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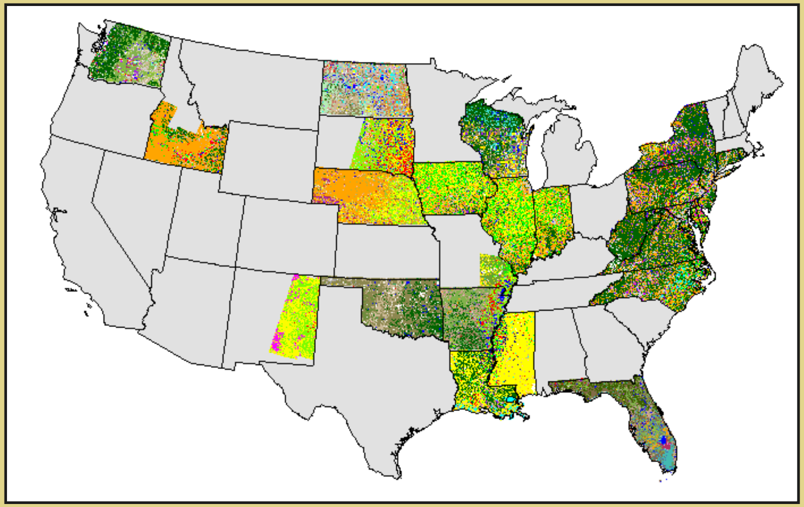
National Agricultural Statistics Service
Research and Development Division
Spatial Analysis Research Section

Classifier Shootout

A quantitative assessment of 3 popular image classification methodologies

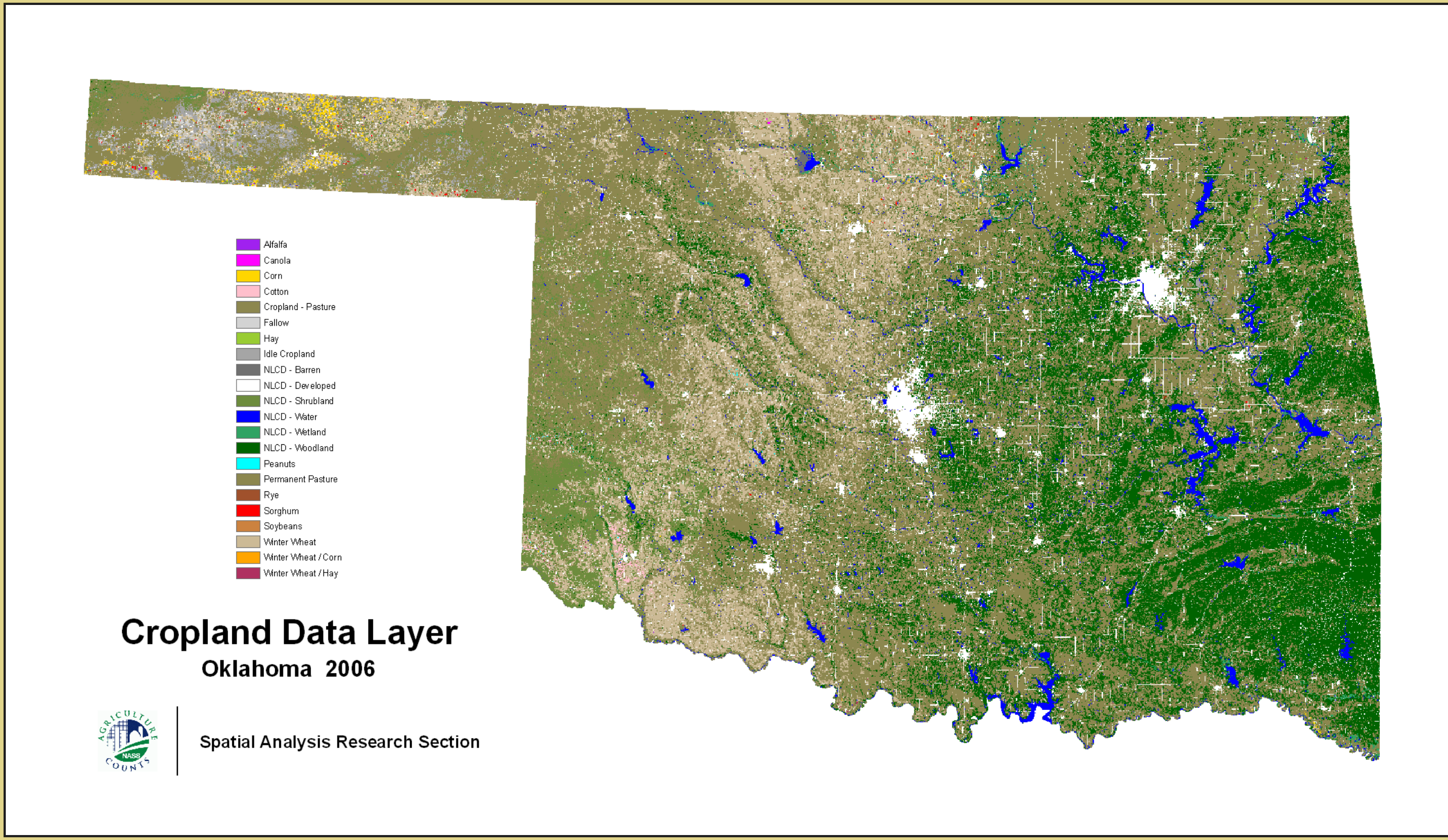
NASS Cropland Data Layer (CDL) Program

- State specific land cover classifications emphasizing row crop agriculture
  - Some regions done annually
    - Corn Belt, The Delta
  - Others “one-and-done”
    - Mid-Atlantic, Idaho, Florida



- Within NASS, CDL used to
  - Tighten confidence intervals on survey derived acreage estimates
  - Improve county level acreage estimates

Example CDL


Alfalfa
Canola
Corn
Cotton
Cropland - Pasture
Fallow
Hay
Idle Cropland
NLCD - Barren
NLCD - Developed
NLCD - Shrubland
NLCD - Water
NLCD - Wetland
NLCD - Woodland
Peanuts
Permanent Pasture
Rye
Sorghum
Soybeans
Winter Wheat
Winter Wheat / Corn
Winter Wheat / Hay
Cropland Data Layer
Oklahoma 2006
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Popular Image Classifiers

- **Maximum Likelihood (ML)**
  - – ERDAS Imagine
- **Object-oriented (OO)**
  - – Definiens Professional (eCognition)
- **Classification Tree (CT)** (Decision Tree)
  - – Rulequest See5.0

Goal

Evaluate which methodology is best

- Classification accuracy
- Large dataset handling
- Ease of use
- Cost
- Stability
- Speed

?

NASS Processing Assumptions

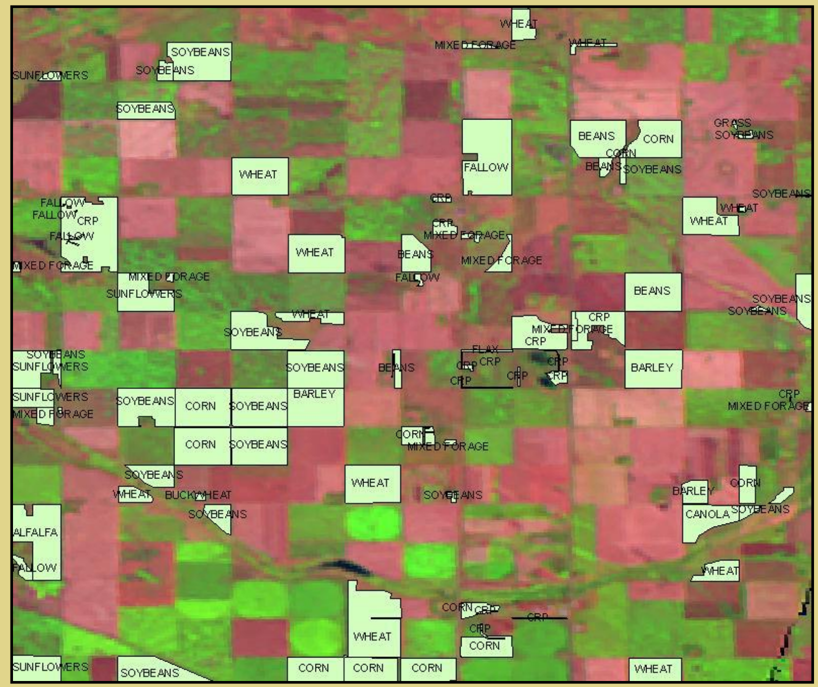
- Representative ground truth data is available
- Imagery data will not be radiometrically calibrated
- Data (imagery or ground truth) will not always be perfect

Supervised Classification Scenario!

Ground Truth – two sources

- NASS - June Agricultural Survey (JAS)
- Farm Service Agency (FSA) - Common Land Unit (CLU) / 578 data

NASS



FSA

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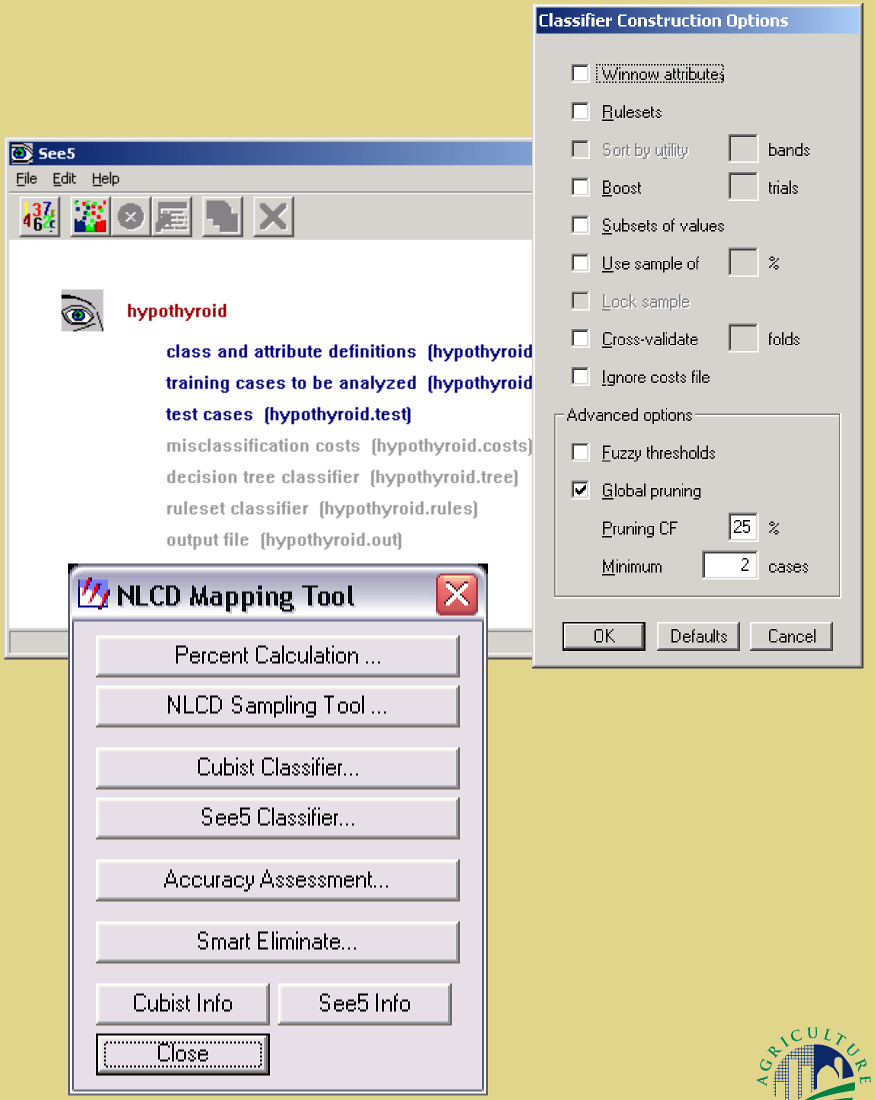
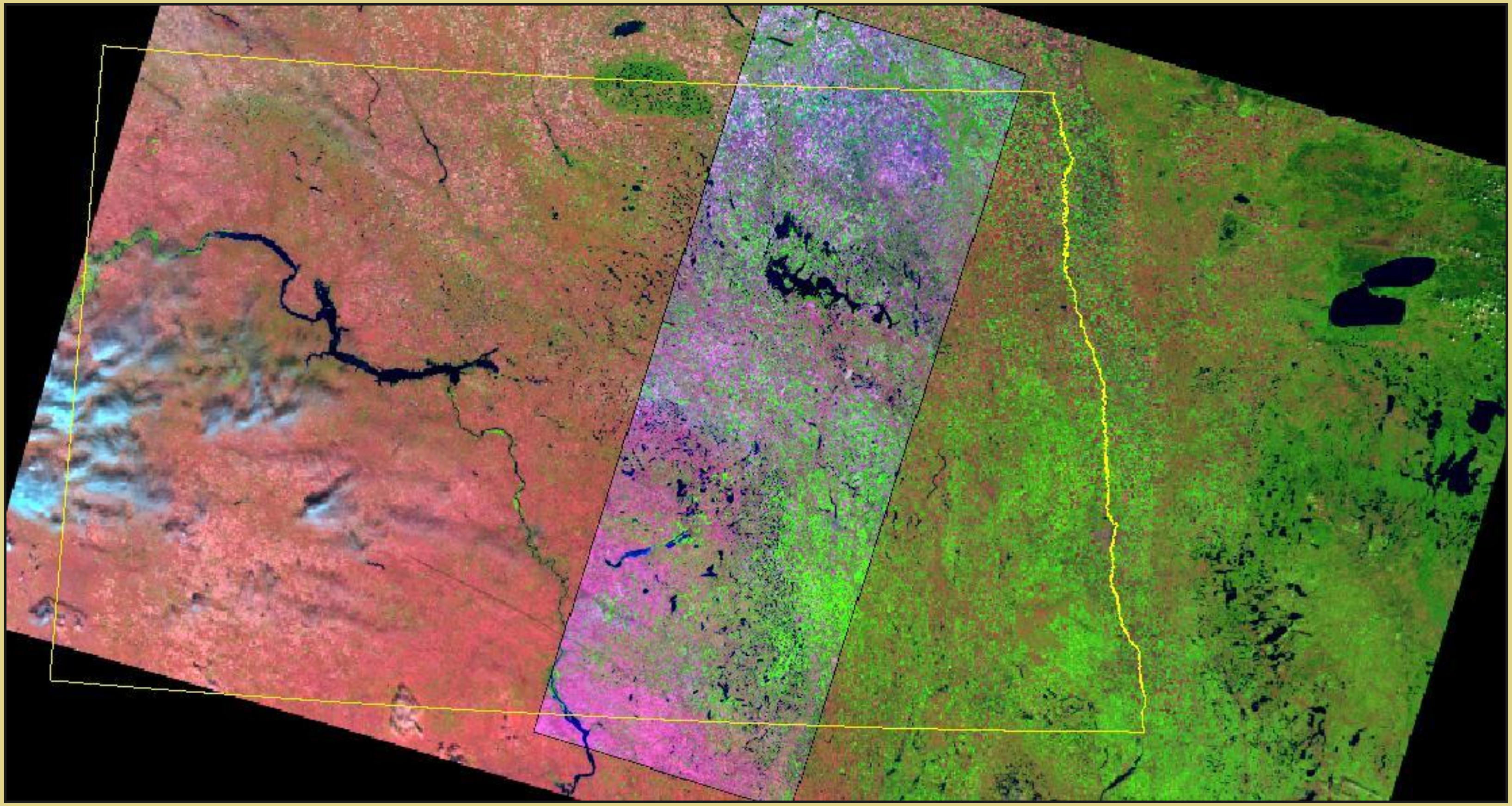
See5.0 *vs.* Other CT Software?

- Relatively cheap ($750)
- Incorporates a powerful ensemble method known as “boosting”
- An interface “NLCD Mapping Tool” has been written to easily interface it with ERDAS Image
  - Provided free by the USGS!



North Dakota Test Case



Resourcesat-1 AWiFS & LISSIII

22 August 2006

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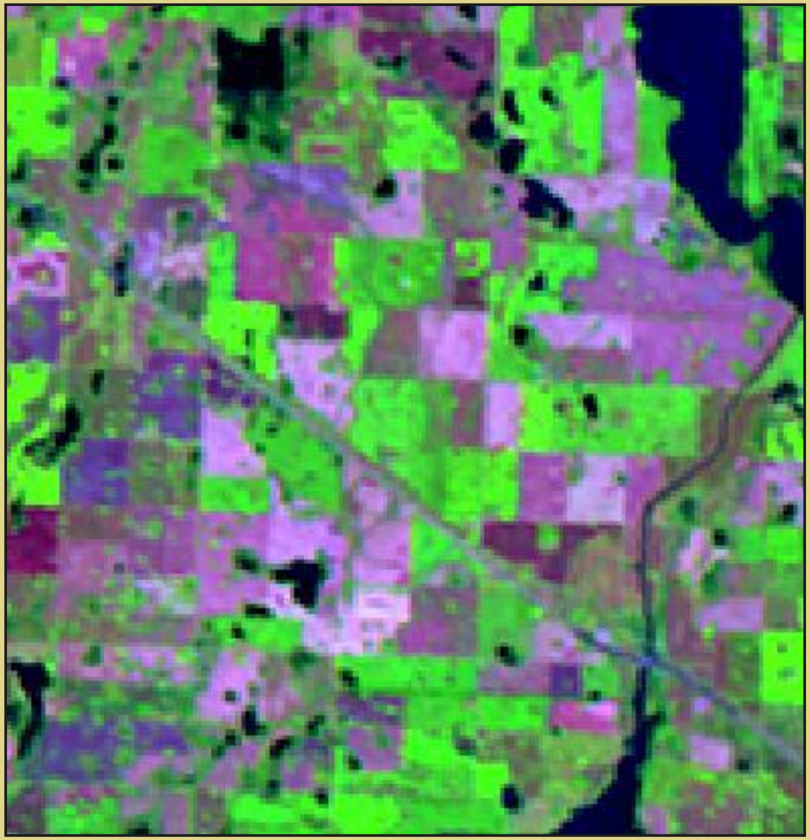
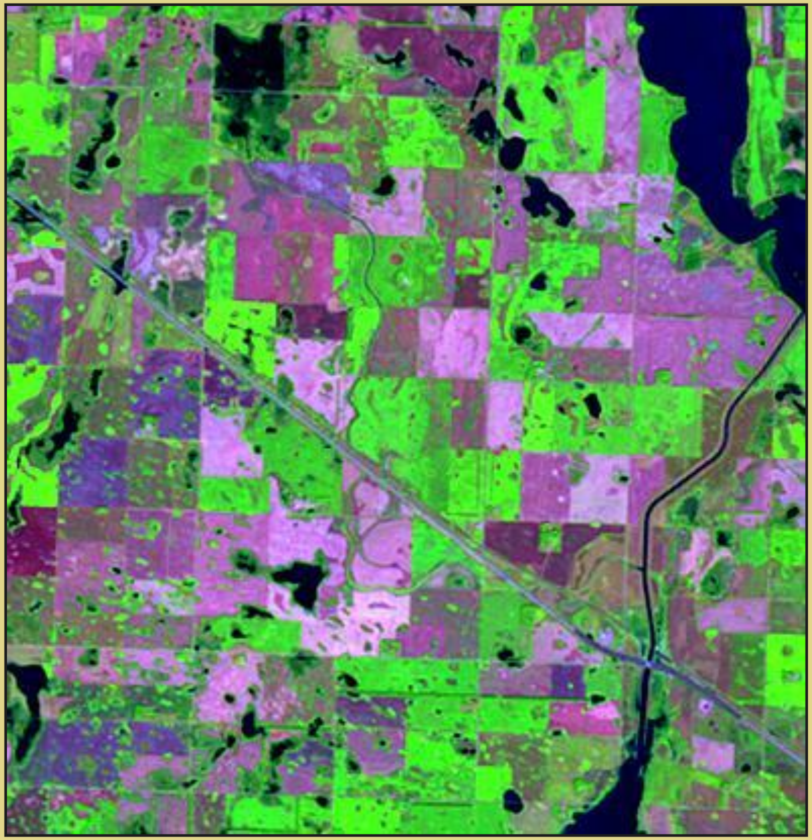
North Dakota Raw Data



AWiFS (56m, 4-band)
Red=Red, Green=NIR, Blue=SWIR



LISS-III (23m, 4-band)
Red=Red, Green=NIR, Blue=SWIR

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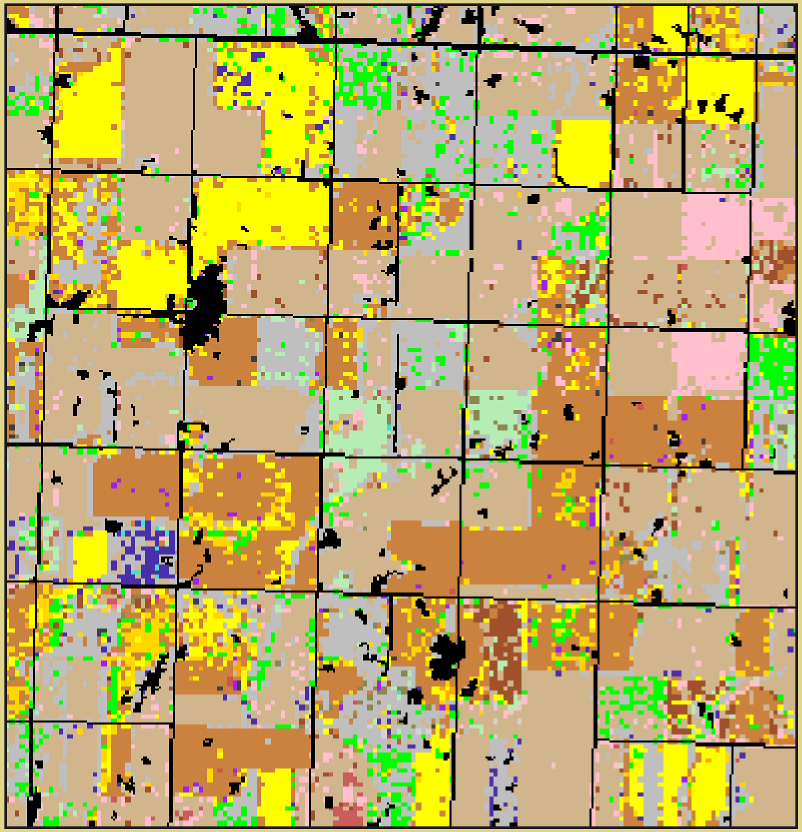
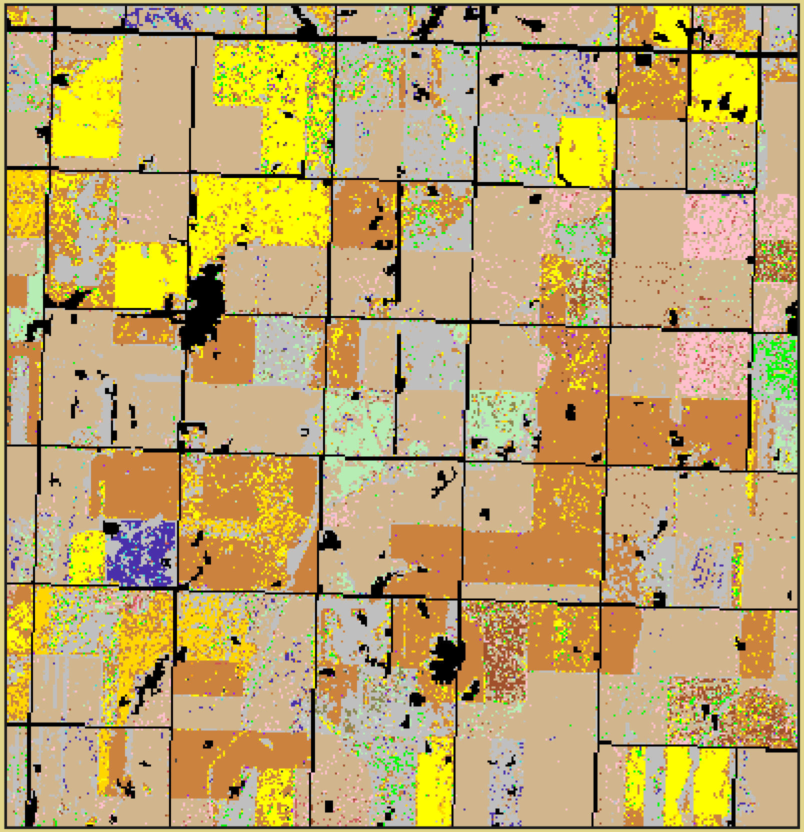
Methodology

- Reprojected/mosaicked to common projection
- Clipped AWiFS to LISS-III's extent
  - Only analyzed the region of overlap
- Built ground truth
  - Random half of FSA CLU/578 utilized for training
- Ran varieties of supervised classifications
  - Classification Tree
  - Object-oriented
  - Maximum Likelihood
  - (also created some hybrid classifications)
- Accuracy assessed
  - Against CLU/578 half that was not used for training

North Dakota Classification – some map results



AWiFS
50.1% pixels correct



LISS-III
52.4% pixels correct

Classification Tree output

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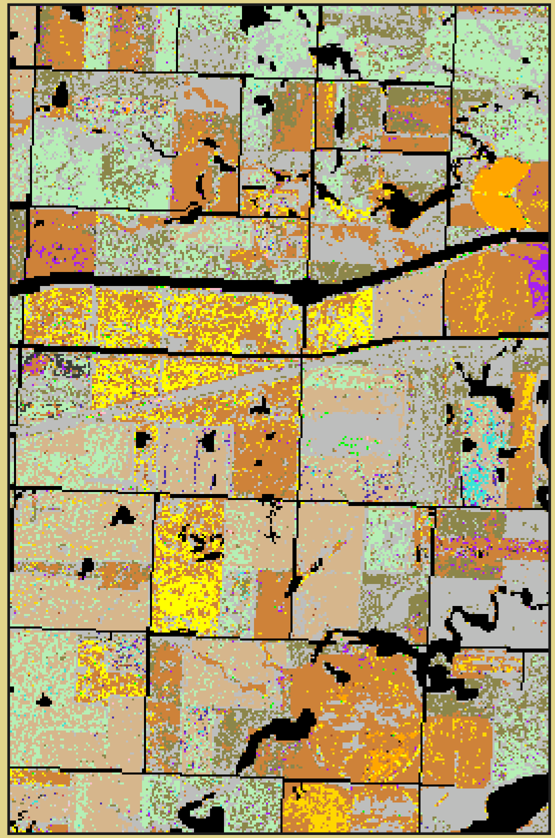
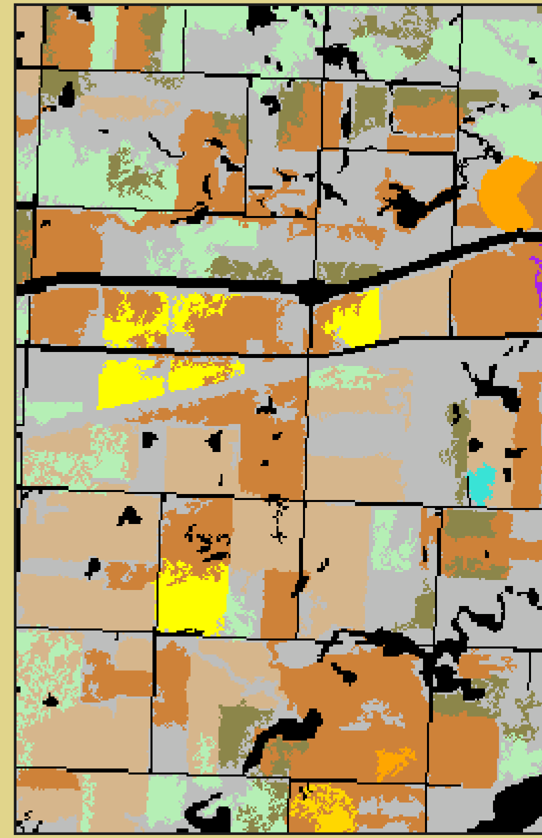
Post Classification Polishing

Applying a 20 acre minimum mapping unit (MMU)

Raw Scene



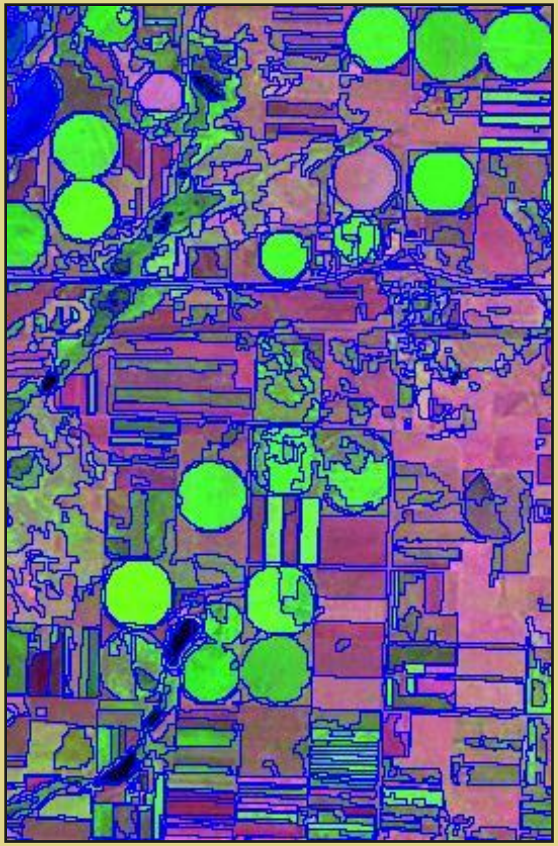
Initial CT Analysis



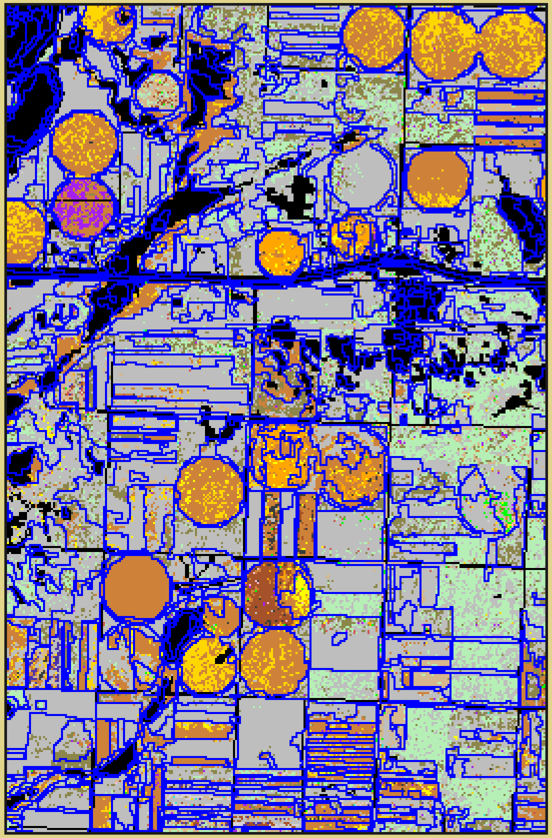
20 acre MMU applied

Post Classification Polishing

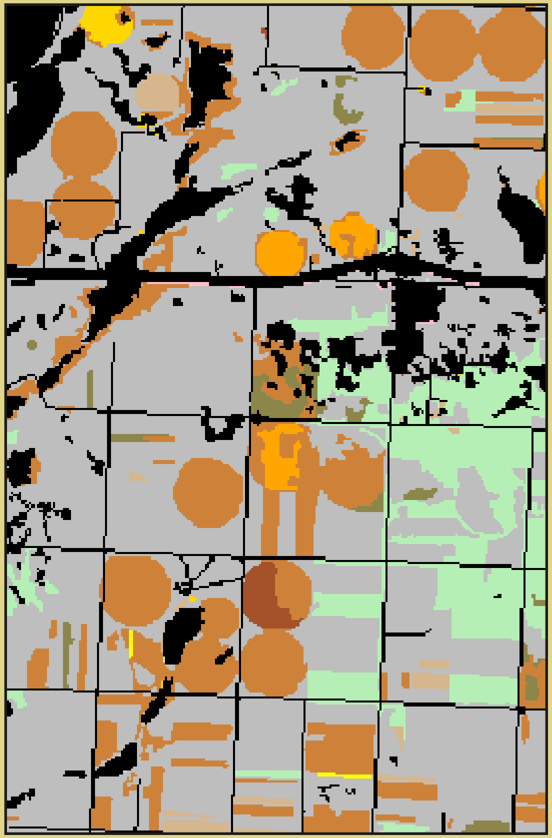
Hybrid approach - Definiens Professional segment fill



Raw Segmented Scene



Initial CT Analysis



Majority Fill Segments

North Dakota Quantitative Results

	AWiFS	LISSIII
Maximum Likelihood	48.1%	50.4%
Maximum Likelihood (20 acre MMU)	51.0%	53.3%
Object-oriented (spectral)	40.8%	40.5%
Object-oriented (geometry*)	17.4%	???
Classification Tree	50.1%	52.4%
Classification Tree (20 acre MMU)	**54.6%**	**57.6**%
Hybrid (OO segment fill of CT)	53.9%	55.5%

? - software/memory file size issue

* - rectangular fit, length/width, radium of smallest enclosing polygon, main direction, and density

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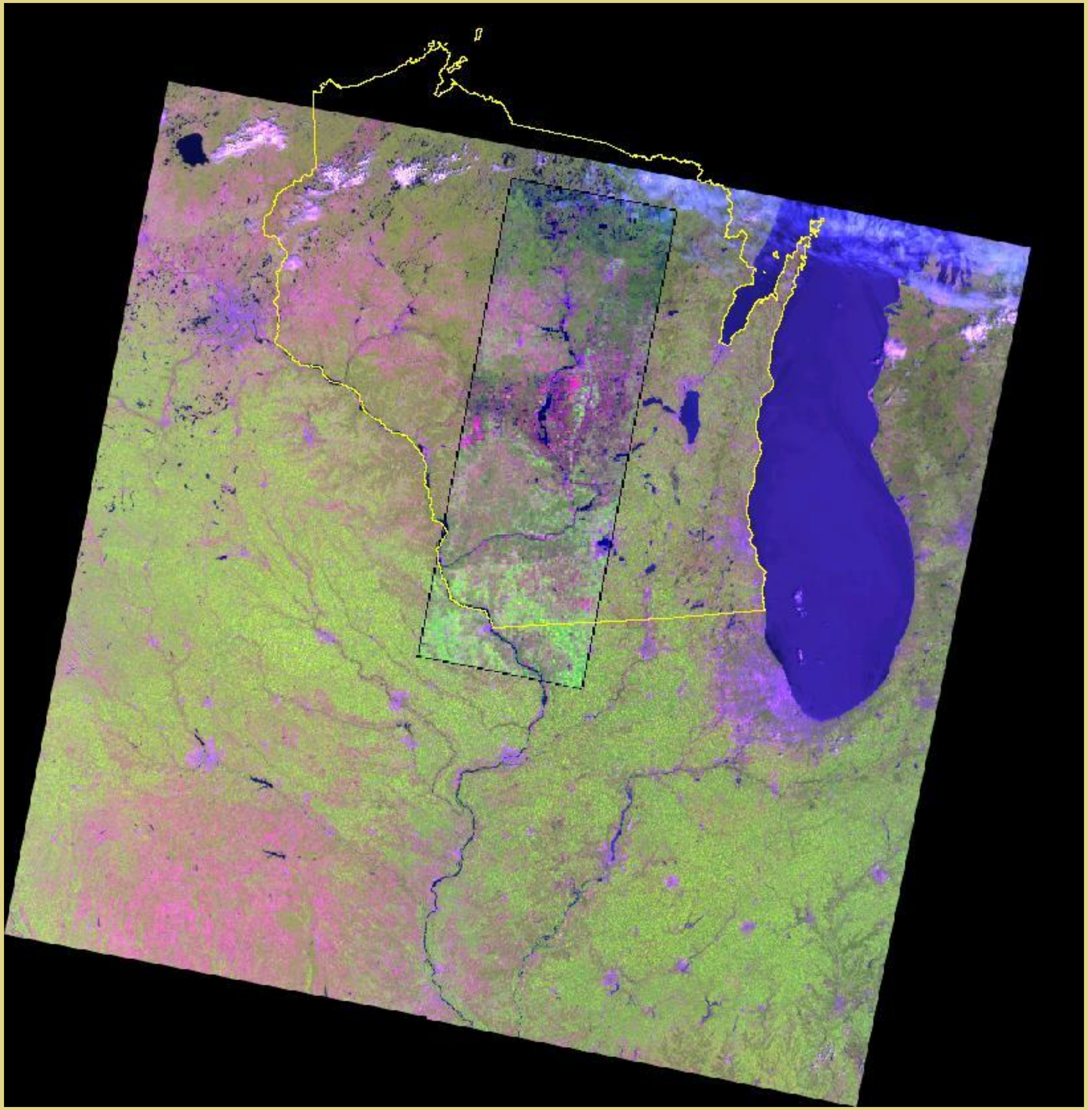
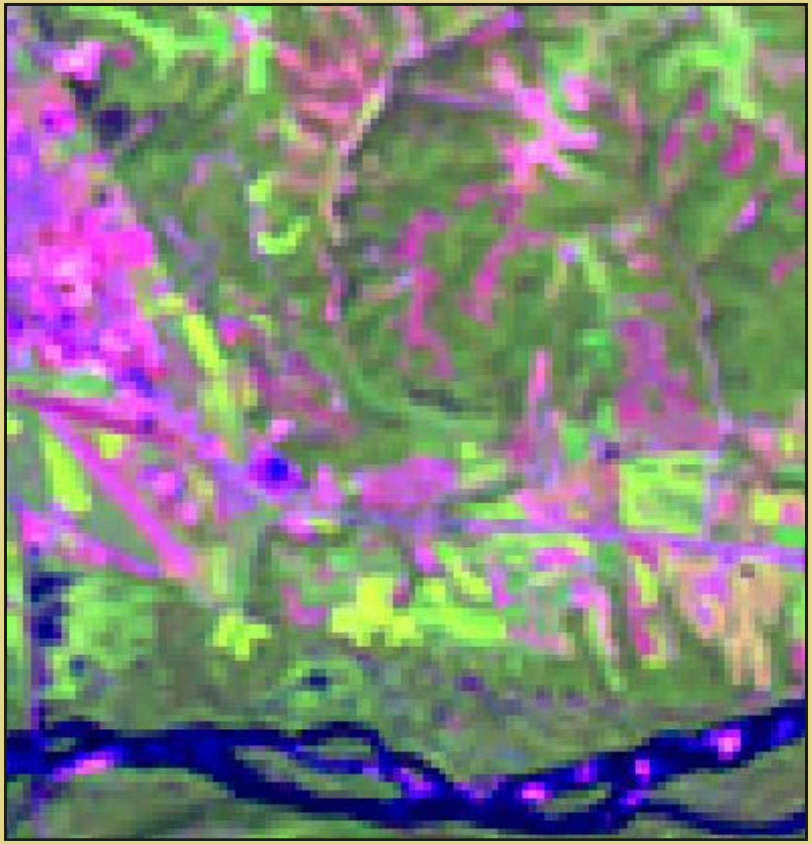
Wisconsin Test Case

31 July 2006



Wisconsin Raw Data



AWiFS (56m, 4-band)

Red=Red, Green=NIR, Blue=SWIR

LISS-III (23m, 4-band)

Red=Red, Green=NIR, Blue=SWIR

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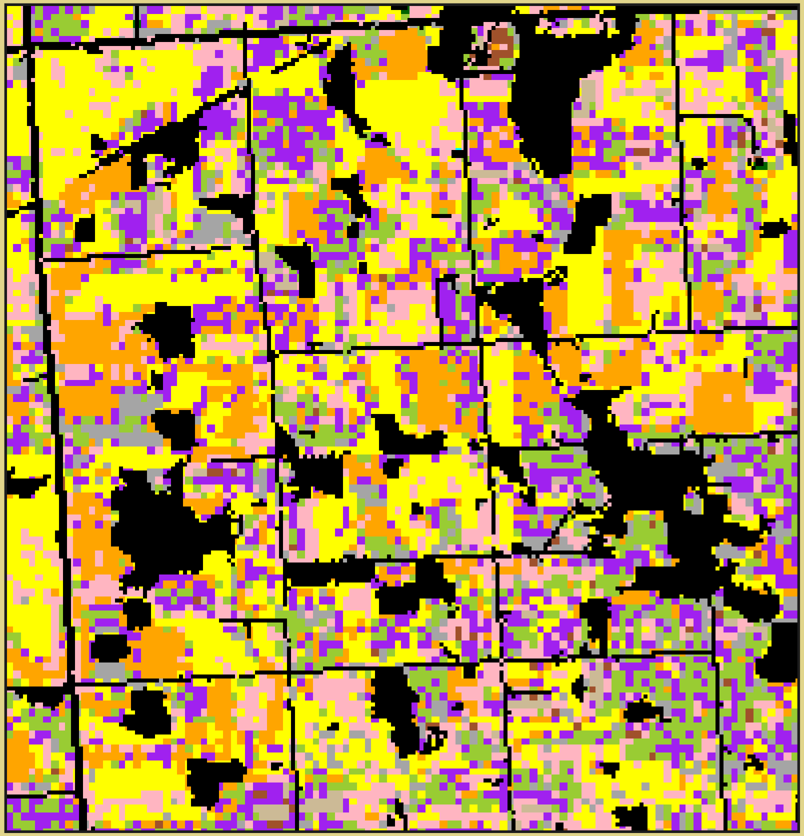
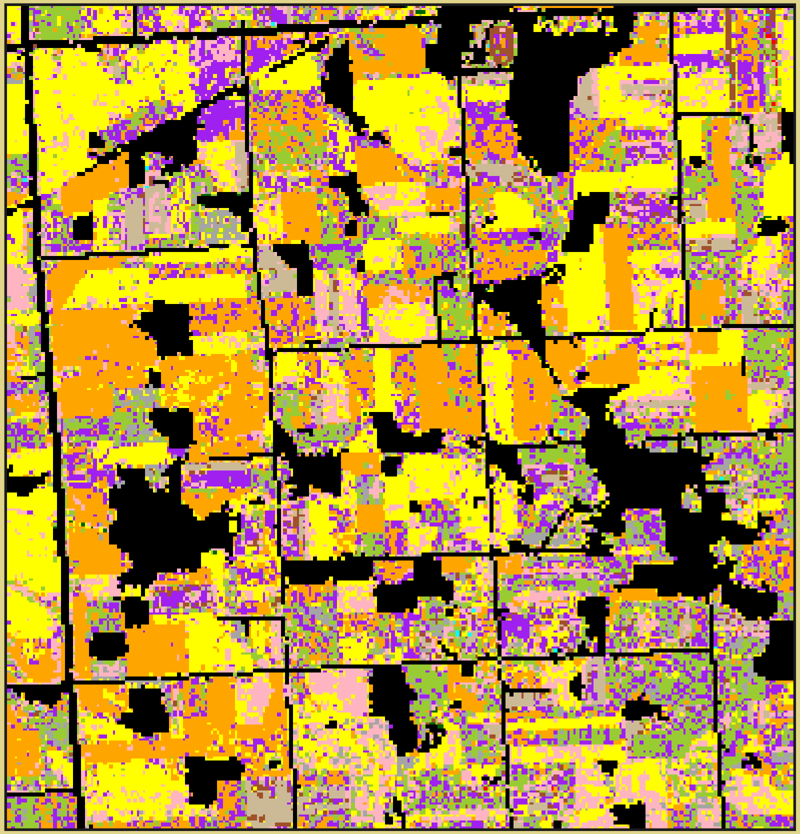
Wisconsin Classification – some map results



AWiFS
50.4% pixels correct



LISS-III
55.9% pixels correct

Classification Tree output

Wisconsin Quantitative Results

	AWiFS	LISSIII
Maximum Likelihood	53.6%	57.5%
Maximum Likelihood (10 acre MMU)	**55.1%**	59.0%
Object-oriented (spectral)	39.2%	?
Object-oriented (geometry*)	?	?
Classification Tree	50.4%	55.9%
Classification Tree (10 acre MMU)	53.0%	**60.0%**
Hybrid (OO segment fill of CT)	51.7%	59.6%

? - software/memory file size issue

* - compactness, asymmetry, main direction, density, and roundness

Classification of citrus groves

Landsat TM 25 Jan. 2005

Red, Green, Blue bands 7,5, 2

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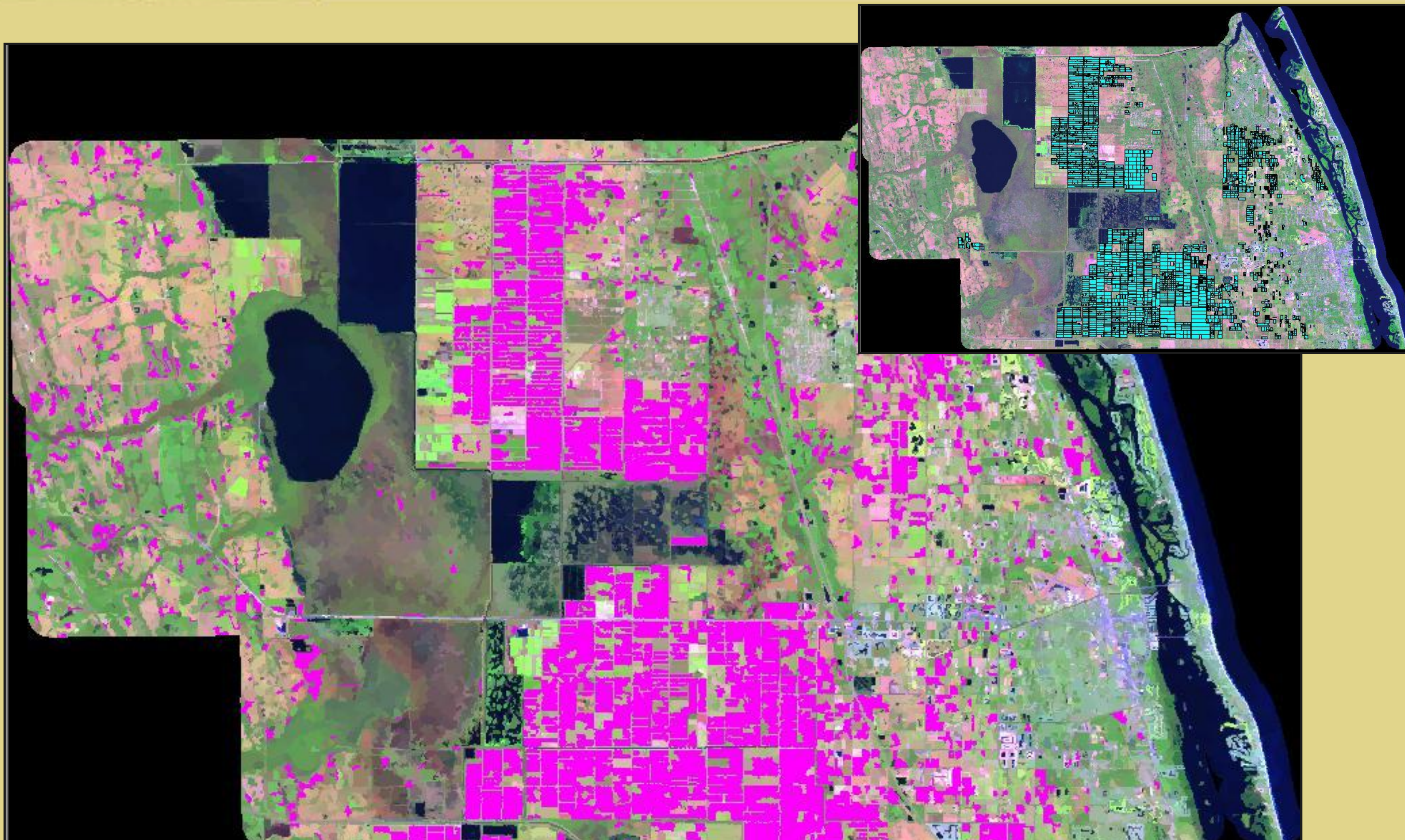
Final eCognition citrus classification



Accuracy = 90.0%   Kappa = 0.65

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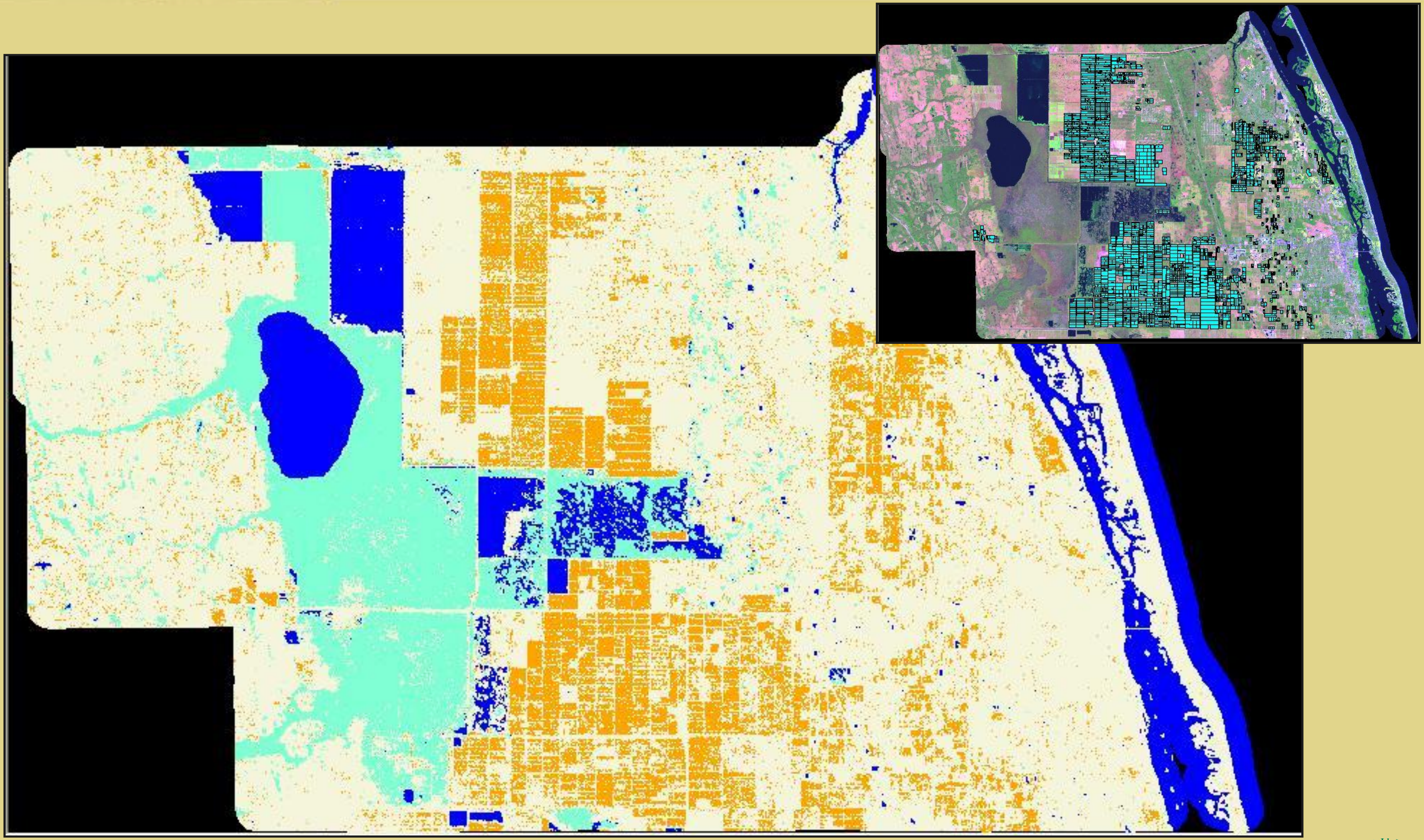
Maximum likelihood classification

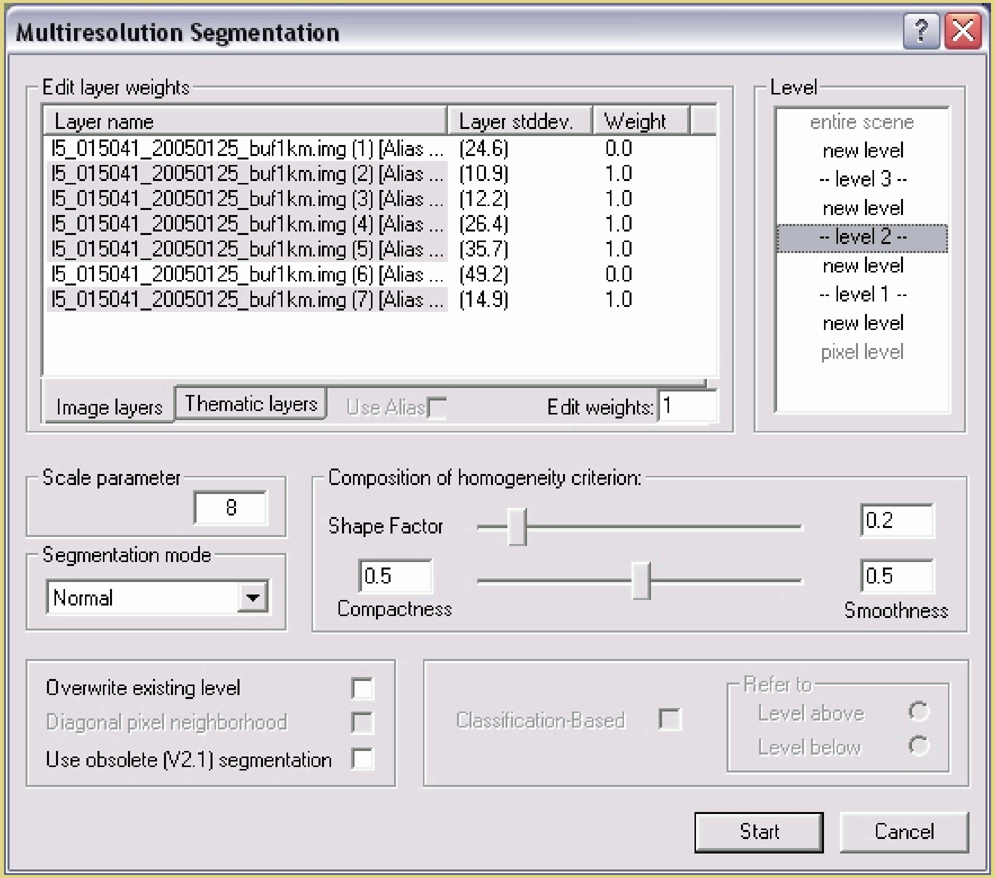


Accuracy = 88.0%   Kappa = 0.57

Citrus Comparison Summary

	Accuracy	Kappa
Maximum Likelihood	88.0%	0.57
Maximum Likelihood (MMU 10 pixels)	91.9%	0.72
Object-oriented (best attempt)	90.0%	0.65
Hybrid (default seg. parameters)	92.9%	0.75
Hybrid (tuned seg. parameters)	**93.5%**	**0.78**

Definiens Professional – a side note



What initial segmentation parameters should one use?

Segment Image - testing different scale factors

Scale = 3
Shape factor = 0.2

Scale = 8
Shape factor = 0.2

Scale = 20
Shape factor = 0.2

Accuracy impact from changes in scale and color

Scale	Shape	Accuracy	Kappa
10	10	92.9%	0.75
10	20	92.9%	0.75
10	30	92.7%	0.75
10	40	93.0%	0.76
20	10	93.1%	0.76
20	20	93.2%	0.77
20	30	**93.5%**	0.78
20	40	93.3%	0.77
30	10	93.3%	0.78
30	20	93.4%	0.78
30	30	93.3%	0.78
30	40	**93.5%**	0.78
40	10	93.4%	0.78
40	40	93.4%	0.78
50	40	93.4%	**0.79**
60	40	92.4%	0.76

Scale and Shape parameters have little impact on classification accuracy

Spectral Difference Segmentation parameter is much more important

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Goals met

Evaluate which methodology is best

– Classification accuracy	– Classification Tree
– Large dataset handling	– Classification Tree
– Ease of use	– (equal) ?
– Cost	– Maximum Likelihood
– Stability	– Classification Tree
– Speed	– Classification Tree

Summary of Comparing Image Classifiers

- NASS has spent considerable time evaluating classification methodologies
  - Maximum likelihood is adequate but somewhat limiting at this point
  - Object-oriented is intriguing and likely useful for particular applications but unwieldy and not improving overall classification efforts
  - All things considered, the decision trees seem to be the way for the Cropland Data Layer program to proceed into the future

Object-oriented Lessons Learned

- Large datasets always problematic
- Geometric segment attributes (versus spectral) have little value for classification
- Initial scale, shape, *etc.* segmentation parameters have little impact
  - Spectral Difference Segmentation has impact though
- Probably best used when the pixel/object ratio is large and features are of radically different scales and shapes
- “Nearest Neighbor” classifier too simplistic
- Derived polygons are useful in external applications

Pixel-based Methods Lessons Learned

- Classification Trees
  - “Boosted” trees always superior to regular
  - Tolerant of outliers
  - Hand large datasets with ease

- Maximum Likelihood
  - Still robust even though may be viewed as old-fashioned

Contextual spatial filtering using appropriate minimum mapping units improves map accuracies by a few percentage points

Thank You

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