaches to mapping LCLUC and spatial accuracy mapping should be explored further**



# New Products

- **Forest cover change maps of California ecoregions available (Time period 1990-1996) featuring the canopy cover change classes, described previously, at:**
- **<http://www.frap.ca.gov>**