

Linear Feature Extraction from Digital Remote Sensing Data Using Neural Network Analysis

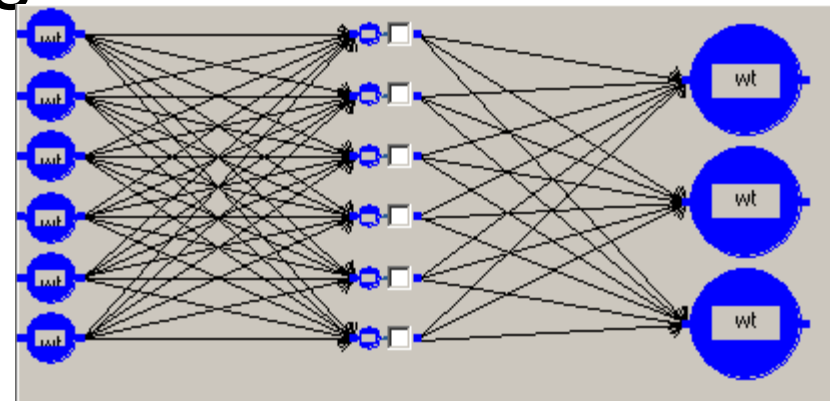
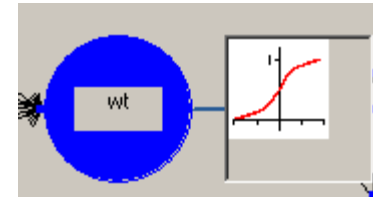
Genong (Eugene) Yu and Ryan R. Jensen

Department of Geography, Geology and Anthropology, Indiana State University, Terre Haute, IN 47807

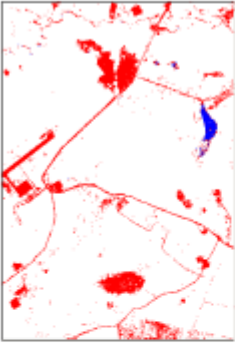
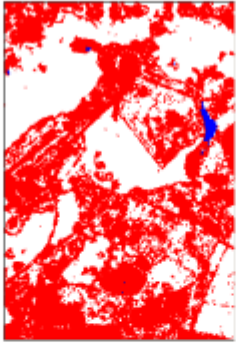
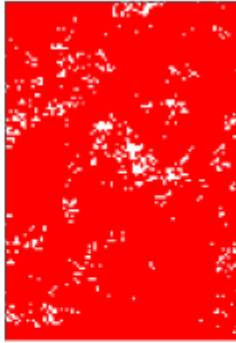
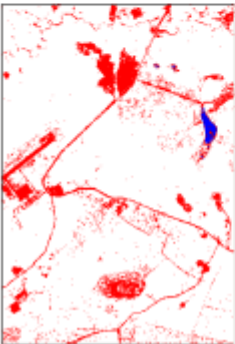
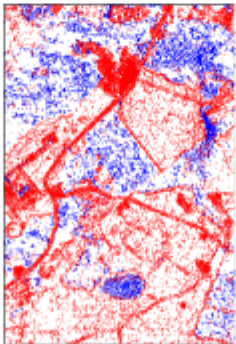
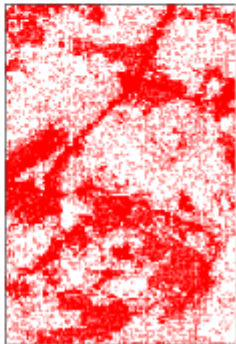
- Linear feature extraction
- Hypotheses
 - NN vs MLC
 - Edge-enhancement
 - Scale effect



Methodology

- Linear feature extraction
 - Sobel edge detector
 - Neural network approach
 - Conventional approach
- Images: IKONOS, ASTER, Landsat TM
- Features: Rivers, roads

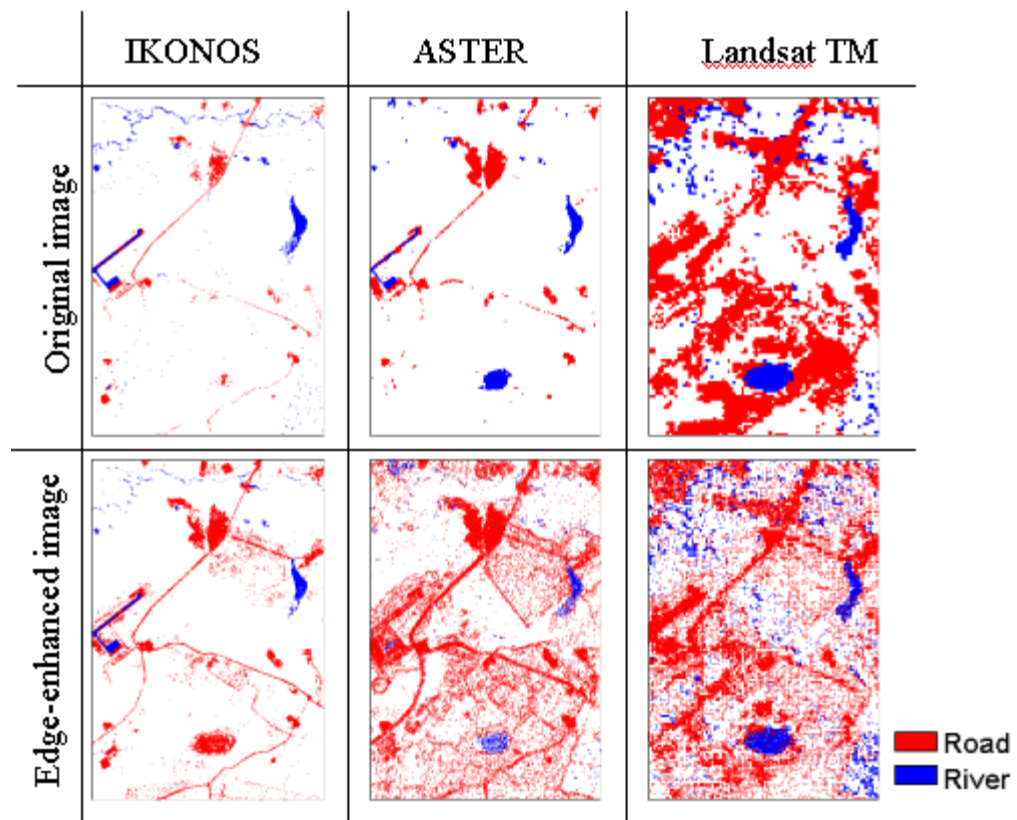


Conventional results

	IKONOS	ASTER	<u>Landsat TM</u>
Original image			
Edge-enhanced image			

 Road
 River

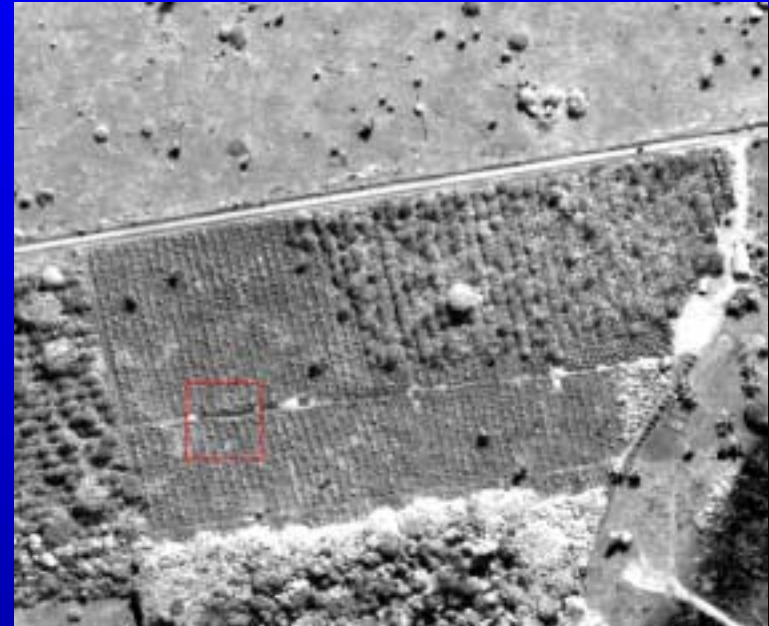
NN results



Thematic information extraction from a high spatial resolution (IKONOS) image of a heterogeneous landscape in Rondônia, Brazil: Coping with sensor tradeoffs



True Color (4m)



Panchromatic (1m)

Bharath Ganesh-Babu

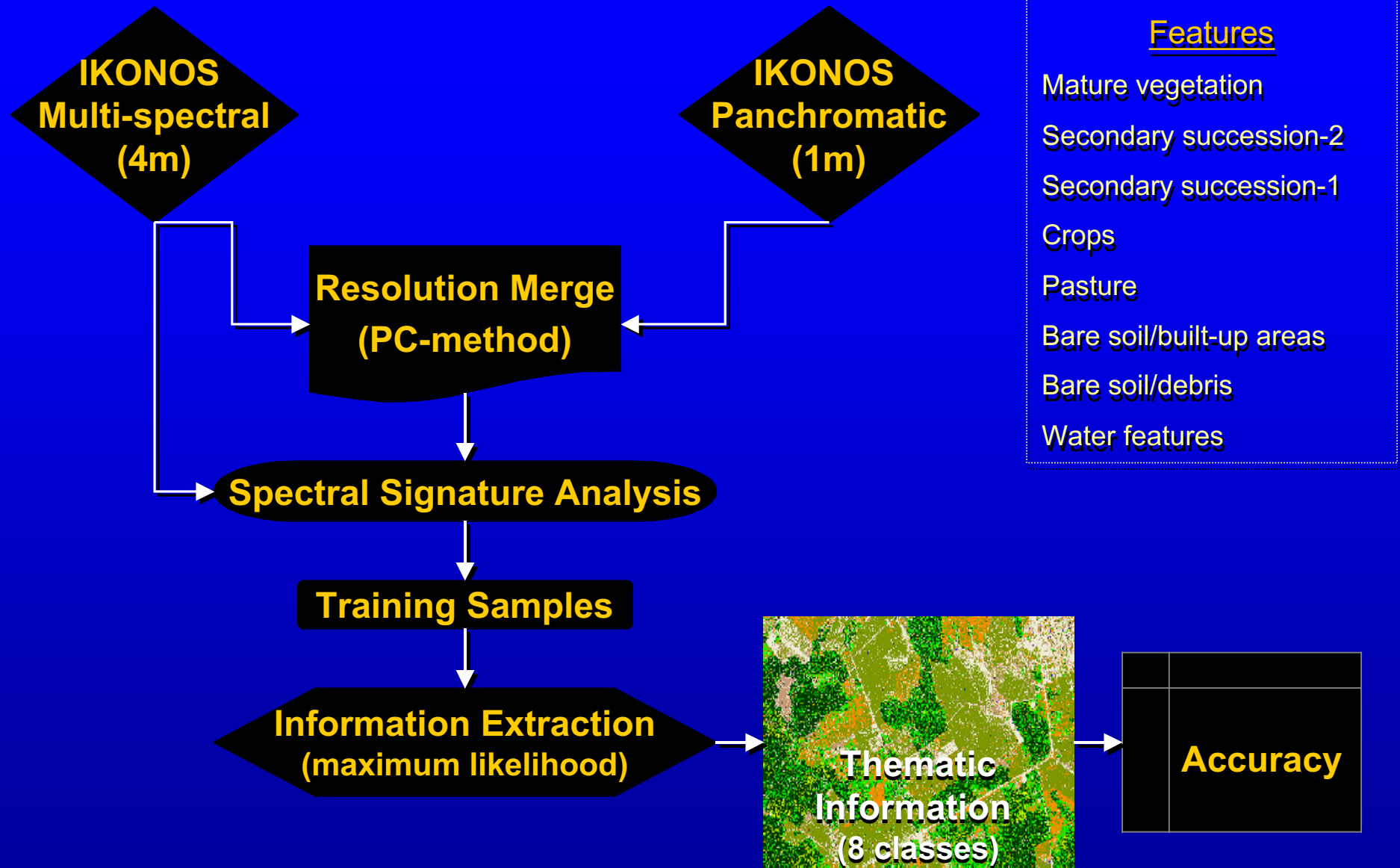
Graduate Student

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Study area and data characteristics

- **Equatorial rainforest (now fragmented)**
 - **June, July and August – Dry; Winter**
 - **Agro-pastoral land uses**
 - **Mature/succession vegetation and riparian land covers**
-
- **Data acquired on: 28th May 2001 (start of dry season)**
 - **Area covered: 154.5 km²**
 - **Bands: Blue, Green, Red and NIR (4m); Pan (1m)**



Findings and lessons learnt

- **Very poor accuracy (similar results for two different training sample sets)**
- **Very difficult to select samples of landscape level features at high spatial resolution**
- **Absence of mid-infrared band, was handicap while differentiating spectral signatures**
- **Enhanced images need longer processing time and larger storage space**

Conclusion and future considerations

- **Are data in high spatial resolution feasible for landscape-wide studies?**
 - **Enhanced image may be used for reference and not training itself**
 - **Future: Reliable ground truth information, multi-sensor/scale (upscaling), explore different classification techniques (ECHO, ANN etc.)**
-

URBAN LU/LC CLASSIFICATION

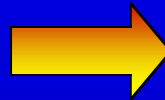


Idrissa Tiemogo
Indiana State University
Geography, Geology, and Anthropology

URBAN LANDSCAPE

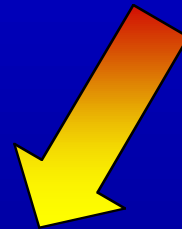
- **Diversity of the Materials**

- Concrete
- Metal
- Plastic
- Water
- Grass, Trees, Shrubs
- Soils, etc .



- **Heterogeneous Features**

- Buildings
- Transportation network
- Utilities
- Recreational areas
- etc .



**SPATIAL/SPECTRAL
COMPLEXITY**

RESOLUTION CONSIDERATIONS

- **Spatial Resolution**

- **Depends on the classification level**
- **Sensors resolution have to be half of the width of the object of interest**
- **In general, higher resolution images are needed**

- **Spectral Resolution**

- **Visible, NIR, MIR, and Panchromatic are commonly used**

OBJECTIVE

To improve urban land use land cover classification accuracy

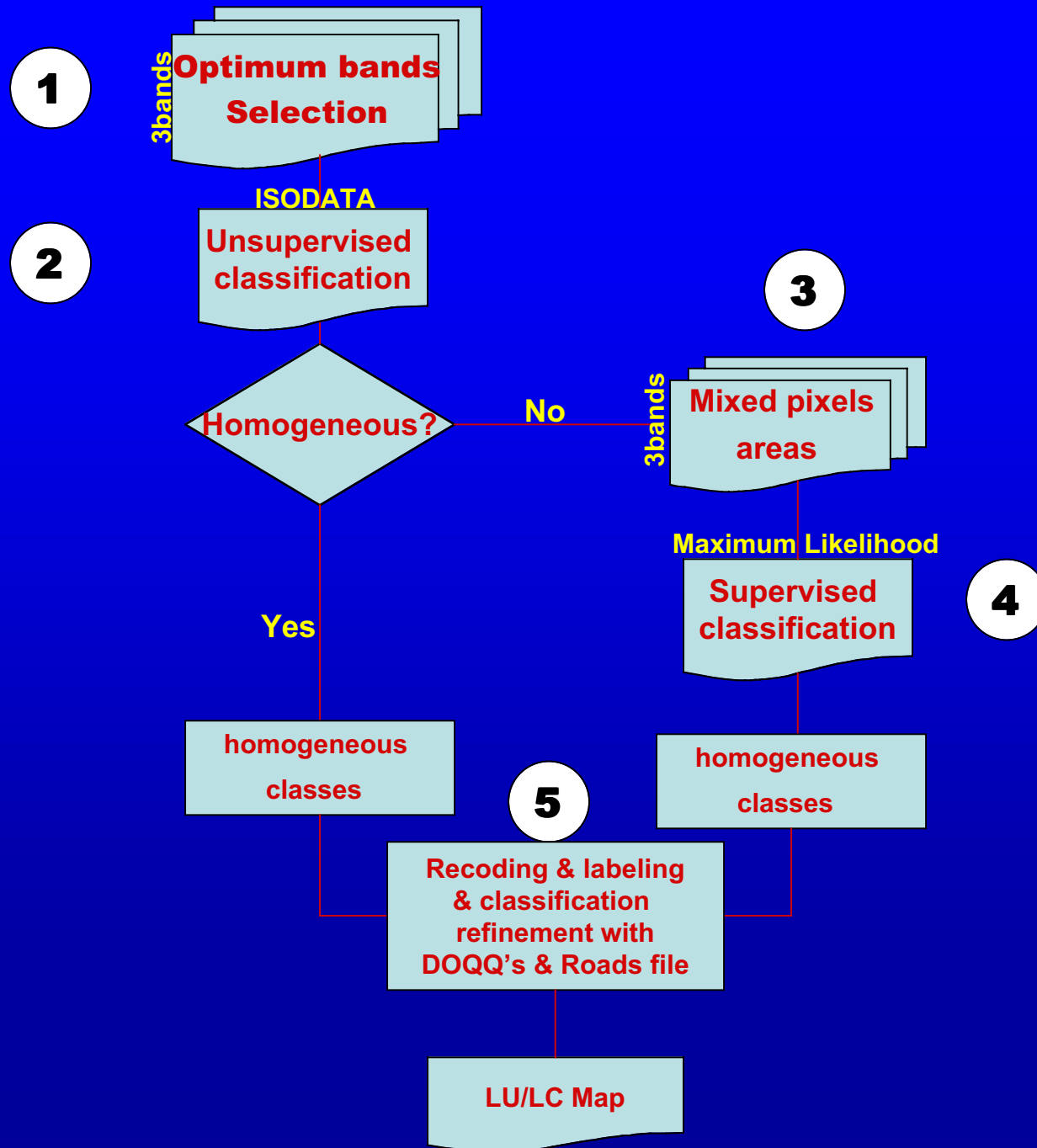
DATABASE

- 30 X 30 meters Landsat TM image acquired in July 1995
- 7.5 ' topographic maps
- 2000 Road network vector files
- 1 X 1 meter resolution DOQQs

STUDY AREA

Marion county, Indiana (main city Indianapolis)

METHODOLOGY



CONCLUSION

- **Due to the complexity of urban landscape, the use of conventional classification methods are not accurate.**
- **Hybrid classification improves urban LU/LC classification**
- **High resolution DOQQ's facilitates the refinement of the classification**
- **Requires more time than traditional methods**

Vegetation Change Detection of Amazon Estuary

Xiaofang Wei

GEOG 667

Ryan Jensen

Introduction

- Objective: Detection of vegetation change in the Amazon estuary
- Study Area: Ponta de Pedras, Brazil
- Data: Landsat TM image
(July 21, 1985 and July 22, 1991)



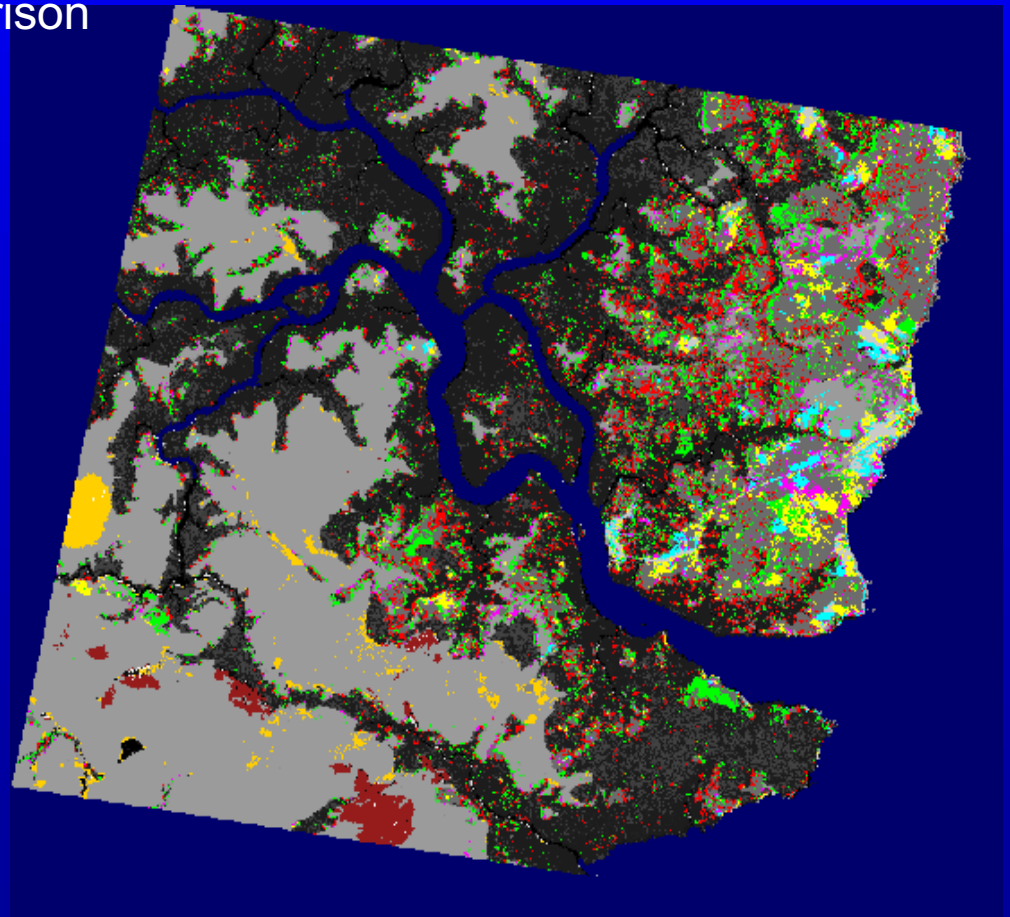
Methodology

- Post-Classification Comparison
 - ≡ Classification of individual image
 - ≡ Change matrix to create the change image
- Principle Component Analysis
 - ≡ Highly-correlated components ----consistent features
 - ≡ Least-correlated components----changes

Analysis and Result

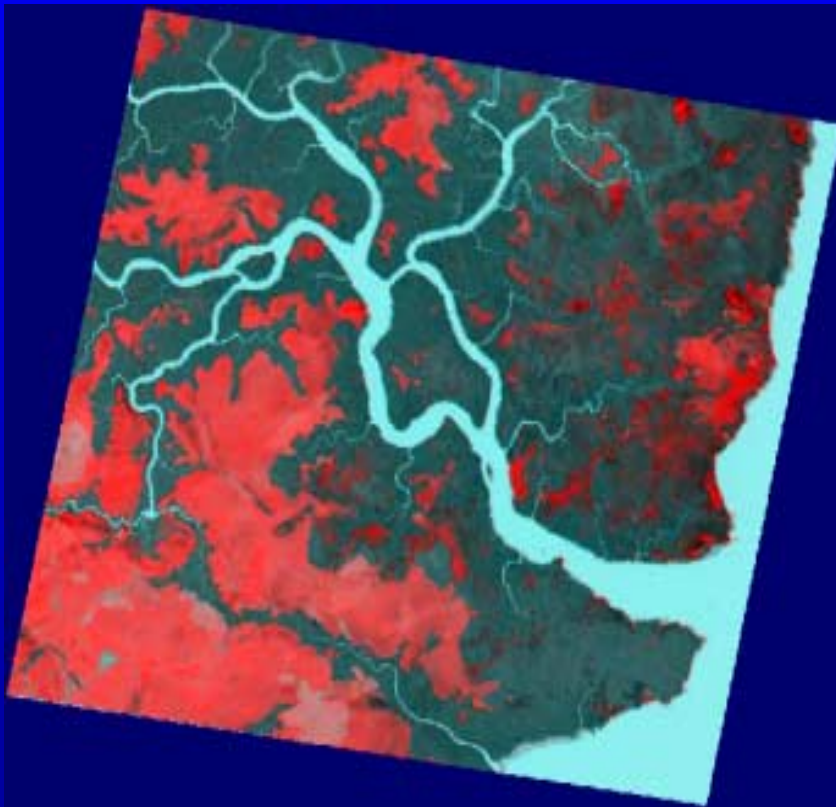
- Post-classification comparison

Selected change image
(1985-1991)

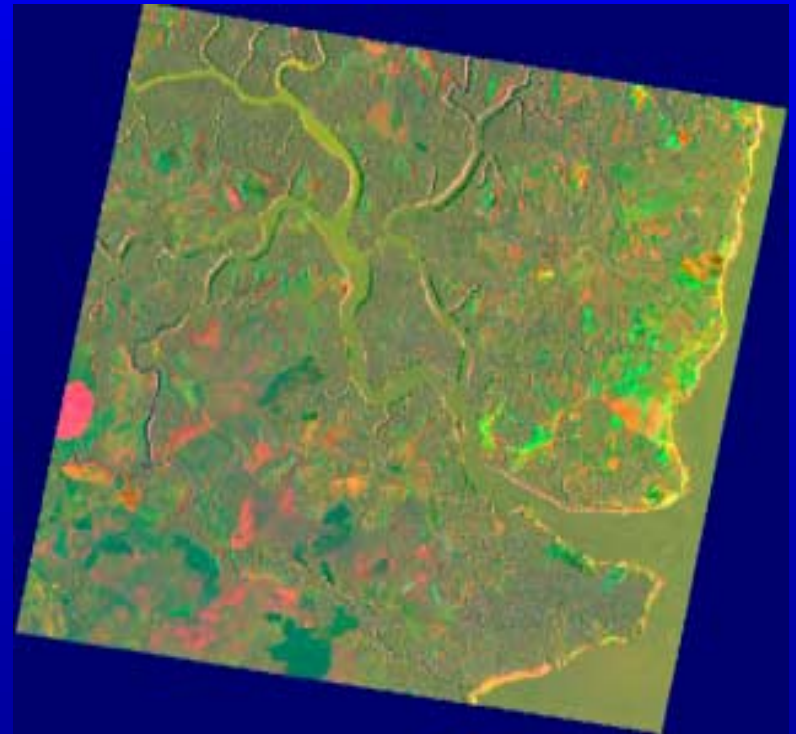


Analysis and Result

- Principle Component Analysis



Unchanged image (R= PC2, G= PC1, B= PC1)



Changed image (R= PC3, G= PC4, B= PC5)

Discussion

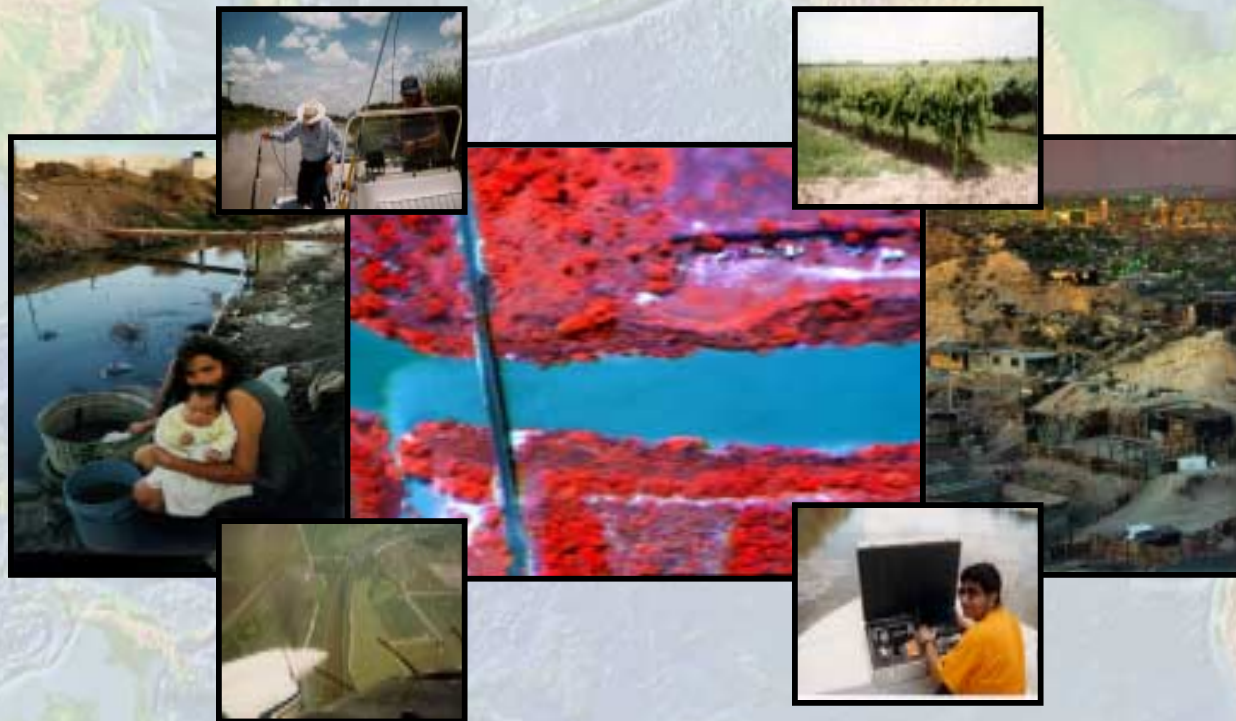
- Post-classification comparison

- ≡ Detailed “from-to” information
- ≡ Dependant on the accuracy of individual classification
- ≡ Time consuming

- Principle component analysis

- ≡ More accurate
- ≡ Spectral change
- ≡ Hard to link the spectral change with the land cover class

Remote Sensing for Water Quality Issues in the Lower Rio Grande Valley (LRGV) of Texas: NAFTA in Perspective



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**Shahriar Nayeri
December 2002**

NAFTA's impacts since 1993

- Rapid population growth
- Economic expansion
- Increased demand for Water

LRGV & Rio Grande

- Agriculturally productive
- Unique Geography
- “The water source”
- Water quality decrease

Arroyo Colorado (AC)

- “The source for LLM”
- Recent pollution
- Significance for LRGV (\$)



Methodology

A. Image data

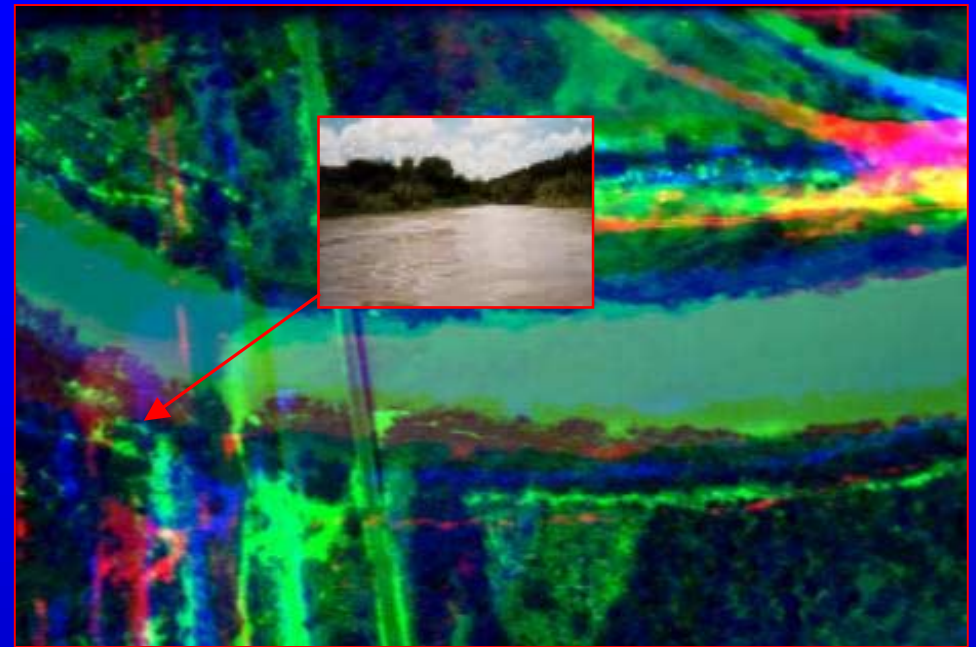
1. Point based collection
2. Pre-processing
3. Classification
4. Image analysis
5. Accuracy Assessment

B. Sample Data

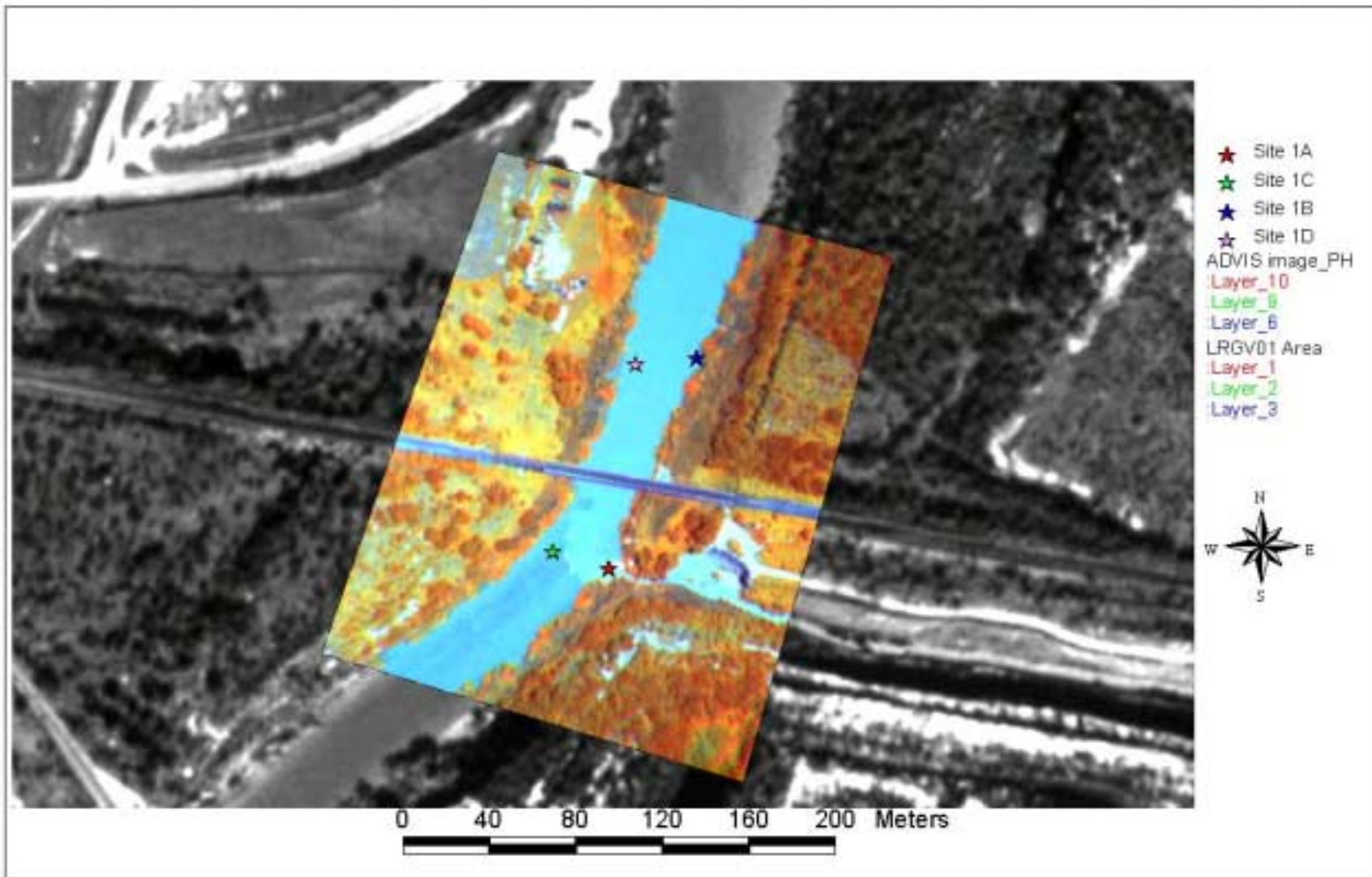
1. In situ water sample collection
2. GPS
3. Laboratory analysis of water samples

C. Data correlation analysis

D. Develop model



(photos 1999)



Water sampling sites located by GPS are shown on georeferenced ADVIS image (10-9-6 RGB), with a JPEG air photo of area in background. Locations M, N, and S represent Middleplume, Upnorthplume, and Upsouthplume coordinates on the image where additional spectral Profiles were generated.

Downstream Collection Sites PH, M22, and M16 - ADVIS bands 12-4-6 RGB

