Integrating Hyperspectral Data and GIS data for Modeling vulnerability from Natural Disasters:

A Case Study from Australia.

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Study Background/Issues

- **Hail Stones. April 14, 1999. Different materials-Different susceptibility**
- **Project collaboration with the New South Wales Fire Brigades (NSWFB)**
- **Prioritizing Resource Allocation during Emergencies**
- **Prior Knowledge of Vulnerable Regions, Planning**
- **Threat of Hail Storm & Mapping regions with Potential Relative Damage**

Why use Remote Sensing?

Why Hyper spectral Remote Sensing?

Modeling Population Dynamics with GIS _ Vulnerability

Hyper spectral Remote Sensing

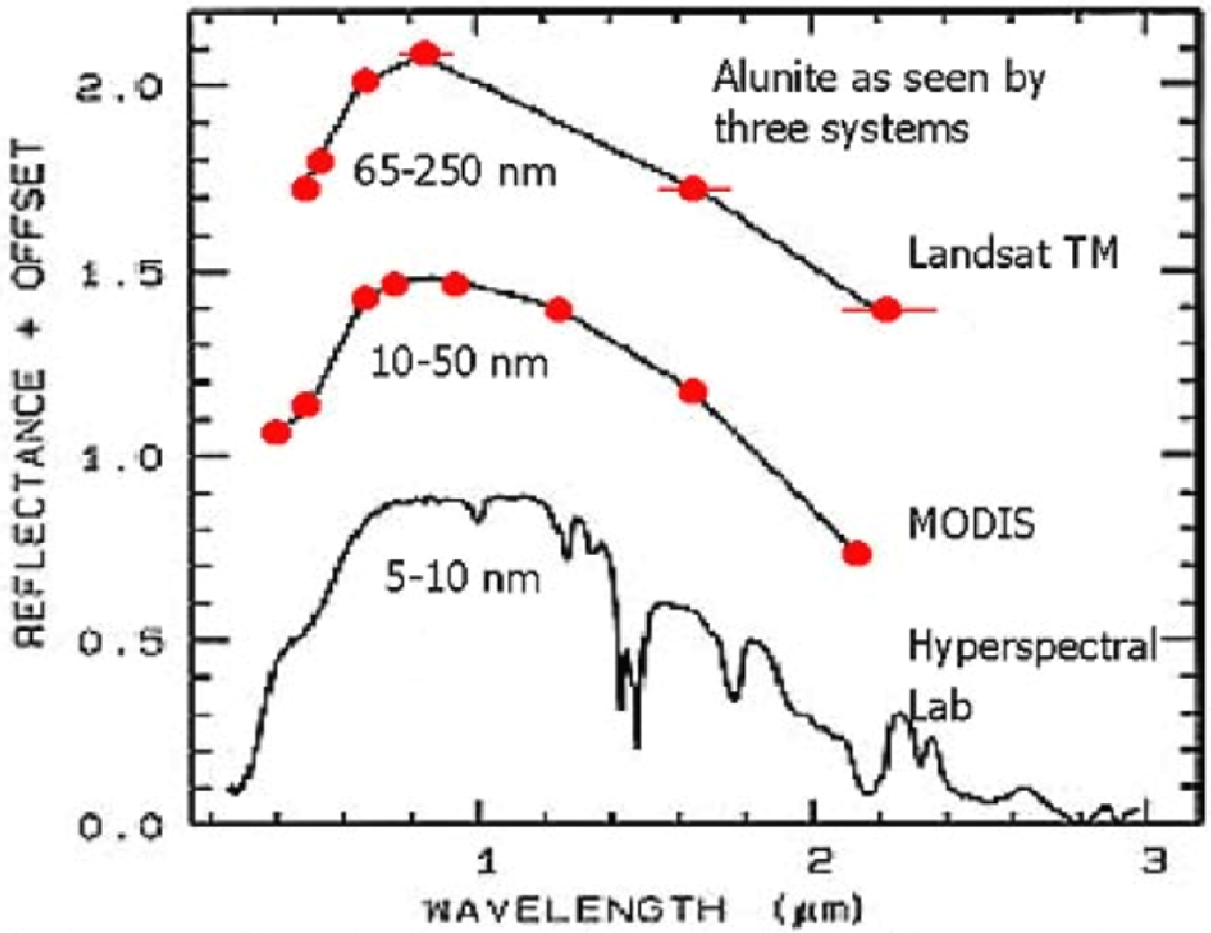


Figure 2. Spectral resolution multispectral and hyperspectral systems.

Objectives

- To develop a methodology to map vulnerable regions exposed to the hazard of Hail Storms

To test potential of HyMap and Analyze at Sub-pixel level for Mapping Urban Surfaces and Roof Resilience.

- Creating a spectral Library of surface materials in Urban areas

- Integrating Hyper spectral Remote Sensing Data with GIS data

Study Area - Sydney

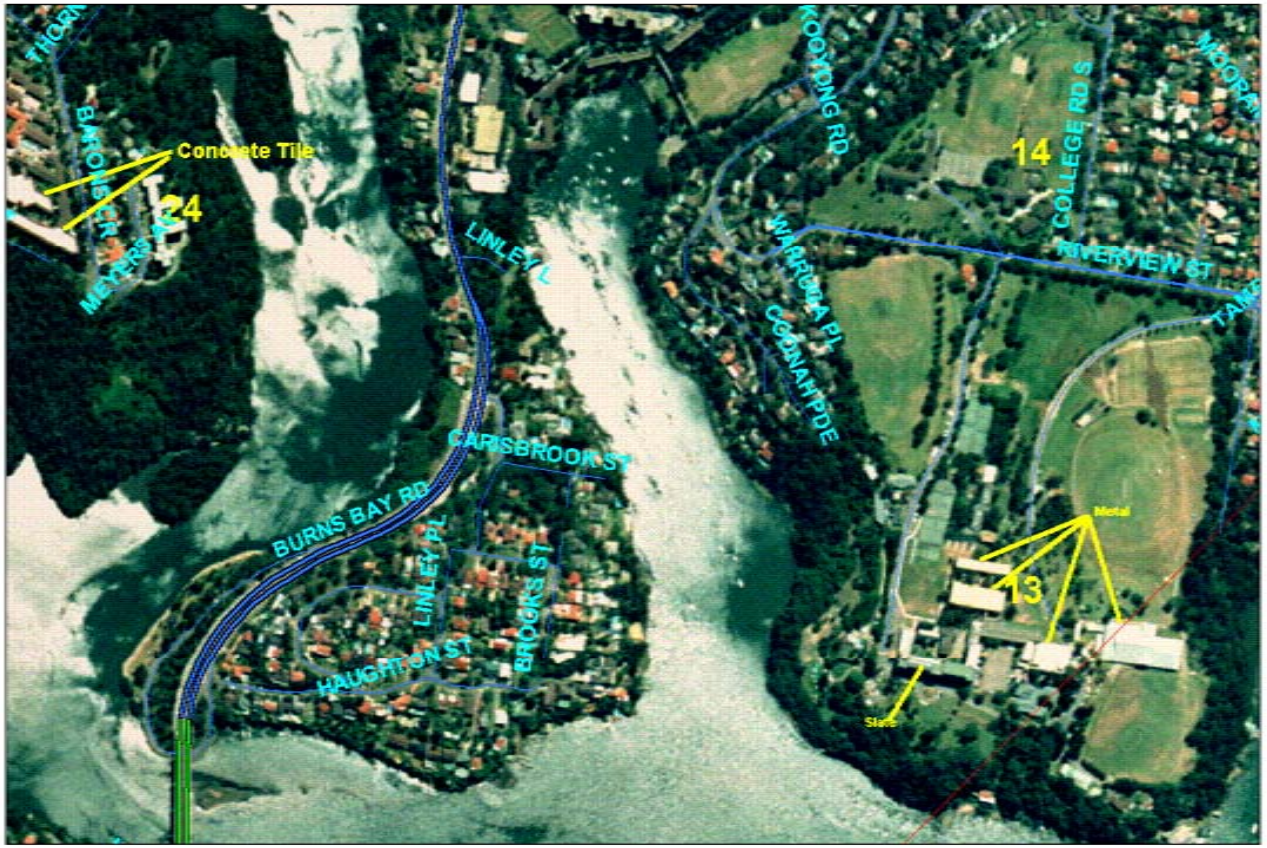
MIRROR REVERSED &

NON-GEOREFERENCED

Field Check

Sample Site locations in Concord Bay.

(Fig xxx) FIELD CHECK OF URBAN SURFACE FEATURES
Study Area, Sydney, Australia



Methodology

Sample Collection Roofing Materials

↓

Extraction of Spectra → **Full Range Spectroradiometer (350-2500 nm)**

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Spectral Plots and Interpretation

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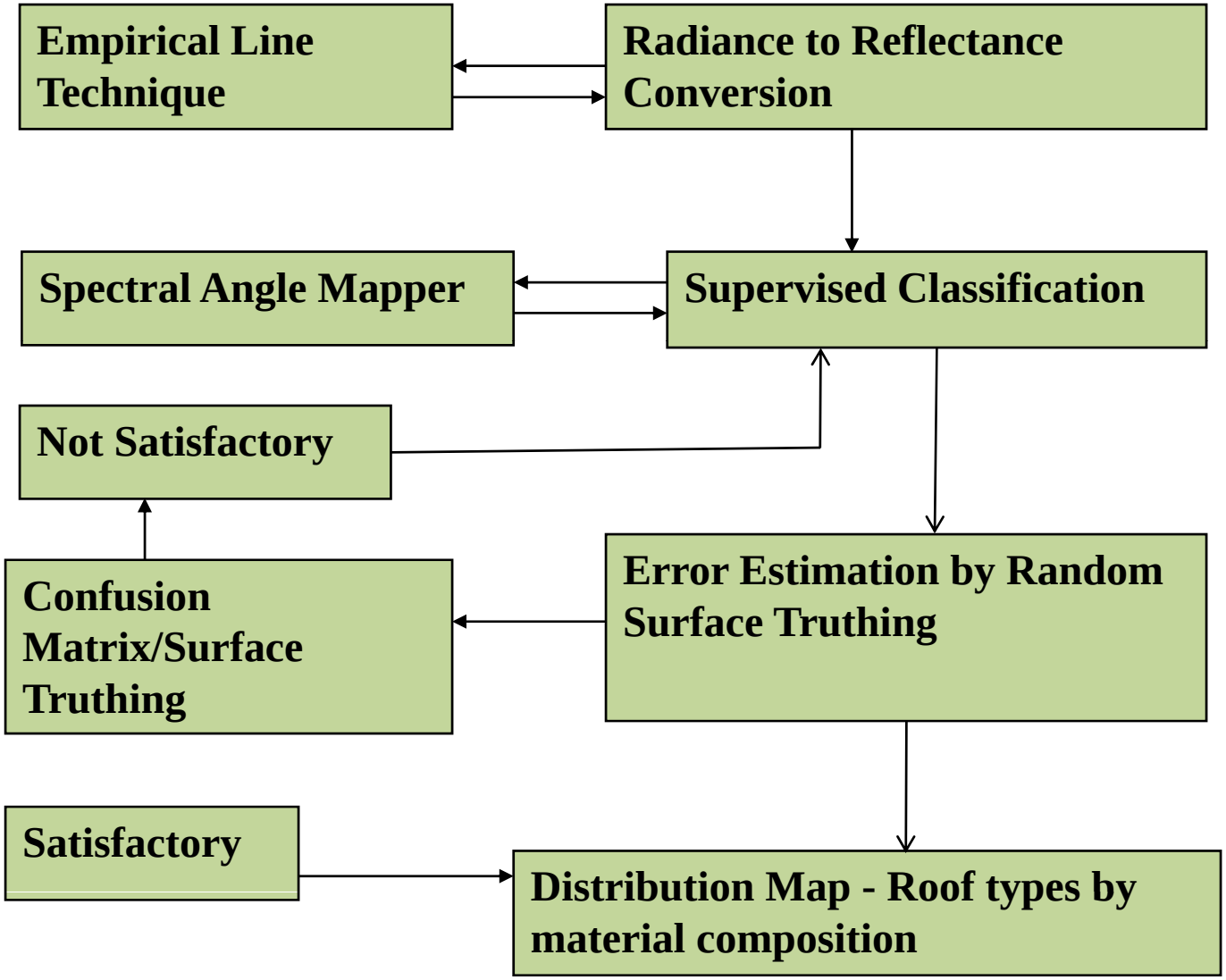
Resampling to HyMap Image Channel Configuration(126 Bands)

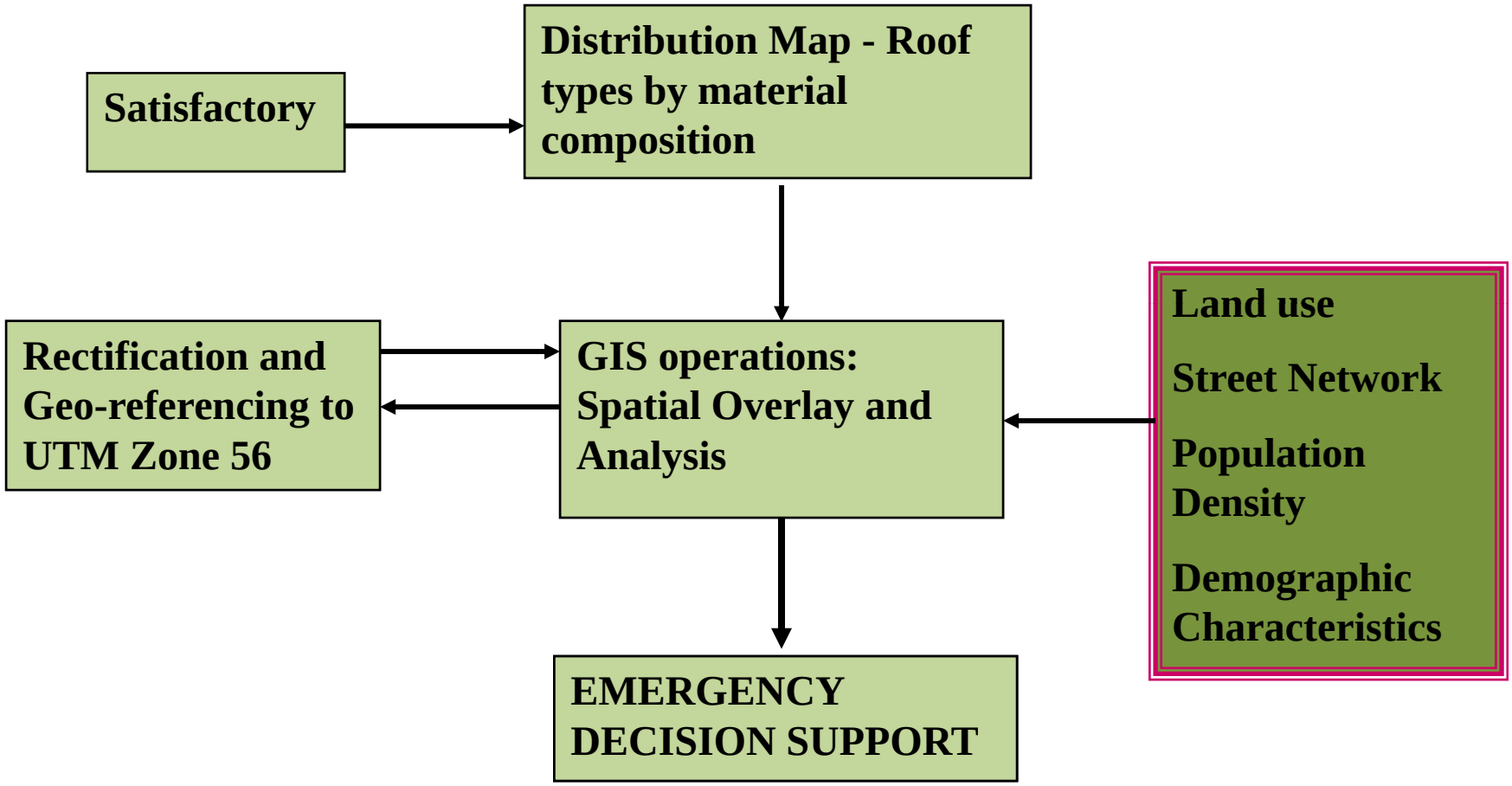
URBAN SURFACE MATERIALS

Ref No	Sample Surface Material
001	Corrugated Fibro
002	Slate (Light Brown)
003	Slate Tile
004	Slate Tile (black weathered)
005	Metal (Colour Bond-Green)
006	Metal Galvanized
007	Concrete Tile (Brown)
008	Terracotta (Red) Old
009	Metal Corrugated painted

Methodology



Methodology



Analysis - Summary

SUPERVISED CLASSIFICATION

SPECTRAL ANGLE MAPPER

RASTER TO VECTOR CONVERSION

IMAGE TO MAP RECTIFICATION, VECTORISATION, SPATIAL OVERLAY,

GIS ANALYSES

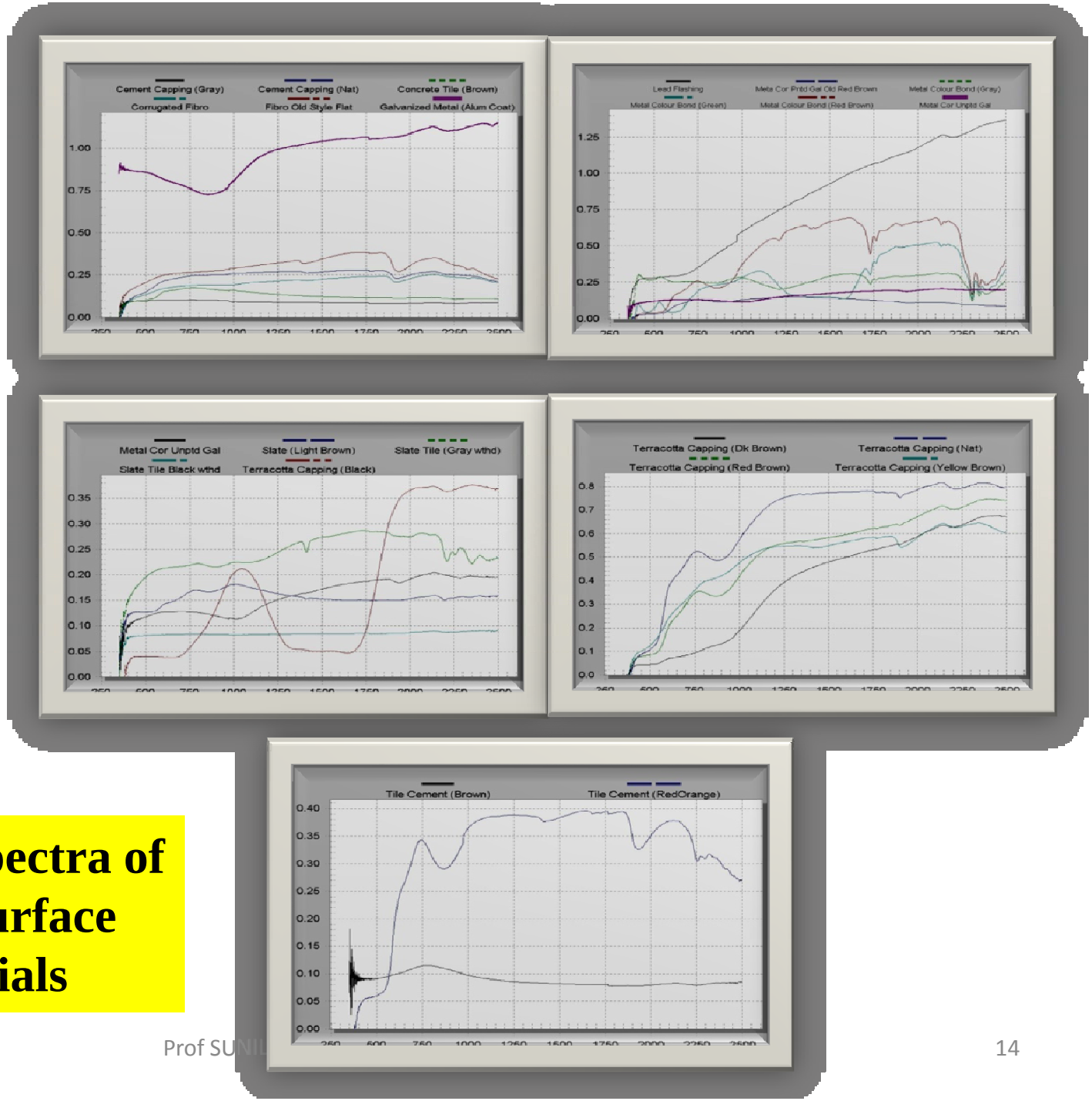
Results & Conclusions

Interpretation of Urban Spectra of Surface Materials

- **Classified Image of Urban Surface Materials (Roofing Materials)**

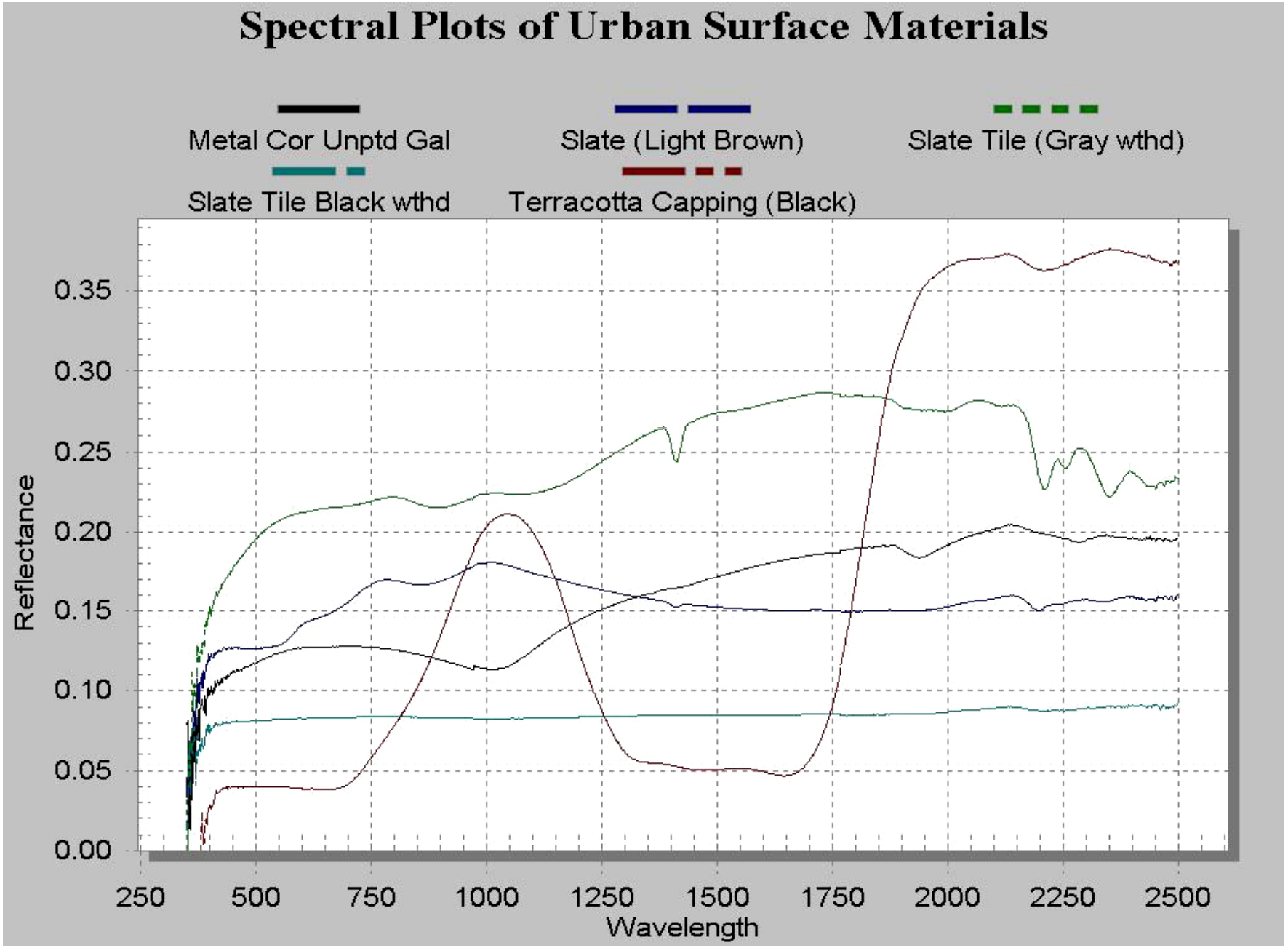
- **Emergency Decision Support Systems integrating Hyper Spectral Sensor Data with GIS data**

- **User Friendly Informed Decisions Support**



Selected spectra of urban surface materials

- **Spectral Footprints**
- **Absorption features**
- **Presence of oxides, Fe, Clay etc**


Spectral Plots of Urban Surface Materials
Metal Cor Unptd Gal
Slate (Light Brown)
Slate Tile (Gray wthd)
Slate Tile Black wthd
Terracotta Capping (Black)
Reflectance
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
250
500
750
1000
1250
1500
1750
2000
2250
2500
Wavelength

Laboratory spectra to Image Calibration

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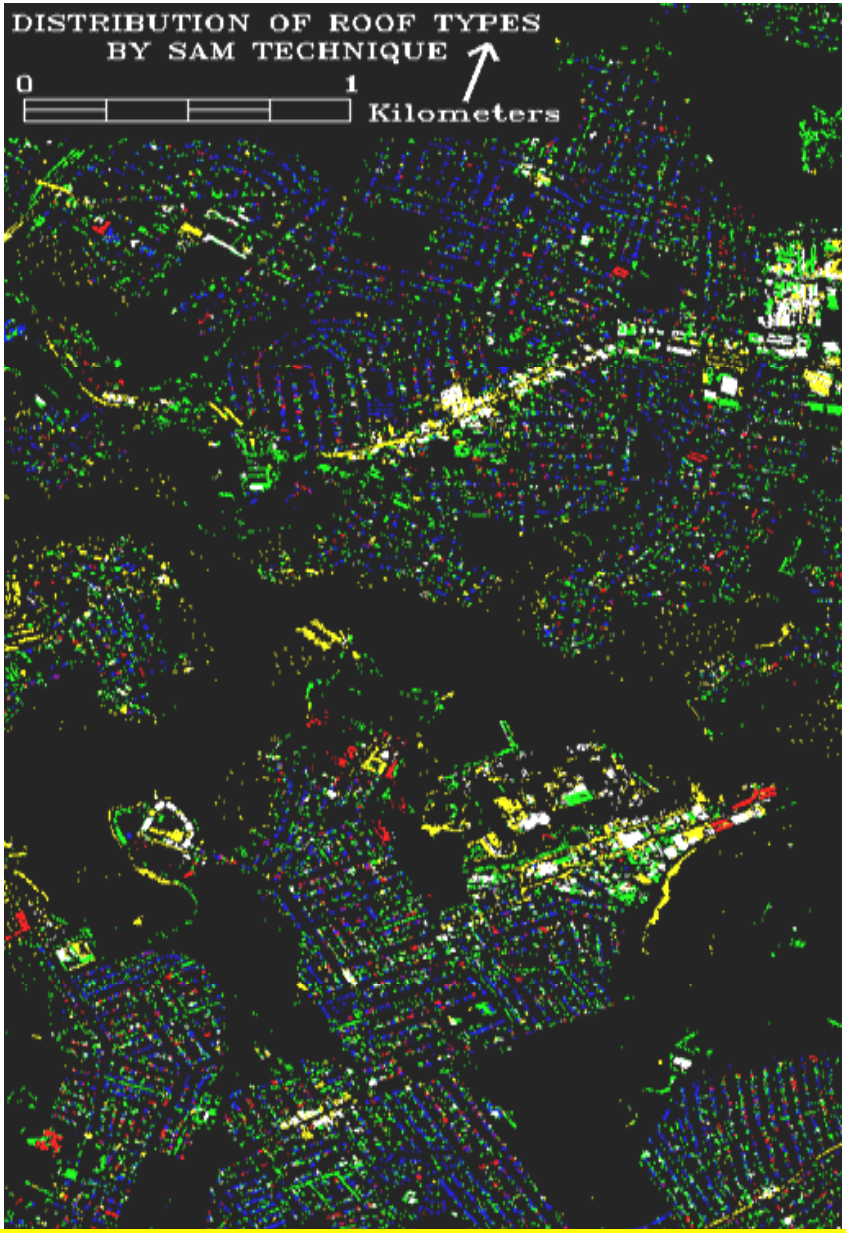
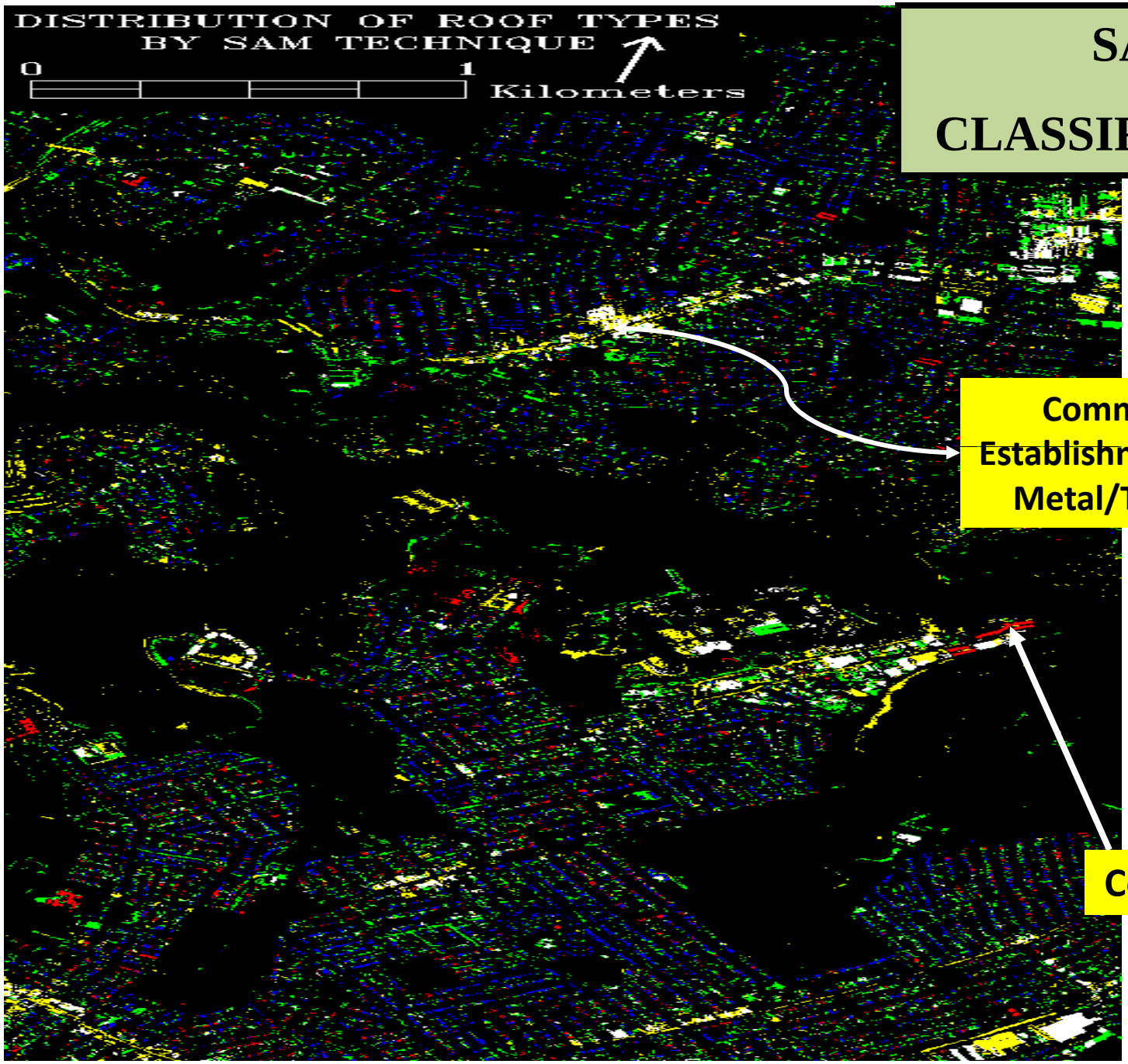
Spectral Angle Mapper

CLASSIFICATION



SAM CLASSIFICATION RESULTS: Yellow & White: Metal; Red: Concrete; Blue: Terracotta, Green: Slate

SAM CLASSIFICATION



Commercial Establishments with Metal/Tin roofs

Concrete Roofs

Accuracy Assessment – Field based

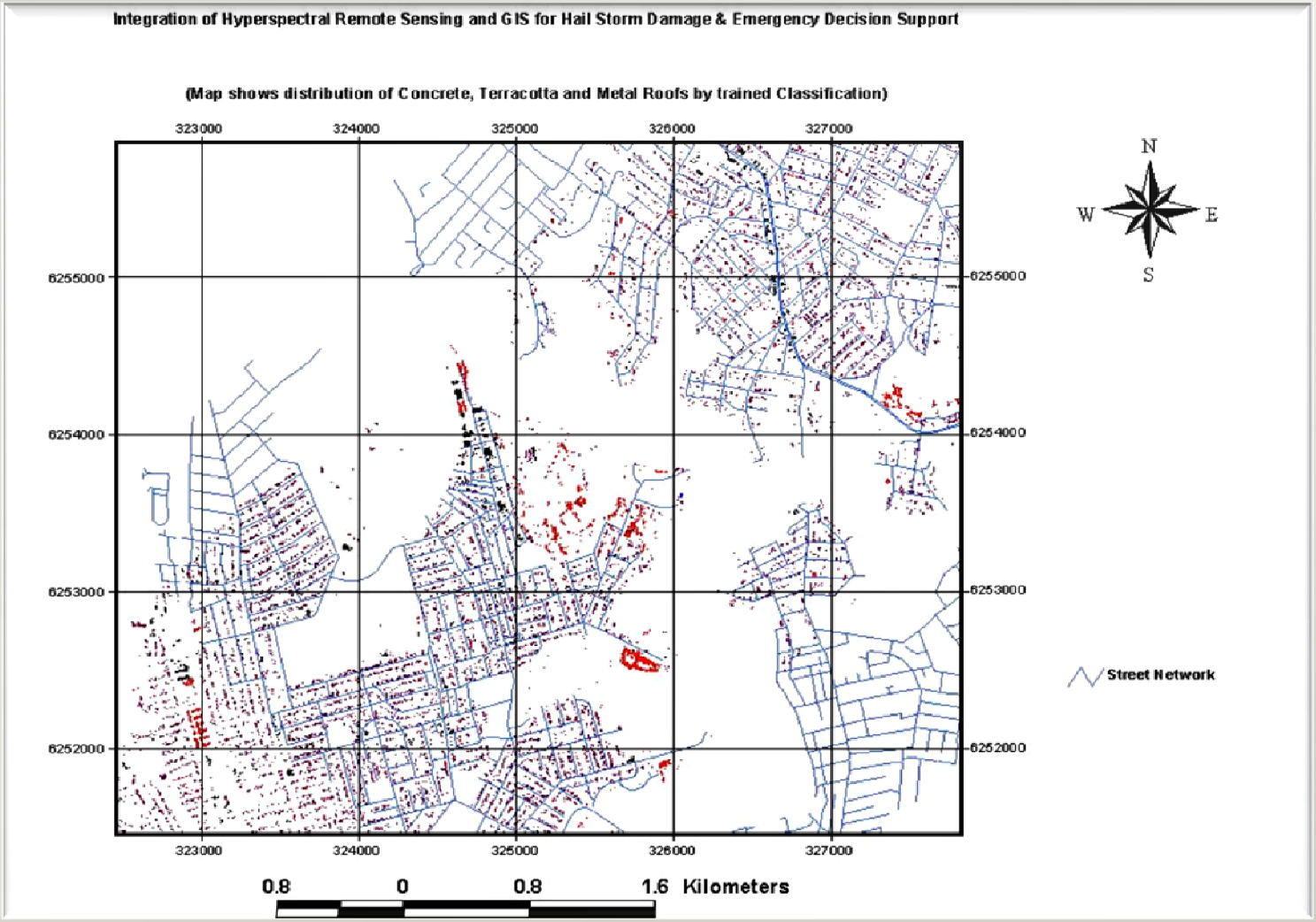
- **Accuracy Assessment: By Surface Truthing**
- **Except for one building most of the sample sites were accurately identified**
- **95% Accuracy**

RASTER TO VECTOR CONVERSION

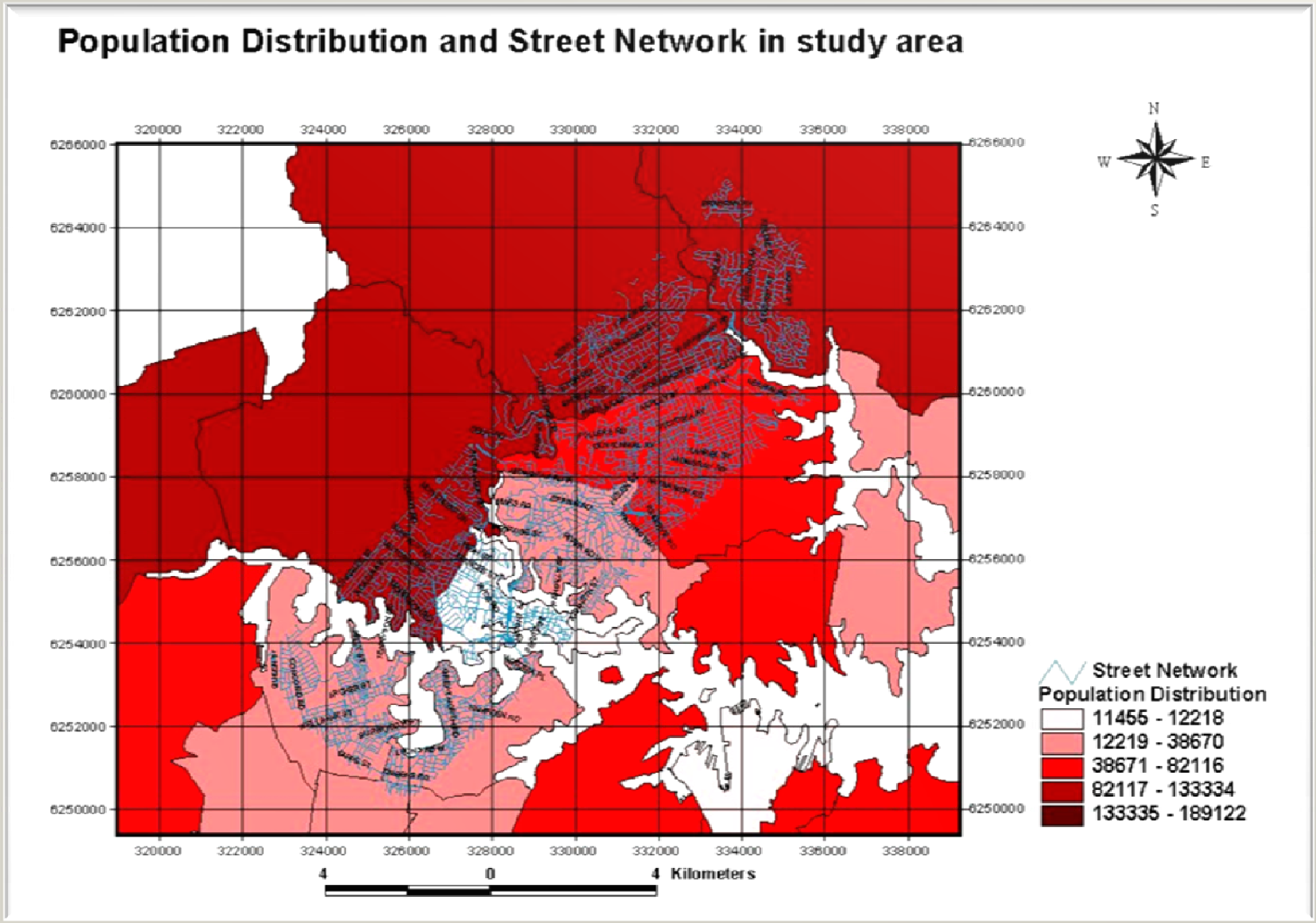
GIS ANALYSES

VULNERABILITY = ROOF TYPES + DEMOGRAPHIC CHARACTERISTICS

Roof Types & Street Network Spatial Overlay and Network Analysis – ArcInfo Network Analyst

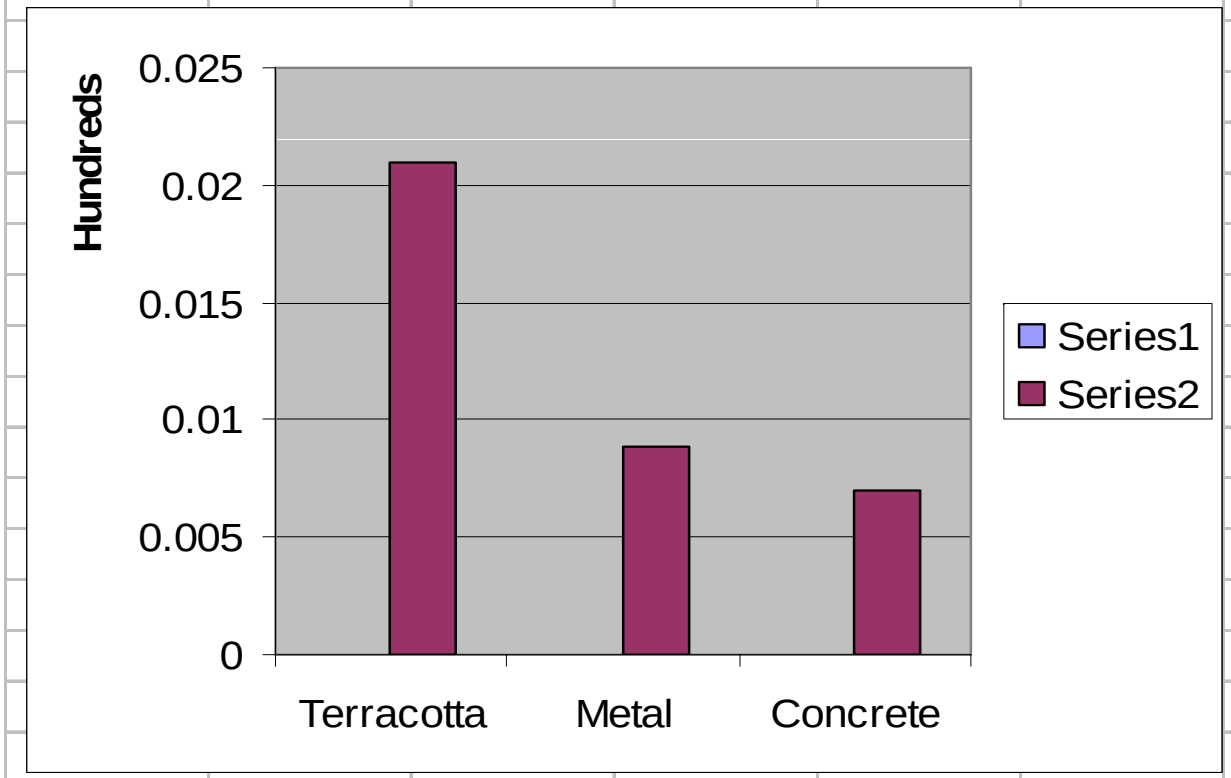


Demographic Analyses- Improved Census Data

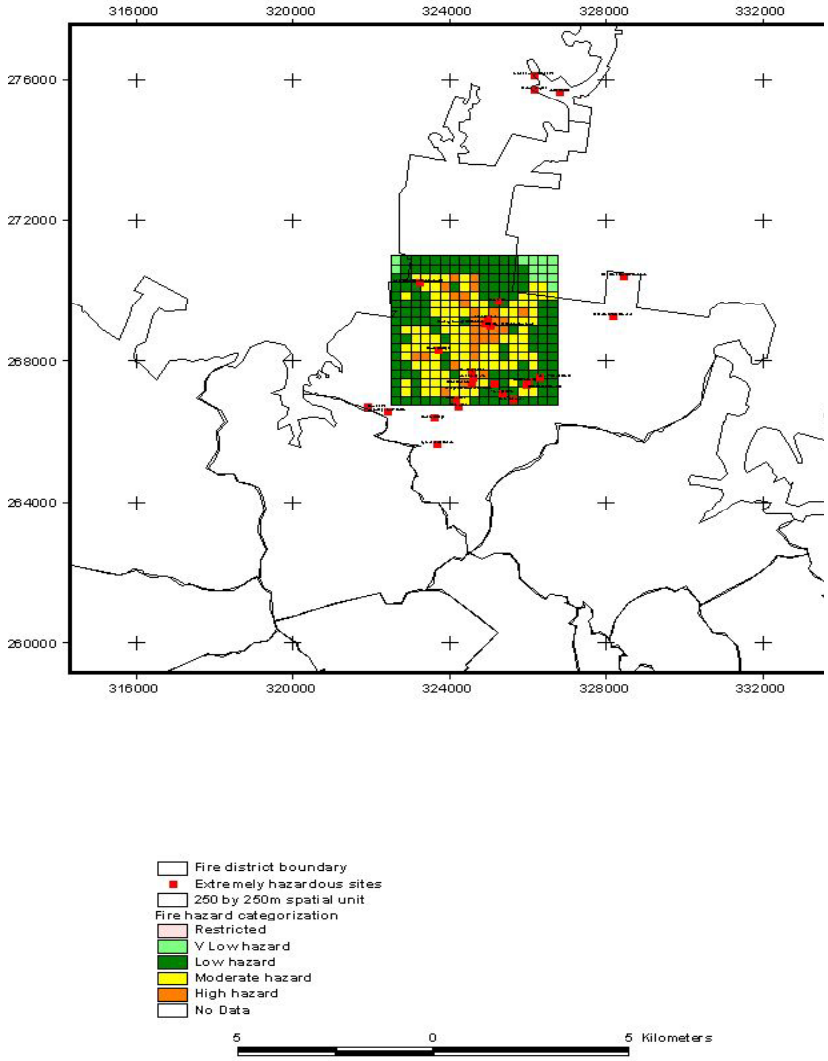


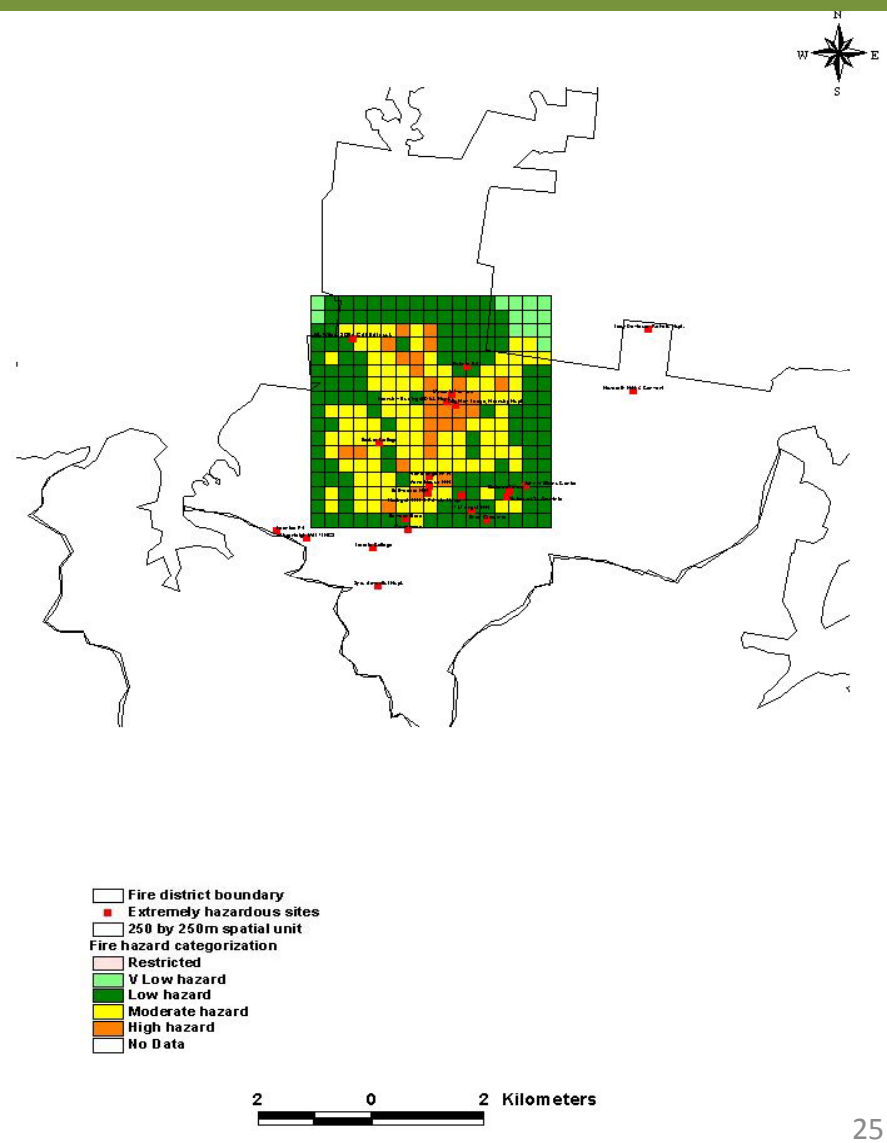
Distribution - Roof Types from classified Pixels

Roof Types	Total Area%
Terracotta	2.1
Metal	0.89
Concrete	0.7



Dynamic Resource Redistribution in Fire Districts, NSW, Australia – Semantic Hazard Model

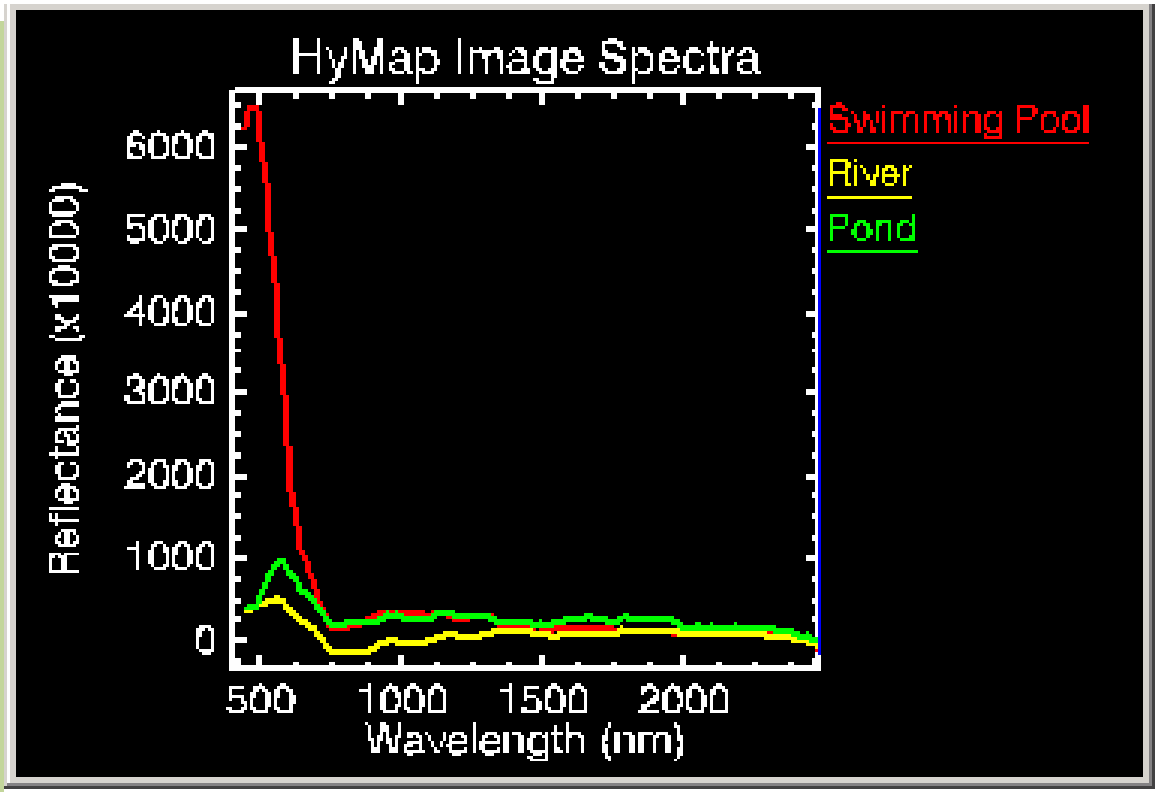




Swimming Pool Identification results:

Swimming Pools generally have a very high reflectance (>20%) in the blue and green wavelengths whereas natural water bodies have low (<10%) reflectance in visible wavelengths (400nm to 700nm).

All water has zero reflectance in NIR (700nm to 1000nm) and SWIR (890nm -2420nm)



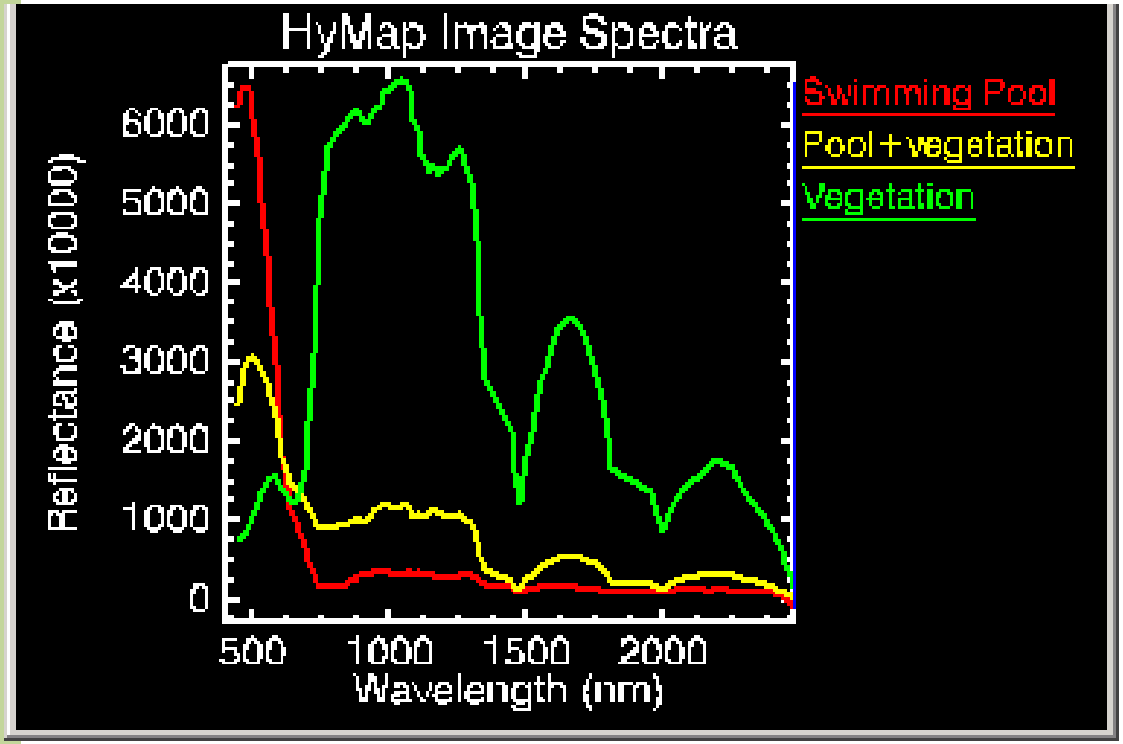
A Blue–Red index was used to separate water from other materials

- **Blue–red index**

Blue-Red = R467nm - R667 nm
Blue+Red R467nm + R667 nm

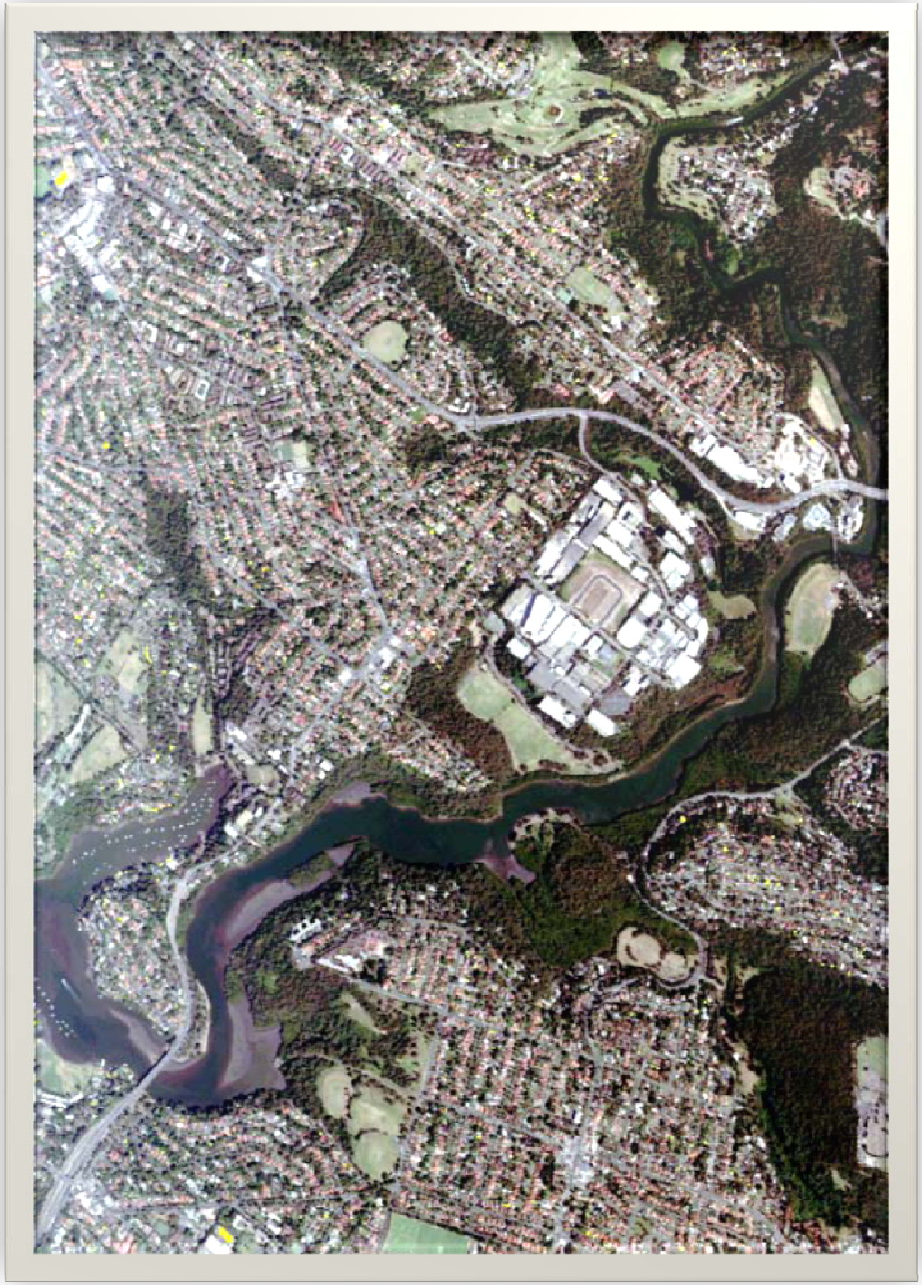
Shows that reflectance values are +ve for water but -ve or near zero for all other materials. The Blue-Red index can also identify swimming pools in pure and also mixed pixels. To separate natural water bodies from pool we used a simple band math algorithm with thresholds or decision tree rules.

Blue-Red index >0.15
& Blue Reflectance > 10%



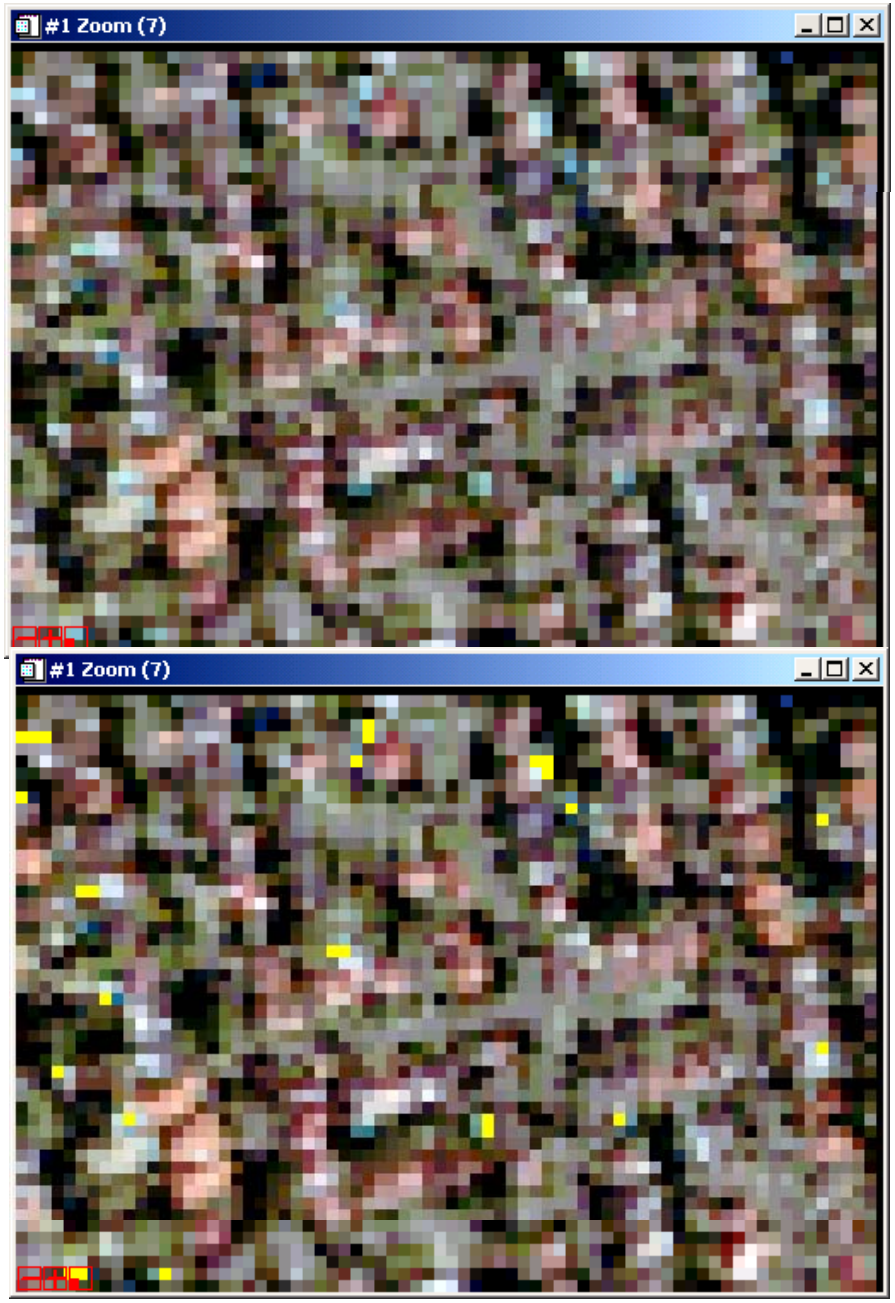
Pool locations (shown in yellow) after applying the Blue -Red Index.

Locations are overlain on a RGB image from the study site. Note that the swimming pools are located mostly in residential areas



Pool location classification results (Shown in yellow) after applying the Blue-Red Index

RGB image showing location of pools on a zoomed image. Note the real world locations of pools on image a (above) and the location of classification on the image below



Spectral footprints showing absorption features at 900nm.

A continuum is defined for each spectrum by finding the high points (local maxima) and fitting straight line segments between these points. The continuum was divided into the original spectrum to normalize the absorption bands to a common reference. A linear continuum removal was fitted between between bands 834nm and 958 nm.

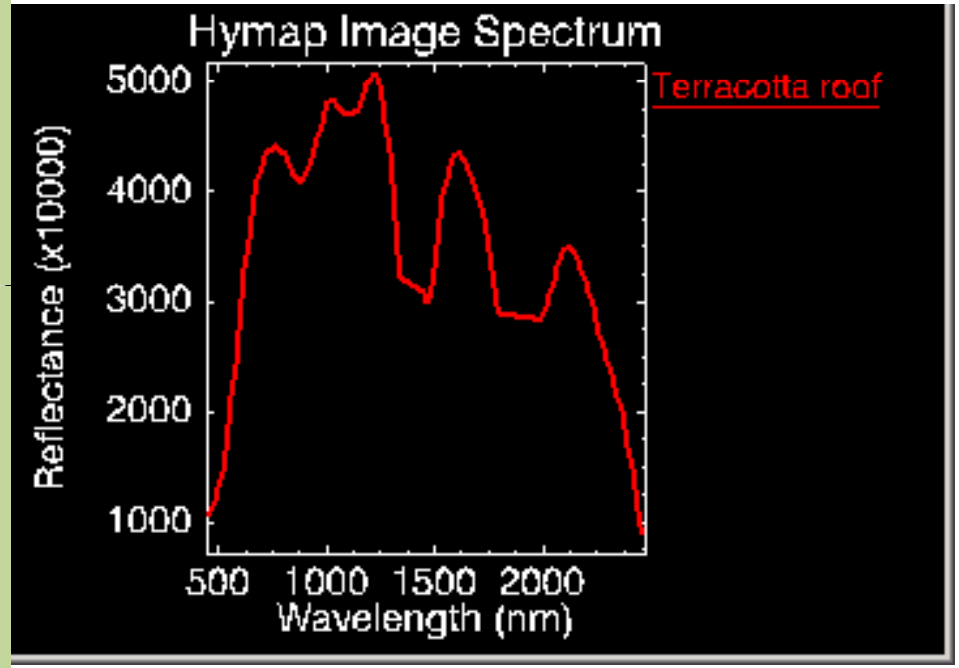
Continuum removed (CR) spectrum obtained

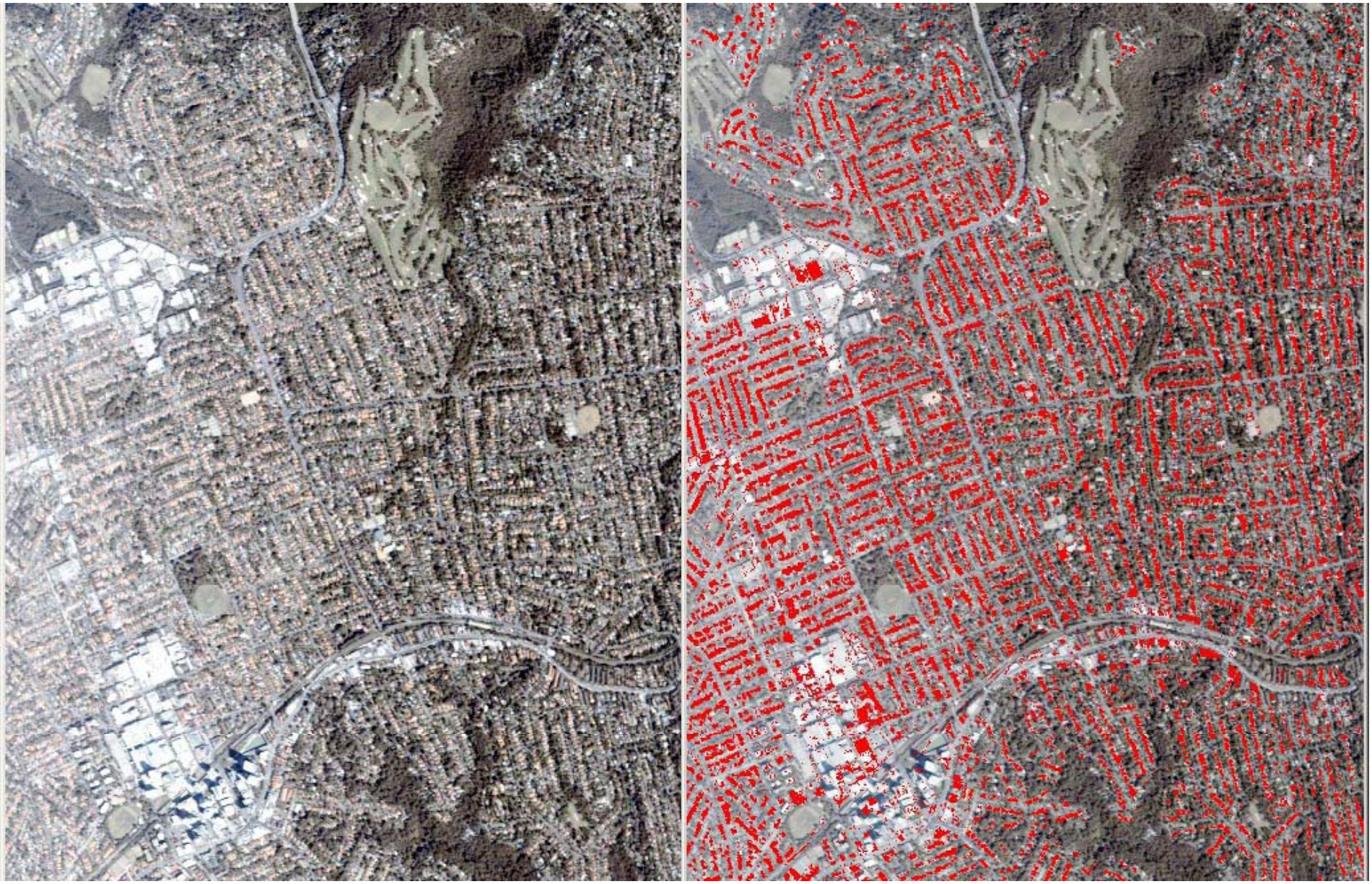
1-CR = absorption depth

The absorption band area was defined by summing the depths of high absorption bands. Absorption depths summed across 834nm and 958 nm bands = absorption band area. Finally to separate the metal roofs and water, we used a band math function with the following conditions:

R530nm < R667nm ,

Absorption band area > 0.10





Figures above shows results of the classification of Terracotta Roofs

A Blue–Red index was used to separate water from other materials

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Blue+Red R467nm + R667 nm

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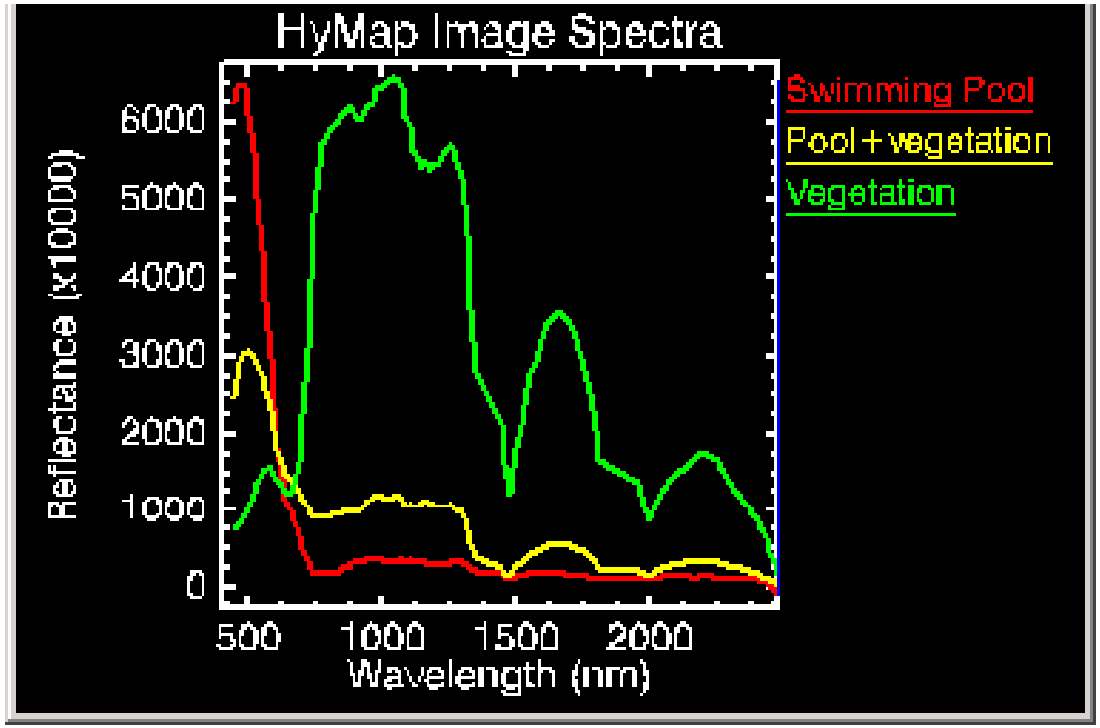

Limitations of Study

Need better Spatial Resolution than existing one

Spectral Confusion-Mixed Pixels

Large Size of Data to be processed

Cost of Data