High Spectral And Spatial Resolution Sensor Images for Mapping Urban Areas

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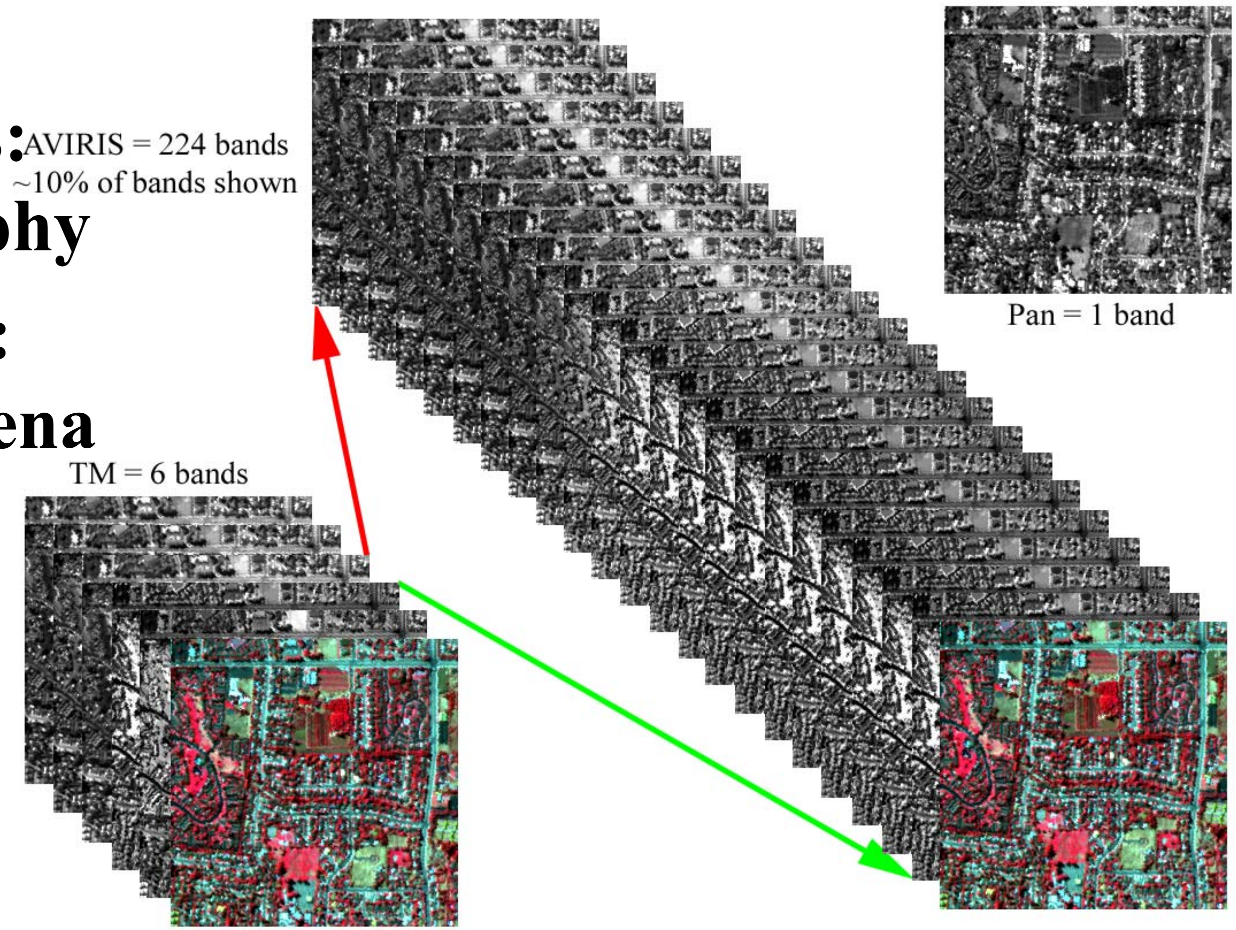


Outline

- Introduction
  - Why urban, why imaging spectrometry?
- Urban spectroscopy
- Example Analysis
  - Classification
    - Spectral separability
    - Spectral and spatial tradeoffs
  - Matched filters
  - Pavement Quality
  - Multiple Endmember Spectral Mixture Analysis
- Summary

Why is Urban remote sensing important?

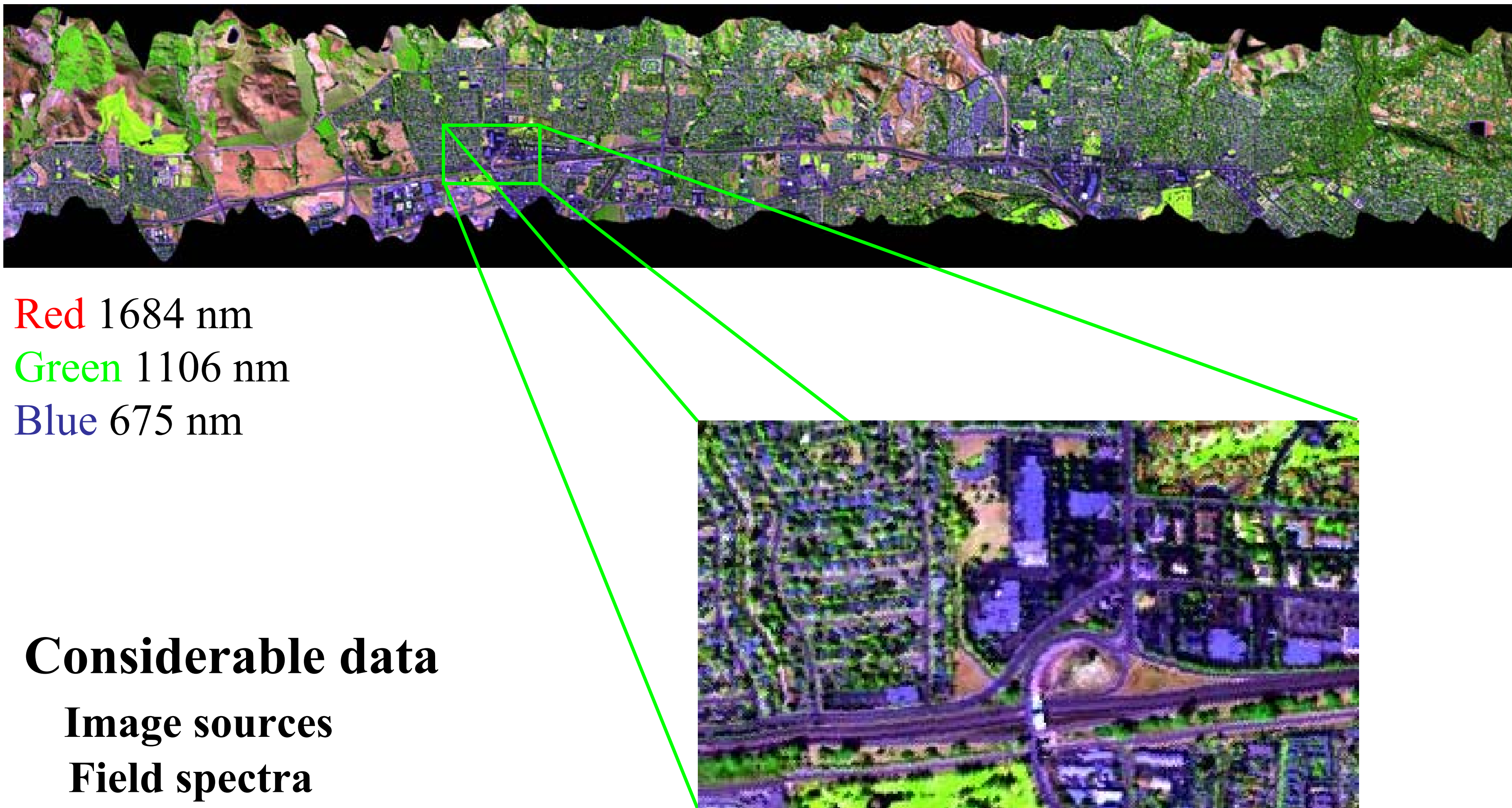
- **Urban areas are where a majority of humans live**
  - **> 50% urban population and rising**
- **Urban areas are centers of human activity**
  - **Major sinks for raw and fabricated materials**
  - **Major consumers of energy, sources of airborne and waterborne pollutants**
- **Urban areas are vulnerable to disaster, require planning**
  - **Flood management/water quality**
  - **Fire danger**
  - **Urban infrastructure, transportation**
    - **Reduced energy consumption, reduced emissions**

Remote Sensing of Urban Environments

- **Remote Sensing is a Crucial Technology**
  - Urban areas are growing rapidly
  - Many urban areas are poorly mapped globally
  - Rapid response and planning require current maps
- **Urban Environments are Challenging**
  - The diversity of materials is high
  - The scale at which surfaces are homogeneous is typically below the spatial resolution of spaceborne and airborne sensors
- **New Remote Sensing Technologies have considerable promise**
  - Hyperspectral: AVIRIS, Hyperion, HYMAP
  - Hyperspatial: IKONOS Panchromatic
  - LIDAR: Fine vertical resolution
  - SAR: Interferometry

Study Site: Santa Barbara, California

Oct 11, 1999 low-altitude data - 4 meter pixels



Red 1684 nm
Green 1106 nm
Blue 675 nm

Considerable data

- **Image sources**
- **Field spectra**

Complex urban environment

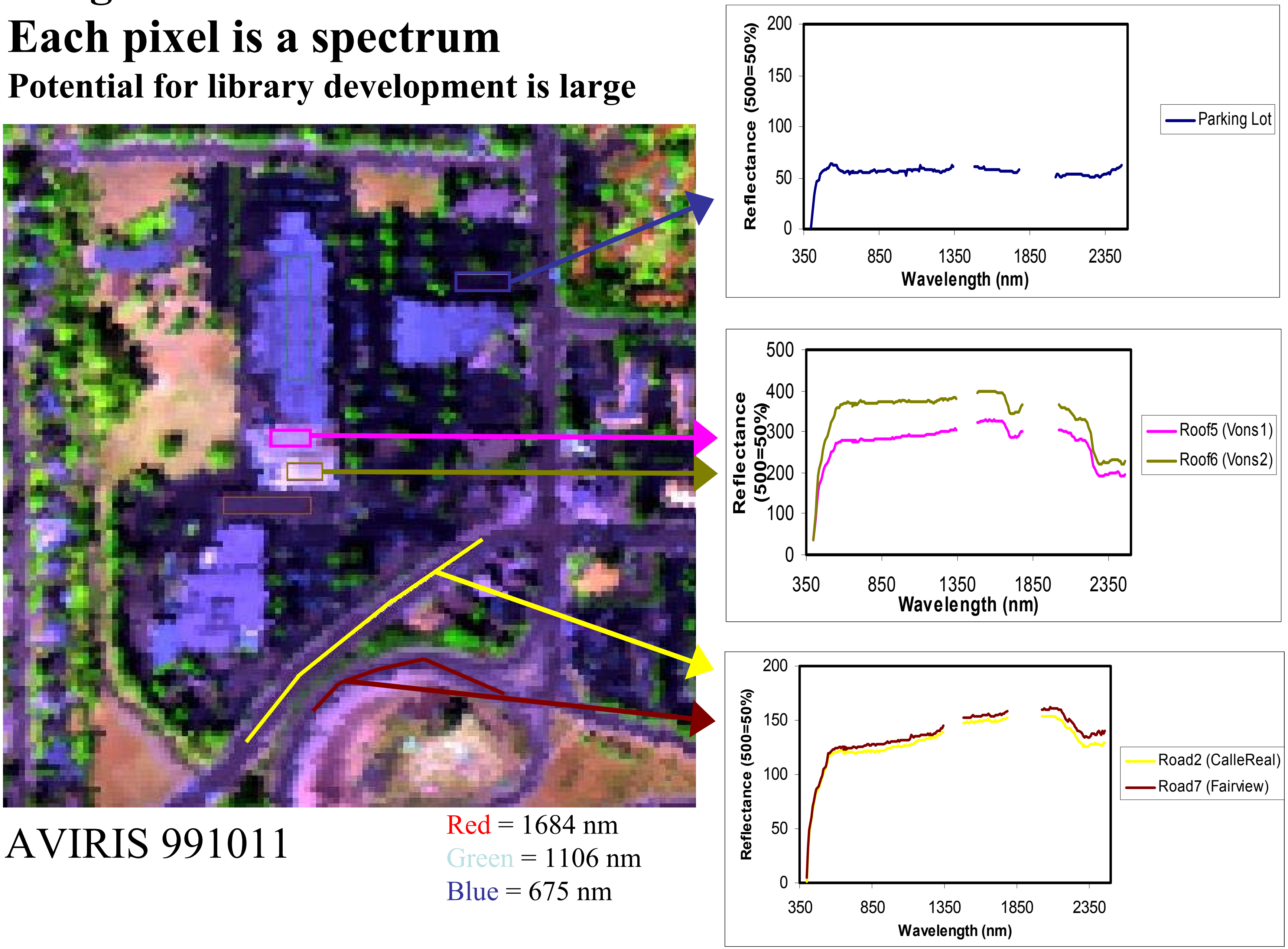
Urban Spectroscopy

- **What are the spectral properties of typical urban materials?**
- **How many unique spectra are present?**
- **Which spectra are likely to be confused?**
- **Which wavelengths are important for distinguishing materials?**
- **How can spectral and spatial information be used to map roads and roof types and road quality?**

Image Sources

Each pixel is a spectrum

Potential for library development is large

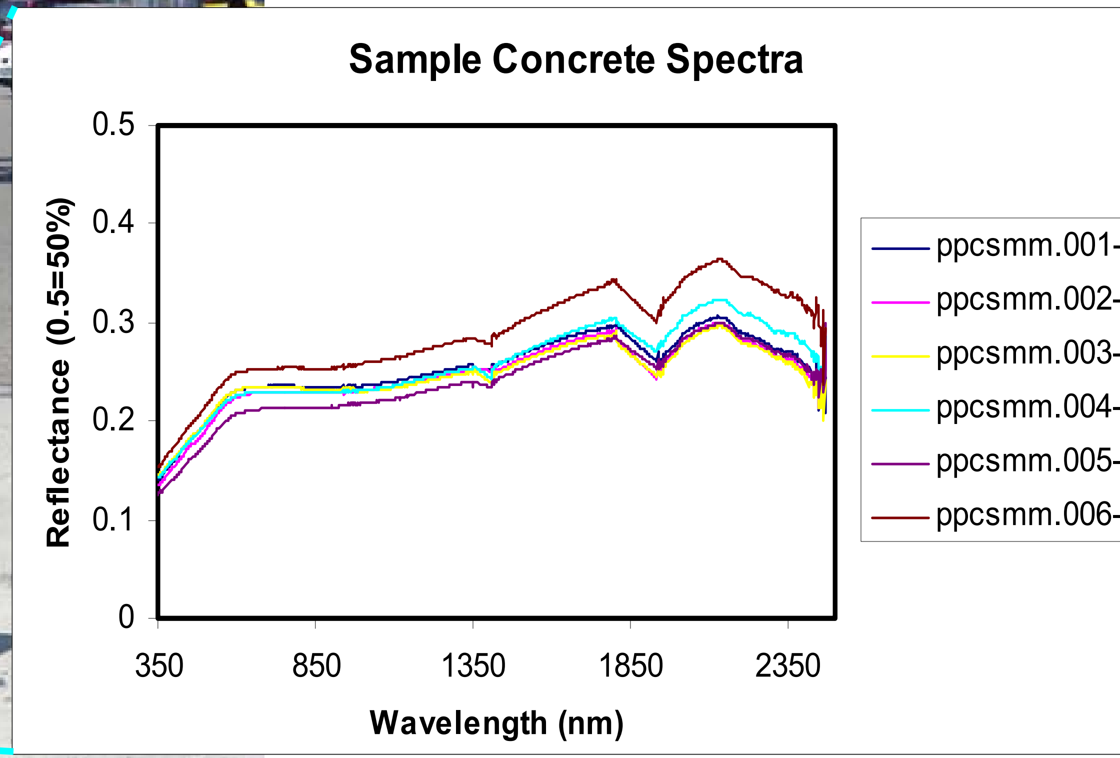


AVIRIS 991011

Red = 1684 nm
Green = 1106 nm
Blue = 675 nm

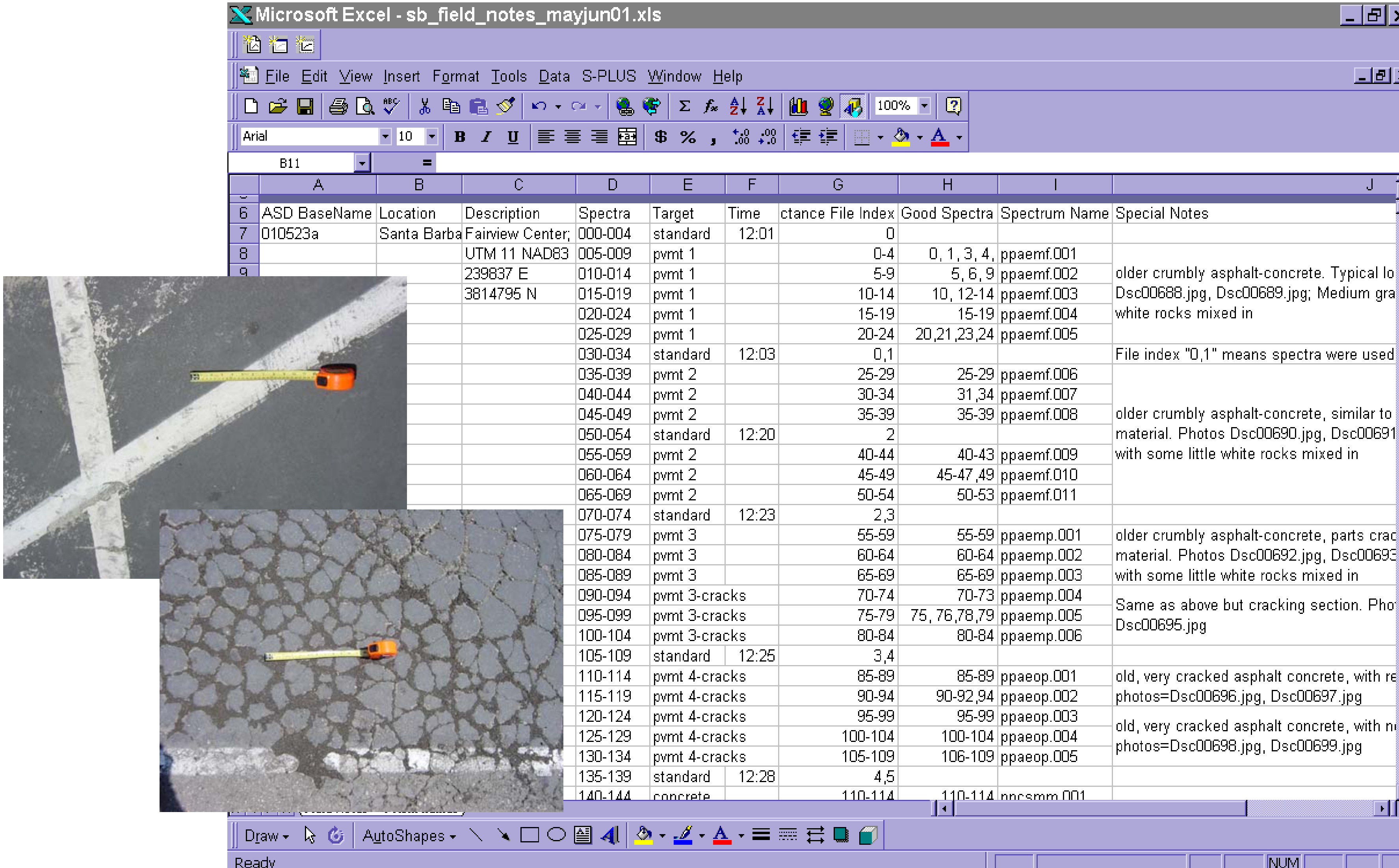
Field Spectra Collection

ASD Full-Range Spectrometer



Roberts and Herold, 2004

Field photos were taken & metadata recorded at each field site...



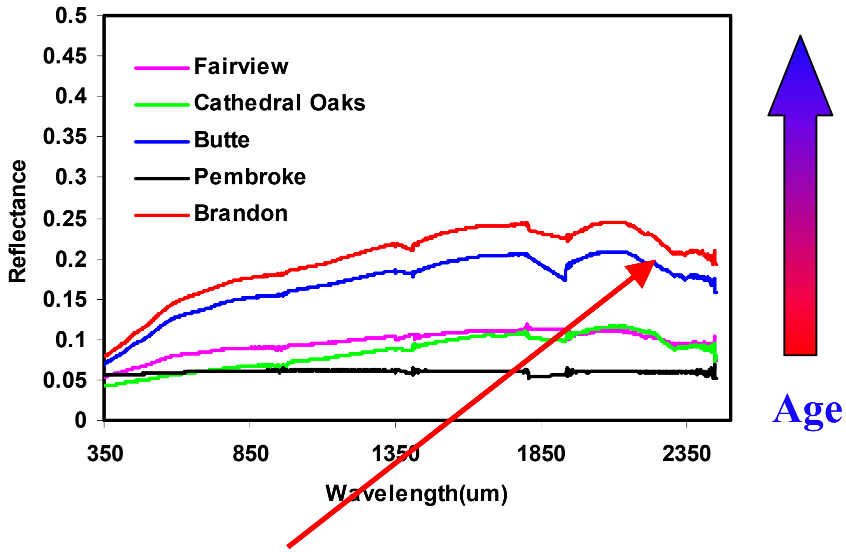
	A	B	C	D	E	F	G	H	I	J
6	ASD BaseName	Location	Description	Spectra	Target	Time	ctance File Index	Good Spectra	Spectrum Name	Special Notes
7	010523a	Santa Barba	Fairview Center;	000-004	standard	12:01	0			
8			UTM 11 NAD83	005-009	pvmt 1		0-4	0, 1, 3, 4,	ppaemf.001	
9			239837 E	010-014	pvmt 1		5-9	5, 6, 9	ppaemf.002	older crumbly asphalt-concrete. Typical lo
			3814795 N	015-019	pvmt 1		10-14	10, 12-14	ppaemf.003	Dsc00688.jpg, Dsc00689.jpg; Medium gra
				020-024	pvmt 1		15-19	15-19	ppaemf.004	white rocks mixed in
				025-029	pvmt 1		20-24	20,21,23,24	ppaemf.005	
				030-034	standard	12:03	0,1			File index "0,1" means spectra were used
				035-039	pvmt 2		25-29	25-29	ppaemf.006	
				040-044	pvmt 2		30-34	31,34	ppaemf.007	
				045-049	pvmt 2		35-39	35-39	ppaemf.008	older crumbly asphalt-concrete, similar to
				050-054	standard	12:20	2			material. Photos Dsc00690.jpg, Dsc00691
				055-059	pvmt 2		40-44	40-43	ppaemf.009	with some little white rocks mixed in
				060-064	pvmt 2		45-49	45-47,49	ppaemf.010	
				065-069	pvmt 2		50-54	50-53	ppaemf.011	
				070-074	standard	12:23	2,3			
				075-079	pvmt 3		55-59	55-59	ppaemp.001	older crumbly asphalt-concrete, parts crac
				080-084	pvmt 3		60-64	60-64	ppaemp.002	material. Photos Dsc00692.jpg, Dsc00693
				085-089	pvmt 3		65-69	65-69	ppaemp.003	with some little white rocks mixed in
				090-094	pvmt 3-cracks		70-74	70-73	ppaemp.004	
				095-099	pvmt 3-cracks		75-79	75, 76,78,79	ppaemp.005	Same as above but cracking section. Pho Dsc00695.jpg
				100-104	pvmt 3-cracks		80-84	80-84	ppaemp.006	
				105-109	standard	12:25	3,4			
				110-114	pvmt 4-cracks		85-89	85-89	ppaeop.001	old, very cracked asphalt concrete, with re
				115-119	pvmt 4-cracks		90-94	90-92,94	ppaeop.002	photos=Dsc00696.jpg, Dsc00697.jpg
				120-124	pvmt 4-cracks		95-99	95-99	ppaeop.003	old, very cracked asphalt concrete, with n
				125-129	pvmt 4-cracks		100-104	100-104	ppaeop.004	photos=Dsc00698.jpg, Dsc00699.jpg
				130-134	pvmt 4-cracks		105-109	106-109	ppaeop.005	
				135-139	standard	12:28	4,5			
				140-144	concrete		110-114	110-114	ppcsmm.001	

Field Spectra Summary

- Over 6,500 urban field spectra were collected throughout Santa Barbara in May & June 2001
- Field spectra were averaged in sets of 5 and labeled appropriately in building the urban spectral library
- The resulting urban spectral library includes:
  - 499 roof spectra
  - 179 road spectra
  - 66 sidewalk spectra
  - 56 parking lot spectra
  - 40 road paint spectra
  - 37 vegetation spectra
  - 47 non-photosynthetic vegetation spectra (ie. Landscaping bark, dead wood)
  - 27 tennis court spectra
  - 88 bare soil and beach spectra
  - 50 miscellaneous other urban spectra

Transportation Surfaces

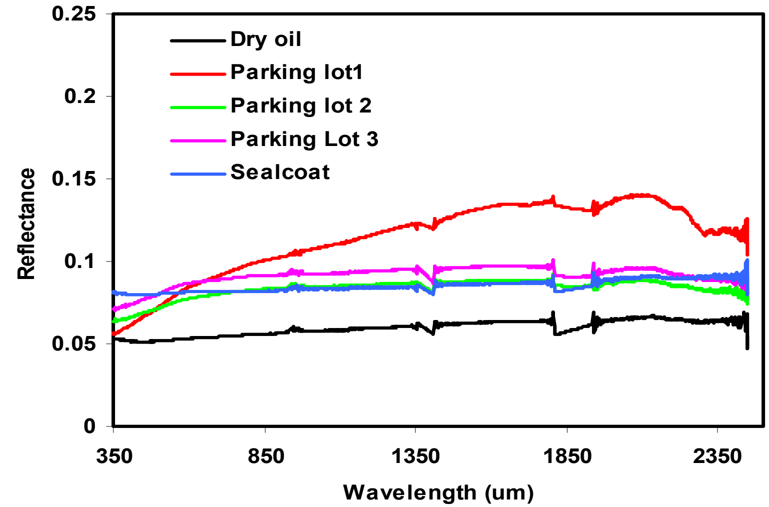
Asphalt Roads



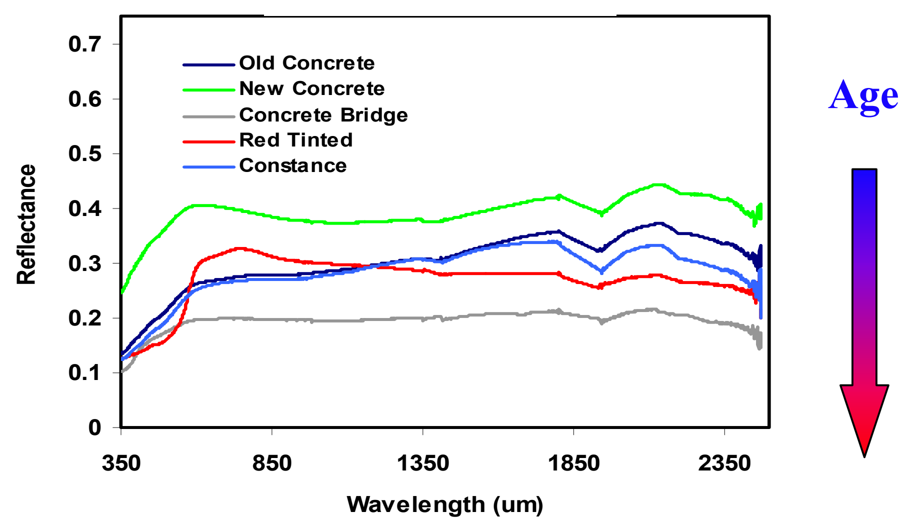
Hydrocarbon absorption

Material compositionand age are critical

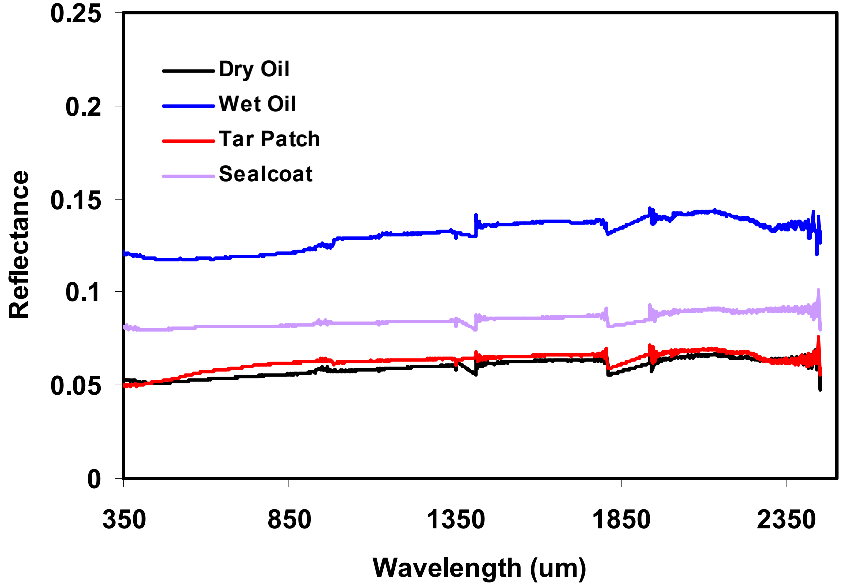
Parking Lots

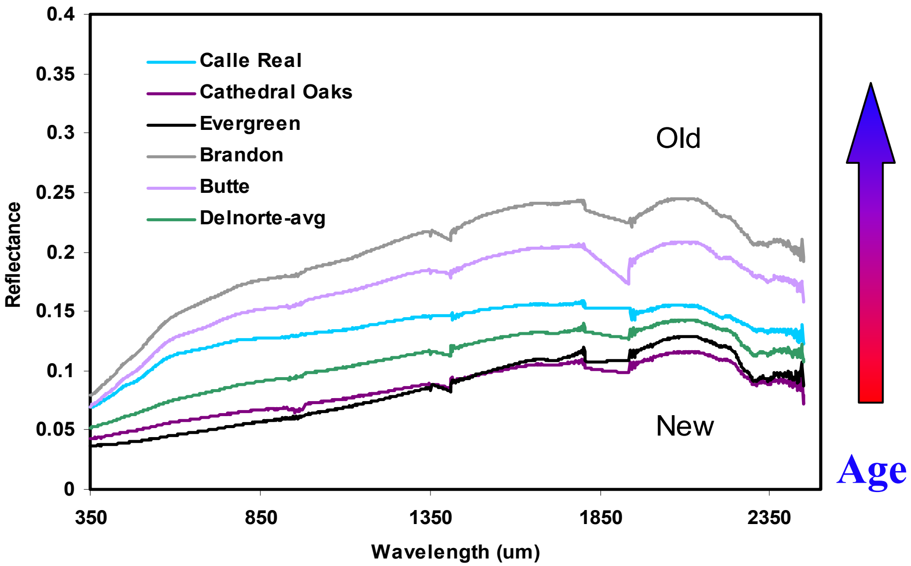


Concrete



Road Surface Modification



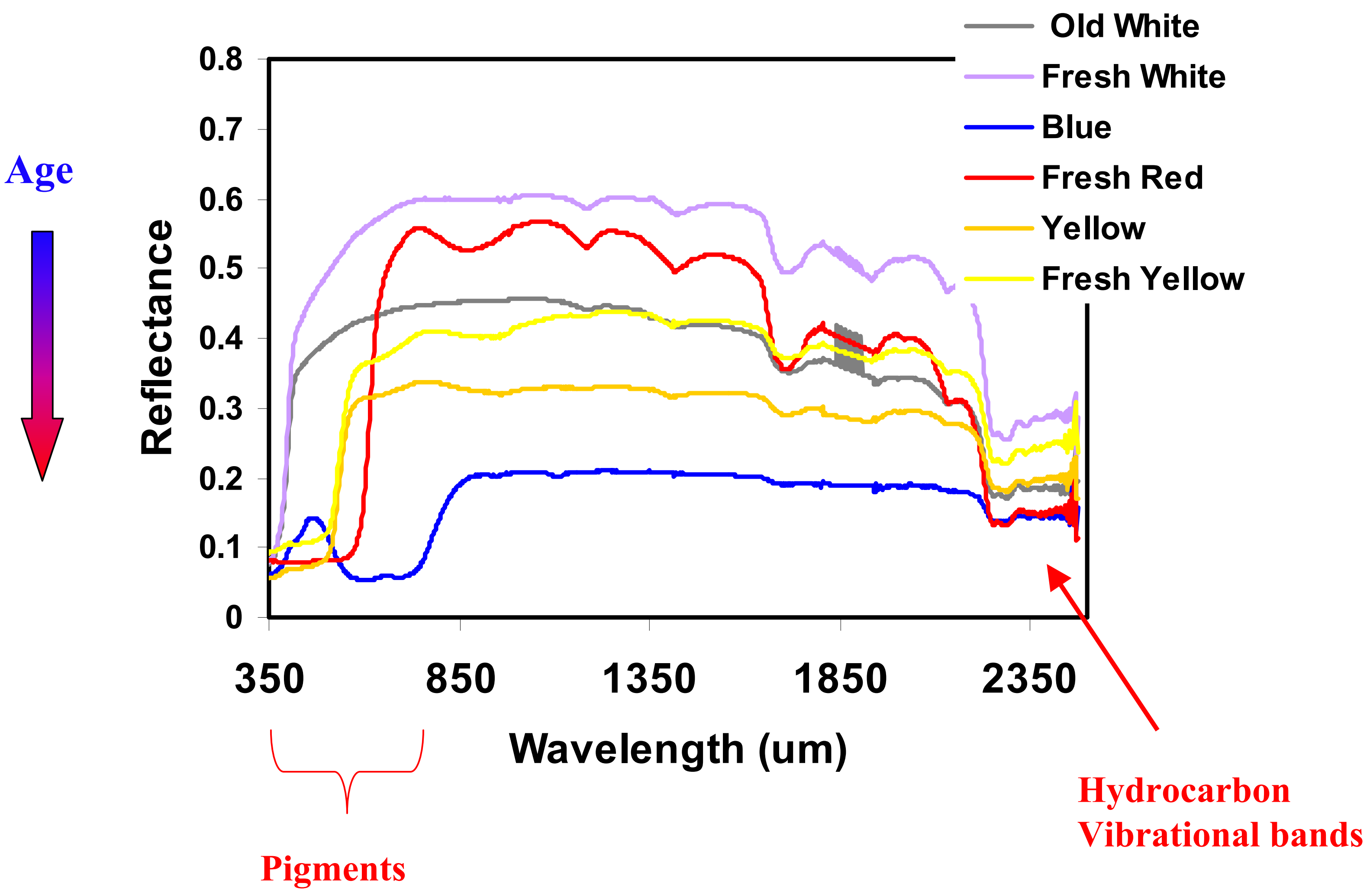


Transportation surfaces change

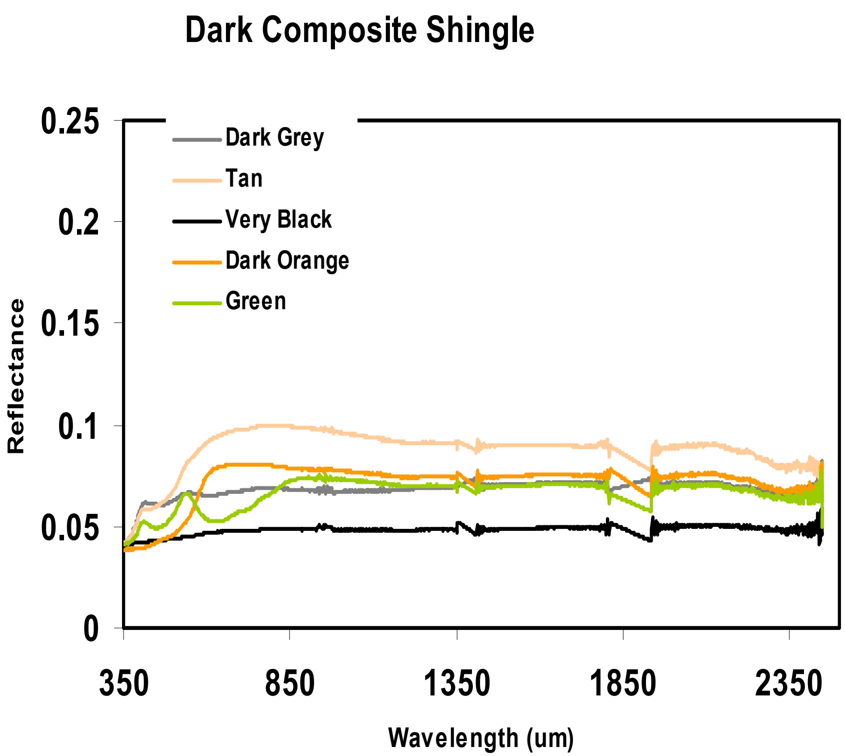
Asphalt roads generally become lighter as they age

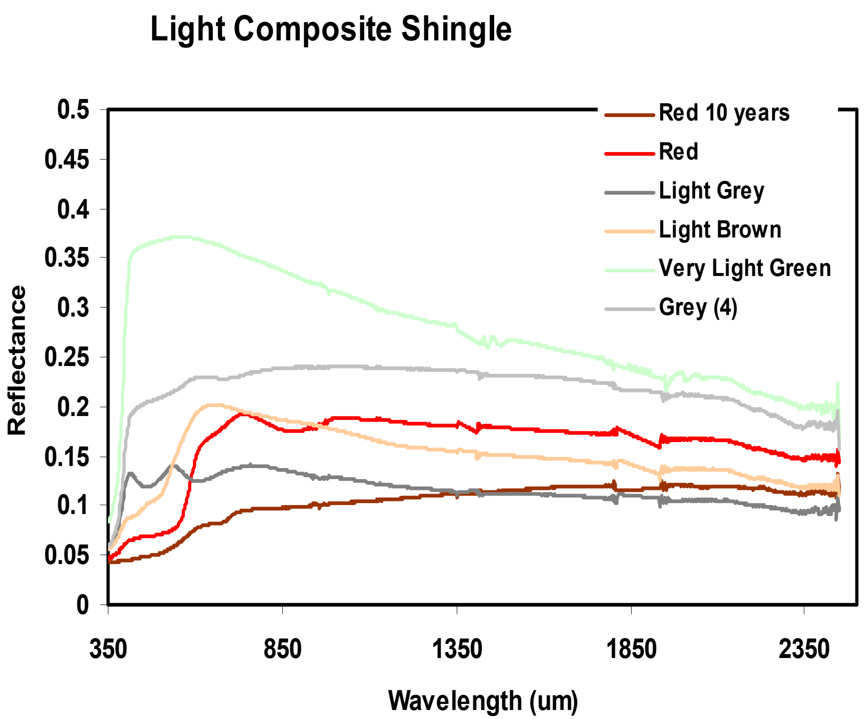
Cracking, patching and oil generally darken road surfaces

Street Paints



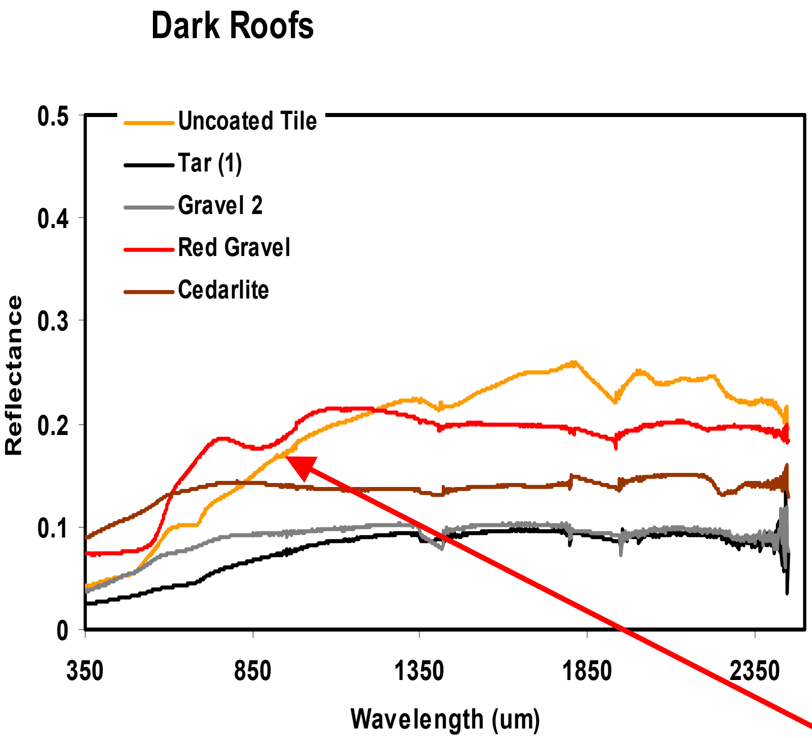
Composite Shingles

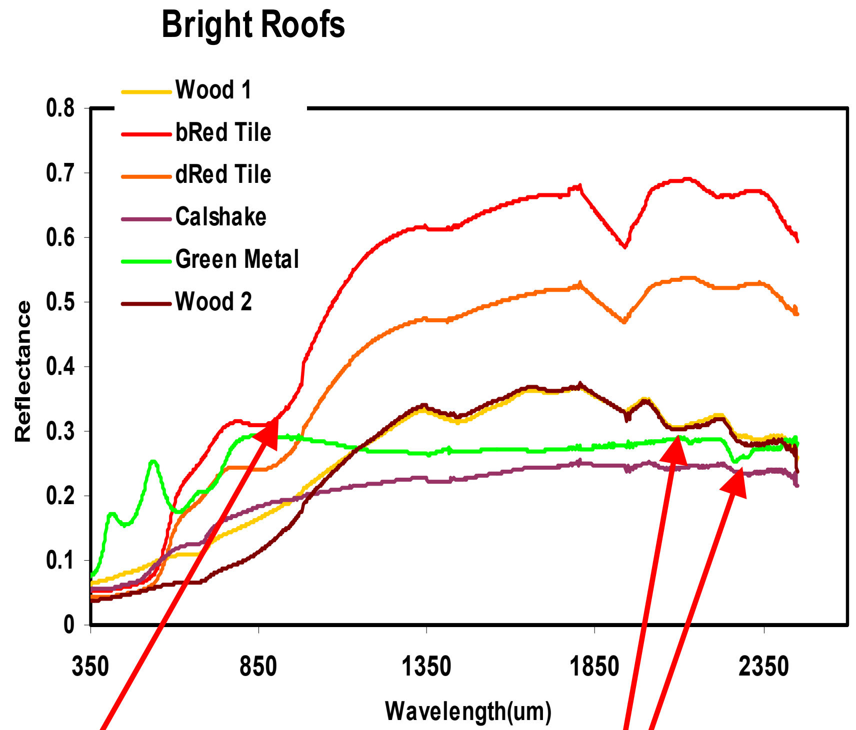




Generally comprised of asphalt with minerals imbedded in the surface for color
Vary depending upon age, mix of materials that provide color
Highly variable – these show only a selection of those present in the region

Other Roof Materials

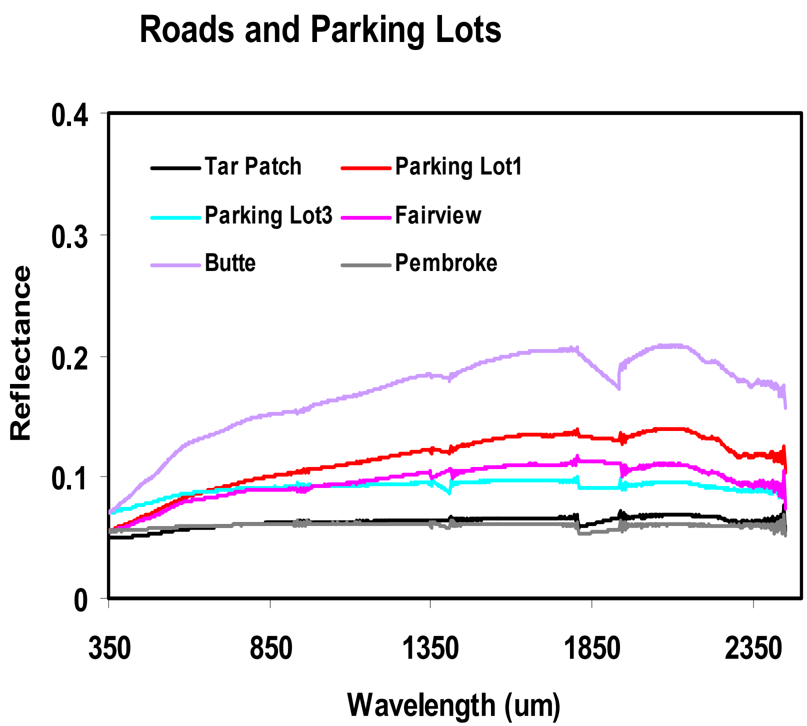


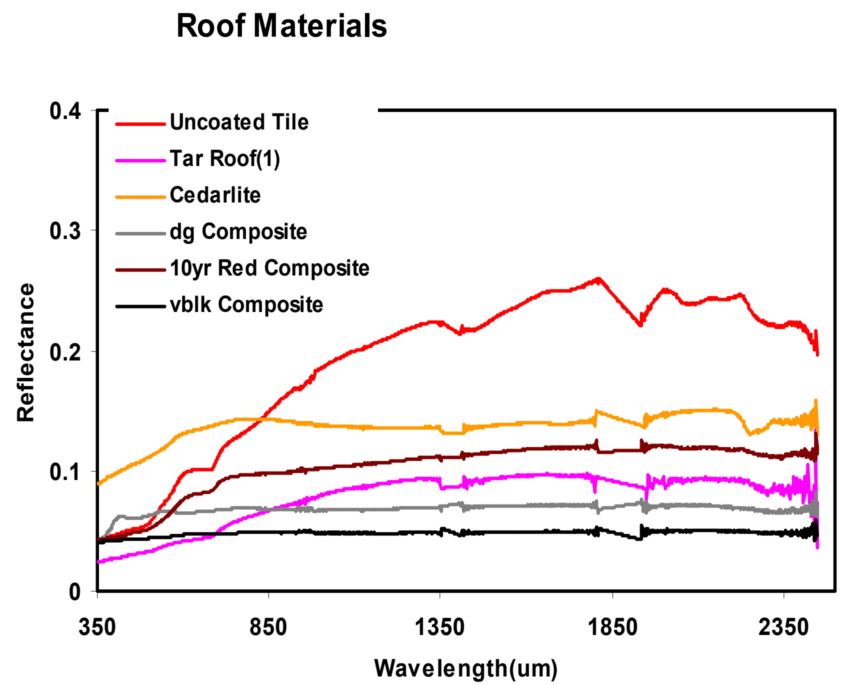


Iron oxide

Ligno-cellulose

The Challenge of Roads and Roofs





Some roads and roofs are quite distinct (Red tile)
Composite shingle and asphalt roofs can be spectrally similar
Aging, illumination and condition complicate analysis

Classifying Urban Landscapes

Key Questions

1) Which classes are spectrally distinct?
2) What is the optimal spatial resolution?
3) How do hyperspectral and broad band sensors compare?
4) How might LIDAR improve analysis?

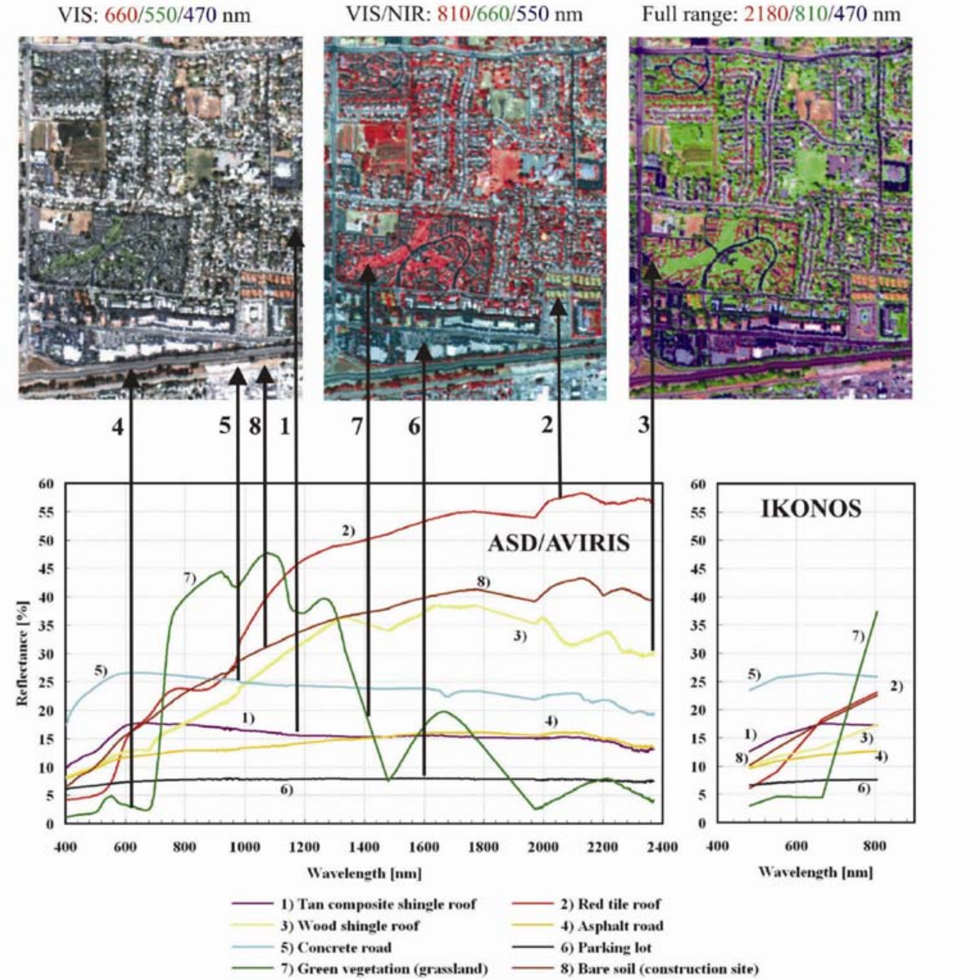


Figure 3: Representation of different urban surface types in different AVIRIS color composites compared to ground spectral measurements convolved to AVIRIS spectral configurations. The VIS and VIS/NIR composites would be similar to measurements taken by the IKONOS satellite. Spectra 1-3 represent roofs, spectra 4 - 6 transportation surfaces, spectra 7 green vegetation and spectra 8 bare soil to refer these spectra to land cover classes used in the classification

From Herold and Roberts, 2006
***Int. J. Geoinformatics* 2(1) 1-14**

Urban Classification Schemes

LEVEL 1	LEVEL 2	LEVEL 3	LEVEL 4
1 Built up	1.1 Buildings/roofs	1.1.1 Composite shingle roof	1.1.1.1 Black shingle
			1.1.1.2 Blue shingle
			1.1.1.3 Brown shingle
			1.1.1.4 Green shingle
			1.1.1.5 Grey shingle
			1.1.1.6 Mixed shingle
			1.1.1.7 Orange shingle
			1.1.1.8 Red shingle
			1.1.1.9 Tan shingle
			1.1.1.10 White shingle
		1.1.2 Plastic roofs	
		1.1.3 Glass	1.1.3.1 Light glass
		1.1.4 Gravel roof	1.1.4.1 Gray gravel
			1.1.4.2 Red gravel
		1.1.5 Metal roof	1.1.5.1 Brown metal
			1.1.5.2 Light grey metal
			1.1.5.3 Green metal
		1.1.6 Asphalt roof	1.1.6.1 Light grey asphalt
		1.1.7 Tile roof	1.1.7.1 Red tile
			1.1.7.2 Gray tile
		1.1.8 Tar roof	1.1.8.1 Black tar
			1.1.8.2 Brown tar
		1.1.9 Wood shingle roof	1.1.9.1 Dark wood shingle
	1.2 Transportation areas	1.2.1 Asphalt roads	1.2.1.1 Light asphalt (old)
			1.2.1.2 Dark asphalt (new)
		1.2.2 Concrete roads	1.2.2.1 Light concrete
		1.2.3 Gravel roads	1.2.3.1 Light gravel
		1.2.4 Parking lots	1.2.4.1 Dark parking lot
		1.2.5 Railroad	1.2.5.1 Railroad tracks
		1.2.6 Walkways	1.2.6.1 Light concrete
			1.2.6.1 Red brick
		1.2.7 Street paint	1.2.7.1 White street marks
			1.2.7.2 Yellow street marks
			1.2.7.3 Red street marks
			1.2.7.4 Blue street marks
			1.2.7.5 Other street marks
	1.3 Sport infrastructure	1.3.1 Tennis courts	
		1.3.2 Red Tartan	
		1.3.3 Basketball court	
2 Vegetation	2.1 Green vegetation		
	2.2 Non-photosynthetic vegetation (NPV)		
3 Non-urban bare surfaces	3.1 Bare soil		
	3.2 Beach		
	3.3 Bare Rock		
4 Water bodies	4.1 Natural/quasi-natural water bodies		
	4.2 Swimming Pools		

Anderson Classification:
Hierarchical classification scheme

VIS model: Vegetation-Impervious-Soil (Ridd, 1995)

Herold et al., 2003

Spectral Separability Measures: Bhattacharrya Distance

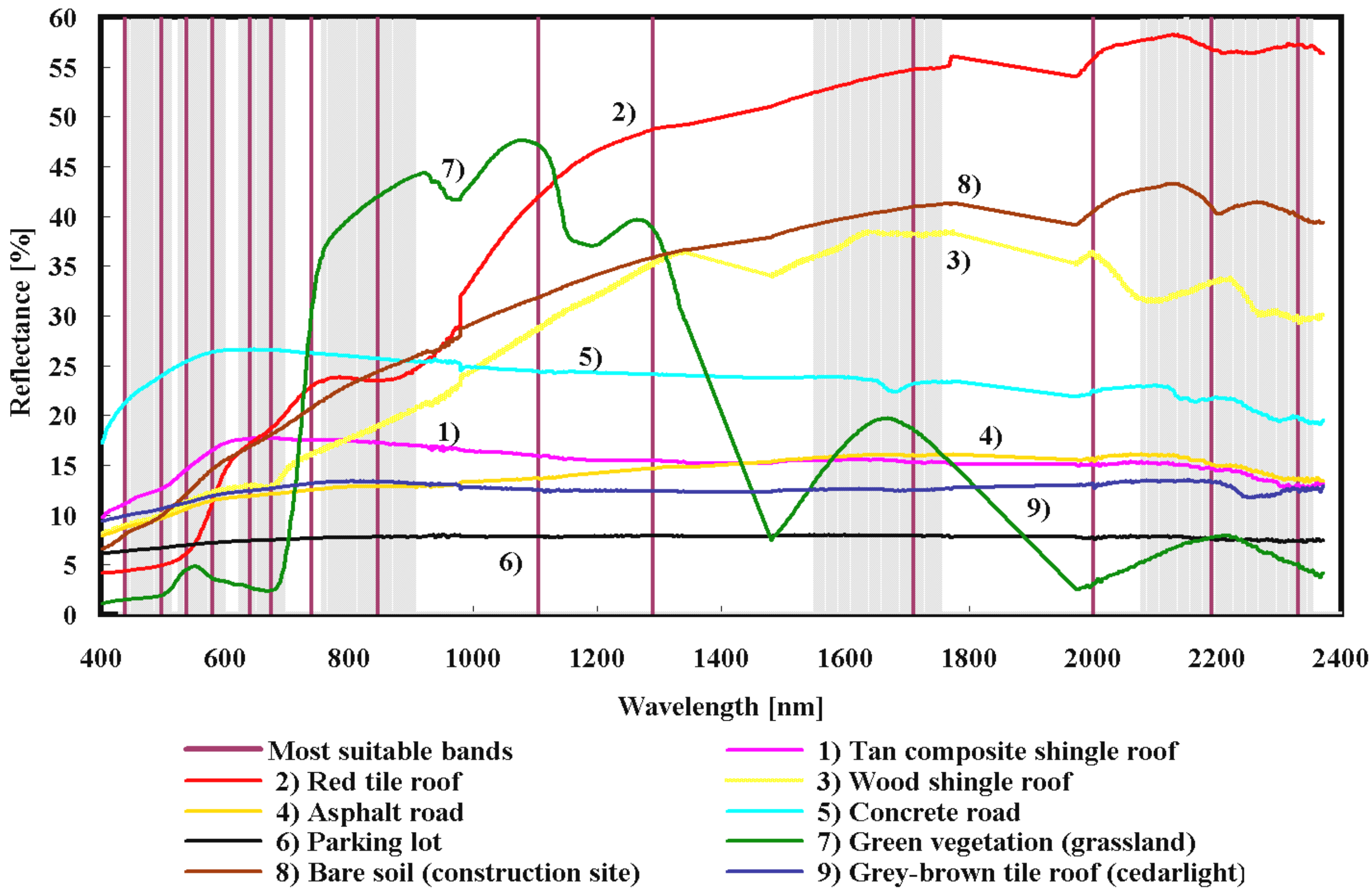
- **Screening of spectral characteristics of urban targets**
- **Separability measures – Bhattacharyya distance:**

$$B = \frac{1}{8}[\mu_1 - \mu_2]^T \left[\frac{\Sigma_1 + \Sigma_2}{2}\right]^{-1}[\mu_1 - \mu_2] + \frac{1}{2} \mathrm{Ln} \frac{\left|\frac{1}{2}[\Sigma_1 + \Sigma_2]\right|}{\sqrt{|\Sigma_1||\Sigma_2|}}$$

(μ - mean value | ∑ - Covariance)

- **Maximum Likelihood based image classification**

Most suitable spectral bands
Top 14 selected based on Bhattacharyya -distance



From: Herold M., Roberts D., Gardner M. and P. Dennison 2004. Spectrometry for urban area remote sensing - Development and analysis of a spectral library from 350 to 2400 nm, Remote Sens. Environ, Vol 91 (3-4) 304-319 .

Spectral Separability Matrix

Table 2
Average and minimum spectral separability (B-distance) for different land cover types

	1: Com_sh	2: Grav_rf	3: Tar_rf	4: Gr_tile	5: Rd_tile	6: Wd_sh	7: Asp_rd	8: Concr	9: Grav_rd	10: P_lot	11: Gr_veg	12: NPV	13: Soil_dk	14: Soil_be
1: Composite shingle		*56*	*19*	*14*	*75*	*61*	*8*	*18*	*106*	*13*	*80*	*70*	*133*	*285*
2: Gravel roof	**405**		*36*	*46*	*109*	*189*	*51*	*17*	*88*	*84*	*97*	*52*	*184*	*480*
3: Tar roof	**190**	**599**		*30*	*69*	*127*	*17*	*20*	*135*	*26*	*66*	*58*	*145*	*285*
4: Gray tile roof	**92**	**178**	**67**		*34*	*32*	*35*	*16*	*61*	*31*	*59*	*31*	*99*	*237*
5: Red tile roof	**549**	**581**	**559**	**375**		*84*	*90*	*52*	*147*	*130*	*92*	*59*	*248*	*748*
6: Wood shingle roof	**315**	**359**	**171**	**172**	**197**		*218*	*31*	*152*	*249*	*119*	*10*	*378*	*899*
7: Asphalt road	**244**	**693**	**119**	**99**	**1331**	**351**		*28*	*68*	*7*	*97*	*64*	*48*	*91*
8: Concrete road	**687**	**735**	**1325**	**423**	**1247**	**977**	**1151**		*29*	*11*	*59*	*42*	*27*	*20*
9: Gravel road	**2533**	**2514**	**1733**	**2460**	**927**	**4370**	**3047**	**1799**		*117*	*79*	*105*	*485*	*632*
10: Parking lot	**194**	**700**	**98**	**81**	**1499**	**436**	**194**	**897**	**3832**		*53*	*171*	*104*	*278*
11: Green veg.	**992**	**1066**	**1023**	**779**	**609**	**426**	**1614**	**1589**	**1106**	**588**		*88*	*64*	*144*
12: Non-photos. veg.	**585**	**646**	**439**	**366**	**511**	**156**	**880**	**887**	**2288**	**953**	**1266**		*72*	*84*
13: Bare soil (dark)	**438**	**627**	**330**	**230**	**652**	**542**	**542**	**840**	**2196**	**801**	**638**	**731**		*218*
14: Bare soil (beach)	**1152**	**780**	**1145**	**477**	**1568**	**1073**	**1413**	**1035**	**1249**	**1614**	**889**	**881**	**354**	

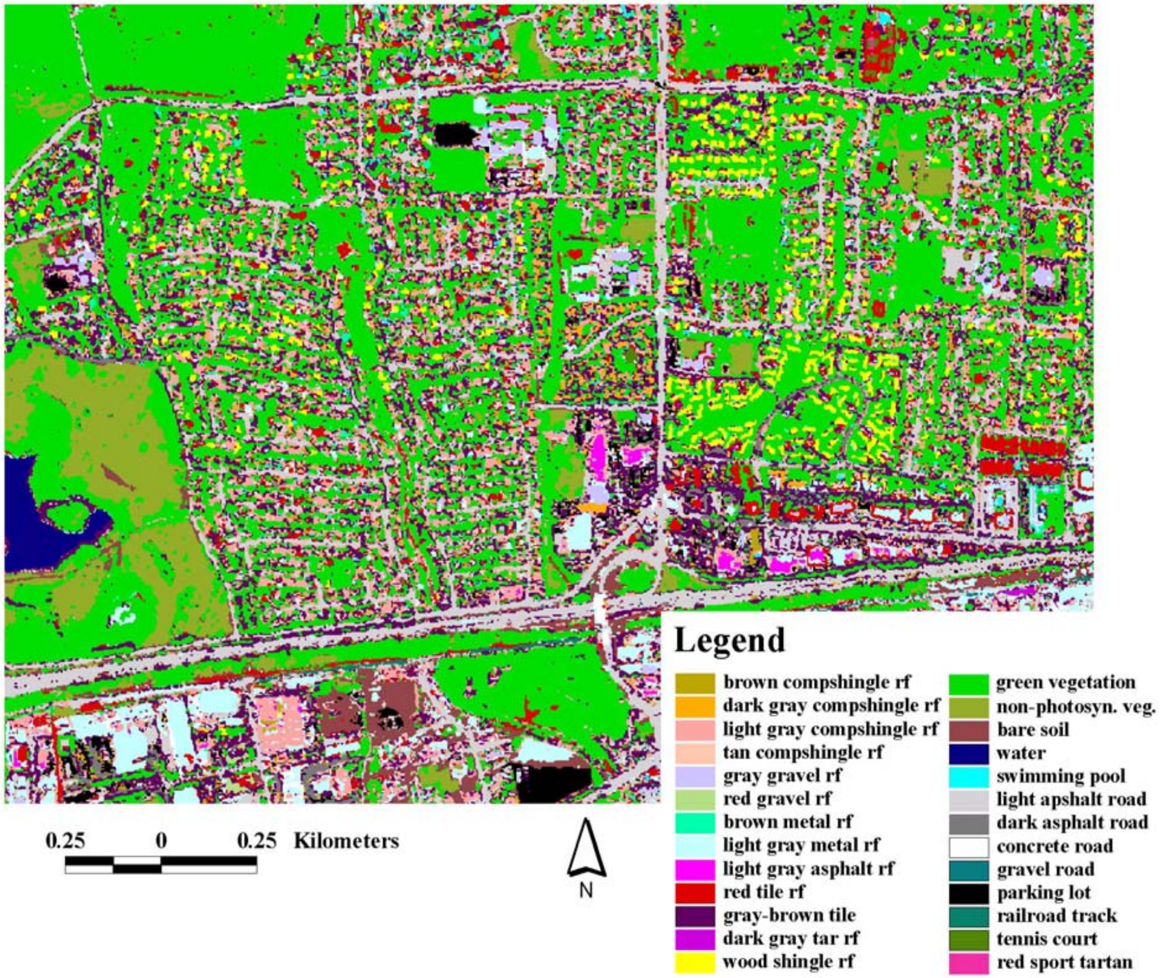
Coding of values: **Bold**: Average separability (lower left part of matrix) / *Italic*: Minimum separability(upper rightpart of matrix)

Coding of background: Average value ≤150 / Minimum value ≤20 — 151 ≤ Average value ≤ 300 / 21 ≤ Minimum value ≤ 40

- **All values are B-distance scores: Larger values = more separable**
- **Lower left part of matrix: average separability**
- **Upper right part of matrix: minimum separability**
- **Light grey are moderately separable, dark grey are problems**

From: Herold M., Roberts D., Gardner M. and P. Dennison 2004. Spectrometry for urban area remote sensing - Development and analysis of a spectral library from 350 to 2400 nm, Remote Sens. Environ, Vol 91 (3-4) 304-319 .

Land Cover Mapping



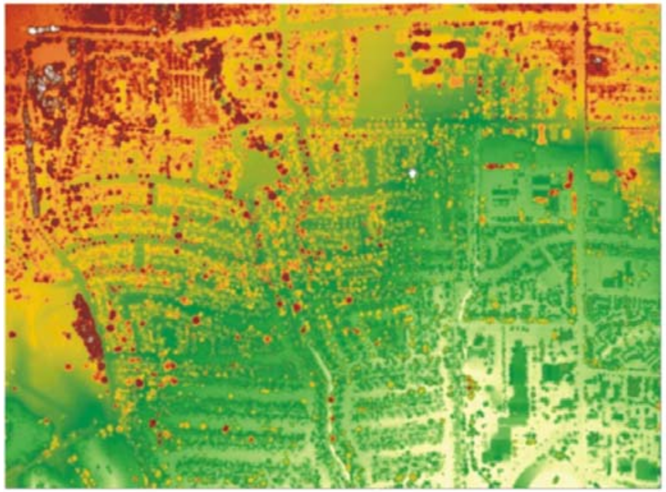
- 14 most suitable bands
- 26 land cover classes
- 22 built up classes
- Inter-class confusion confirms sep. analysis
- Spectral limitations:
  - # and location of bands
  - Narrow vs. broadband

Overall Accuracy

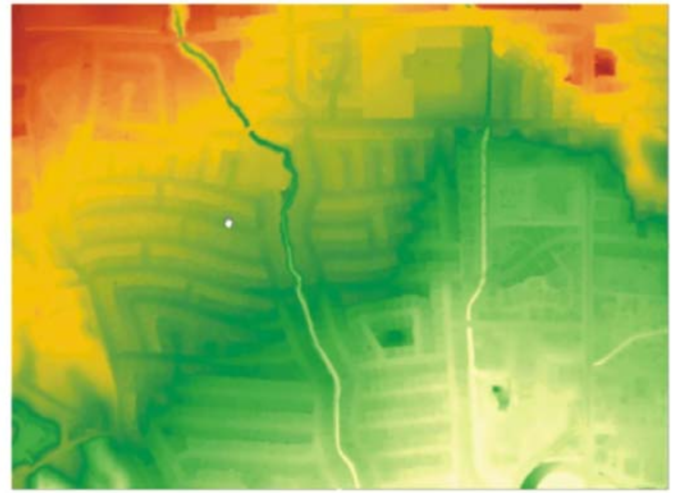
	Mean accuracy	Kappa coefficient	Area weighted accuracy	Built classes accuracy
IKONOS (4 bands)	61.8 %	60.2 %	66.6 %	37.7 %
Landsat TM (6 bands)	68.9 %	67.7 %	75.8 %	53.9 %
AVIRIS (14 bands)	73.5 %	72.5 %	82.0 %	66.6 %

From: Herold M., Gardner M. and Roberts D. 2003. Spectral Resolution Requirements for Mapping Urban Areas, IEEE Transactions on Geoscience and Remote Sensing, 41, 9, pp. 1907-1919

Small-footprint LIDAR



LIDAR first return elevation



LIDAR last return elevation

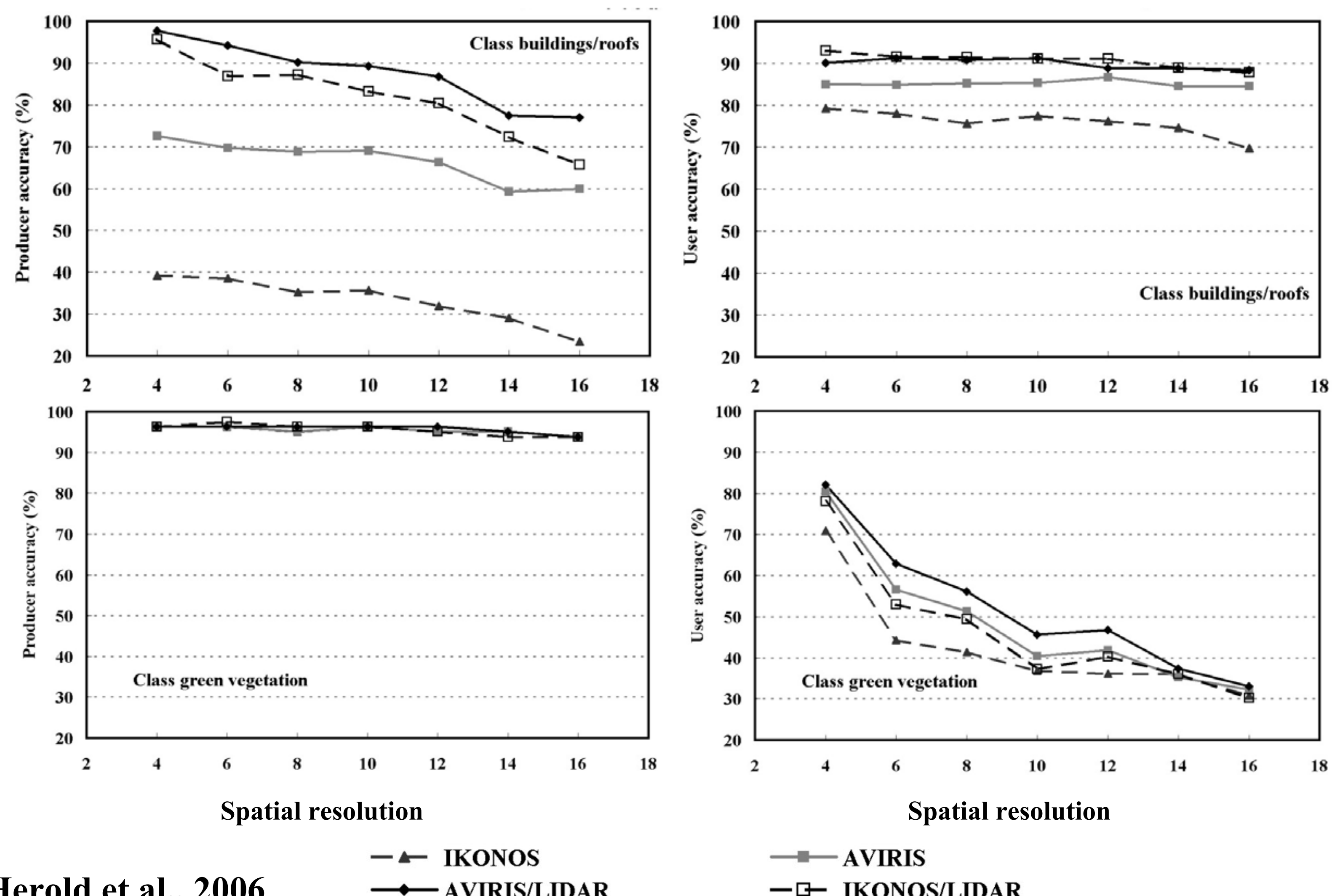
IKONOS 4/2/1

Elevation difference first/last (m)

Spatial-spectral tradeoffs

Producer's accuracy
Correct/Reference

User's accuracy
Correct/Mapped



Herold et al., 2006

Matched Filter Analysis

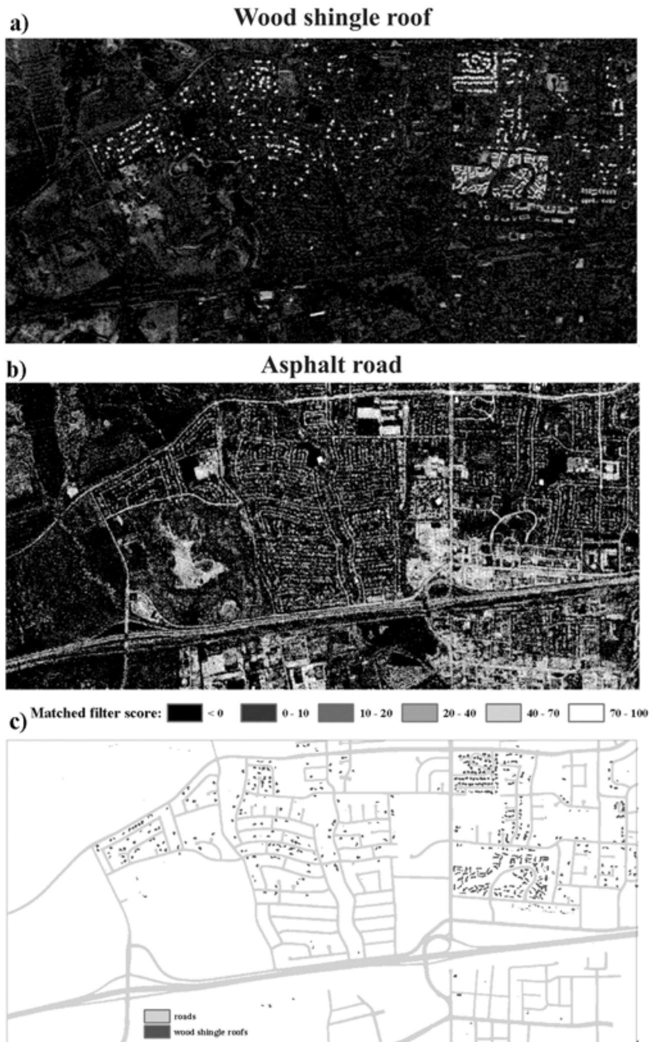
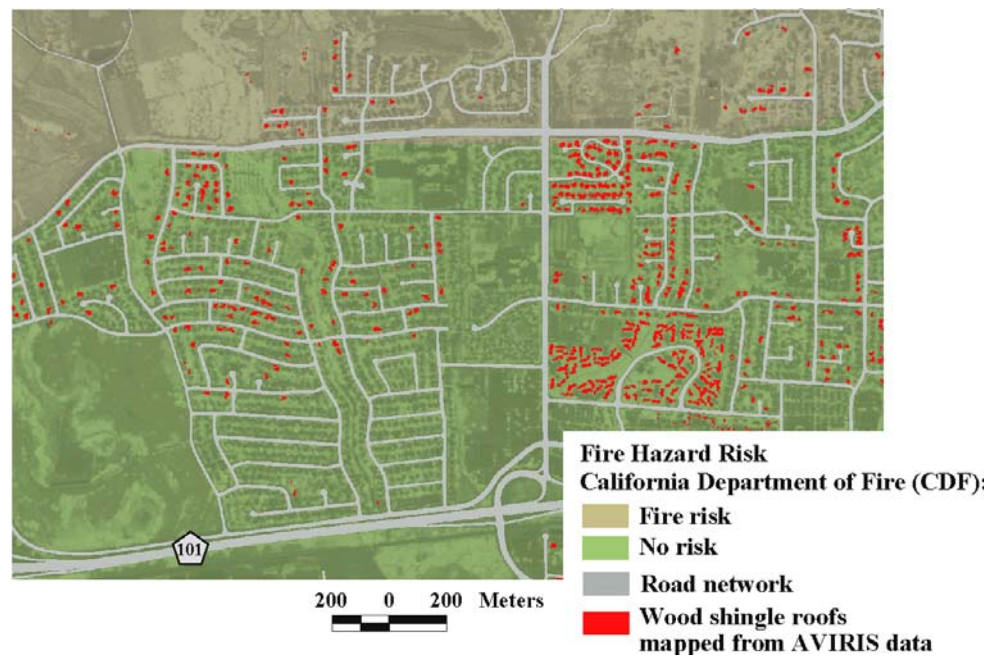


Figure 11



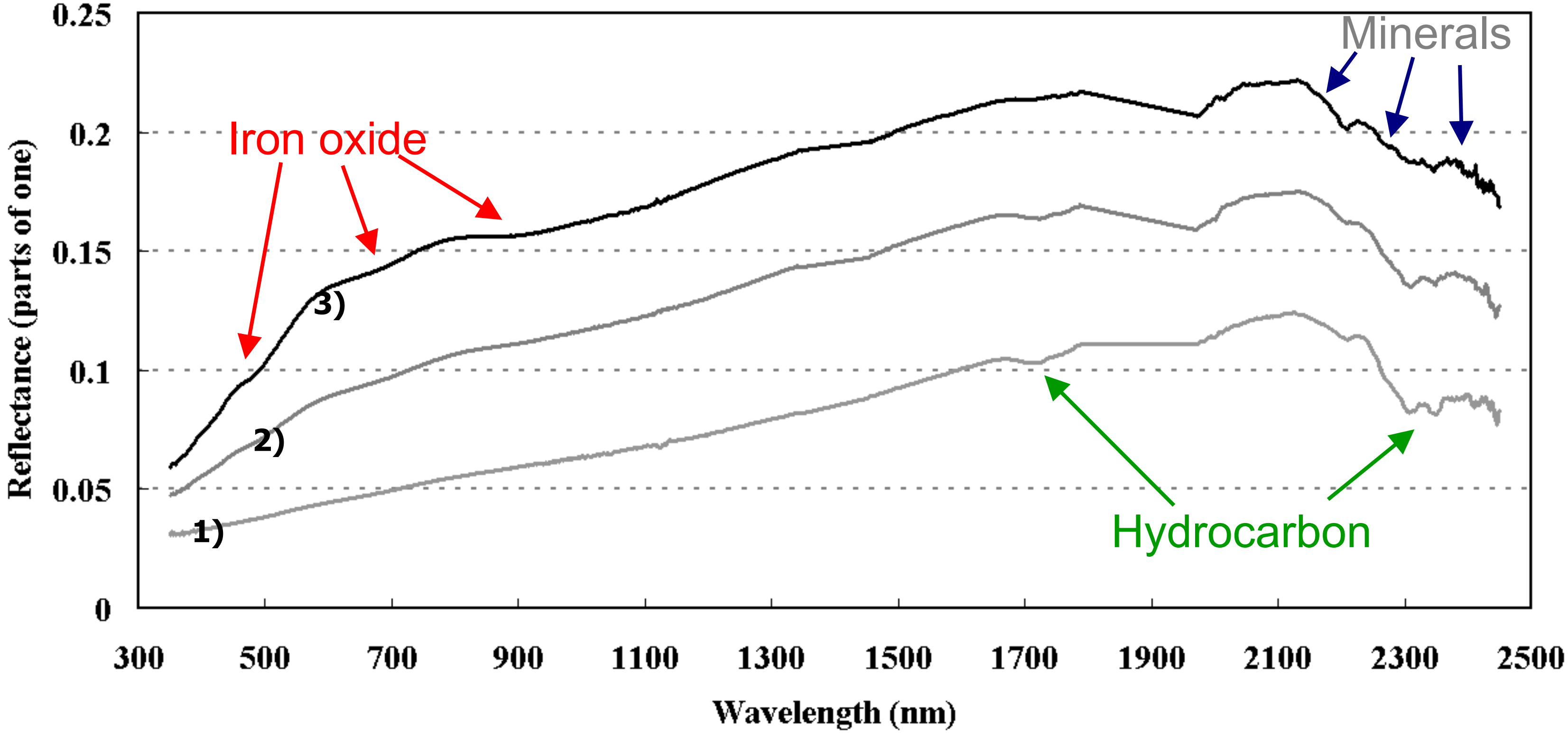
Confusion is minimal between wood shingle and other materials
Considerable error occurs between
Roads and composite shingle roofs

Roberts and Herold, 2004

Pavement Quality

- Two aspects are of interest
  - How old is a road?
  - What is its condition?
    - Cracks, patches
- Data Sources
  - Field spectra
  - High spatial resolution imagery

Asphalt Aging

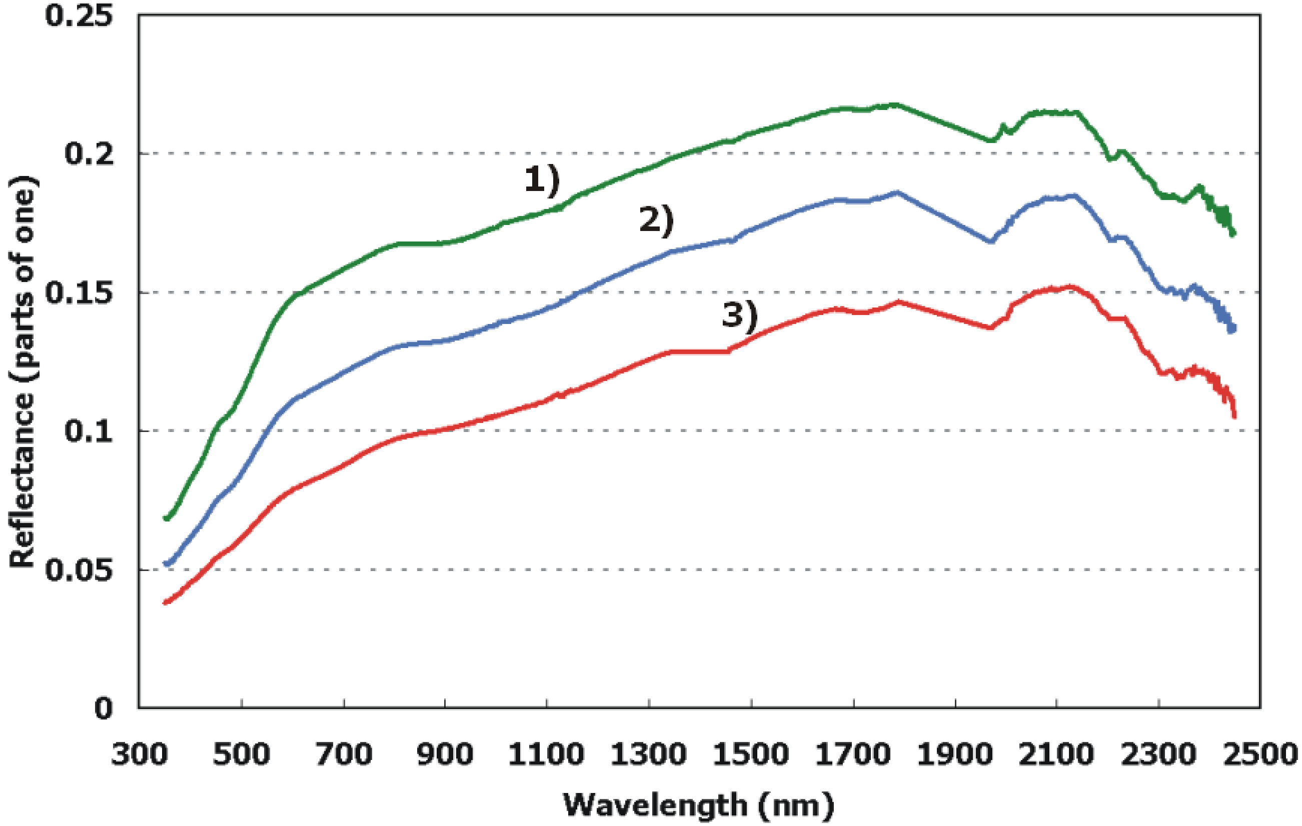


	Surface spectra 1	Surface spectra 2	Surface spectra 3
			
Age:	**less than 1 year**	**3 years**	**more than 10 years**
PCI (Roadware):	**99**	**86**	**32**
Structure (Roadware):	**100**	**100**	**63**

Herold and Roberts,2005

Asphalt Condition

Asphalt ASD ground spectra - cracking



Spectrum 1

Good Pavement

Spectrum 2

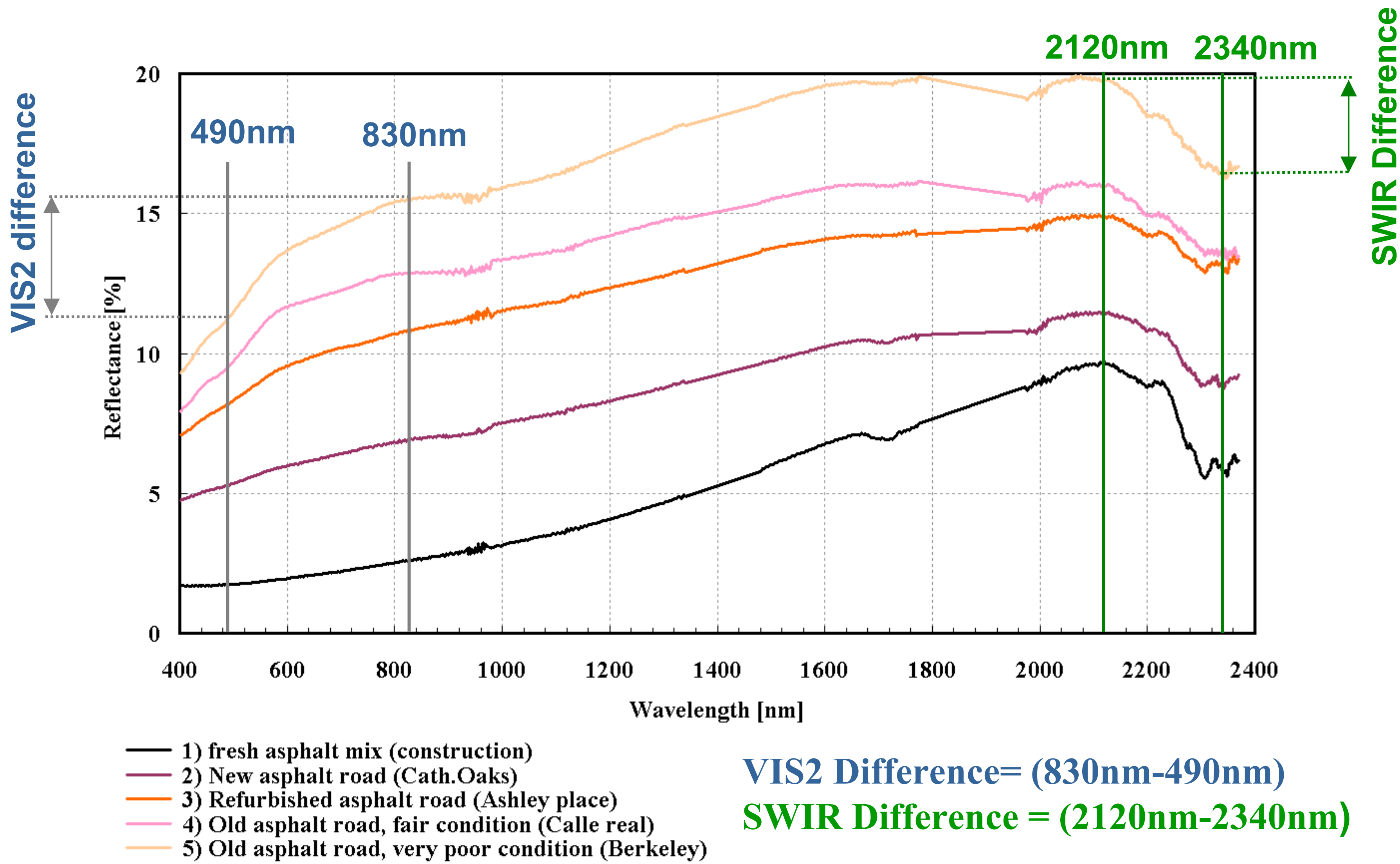
Low severity crack

Spectrum 3

Severe alligator crack

Herold and Roberts,2005

Band Differences for RS data analysis

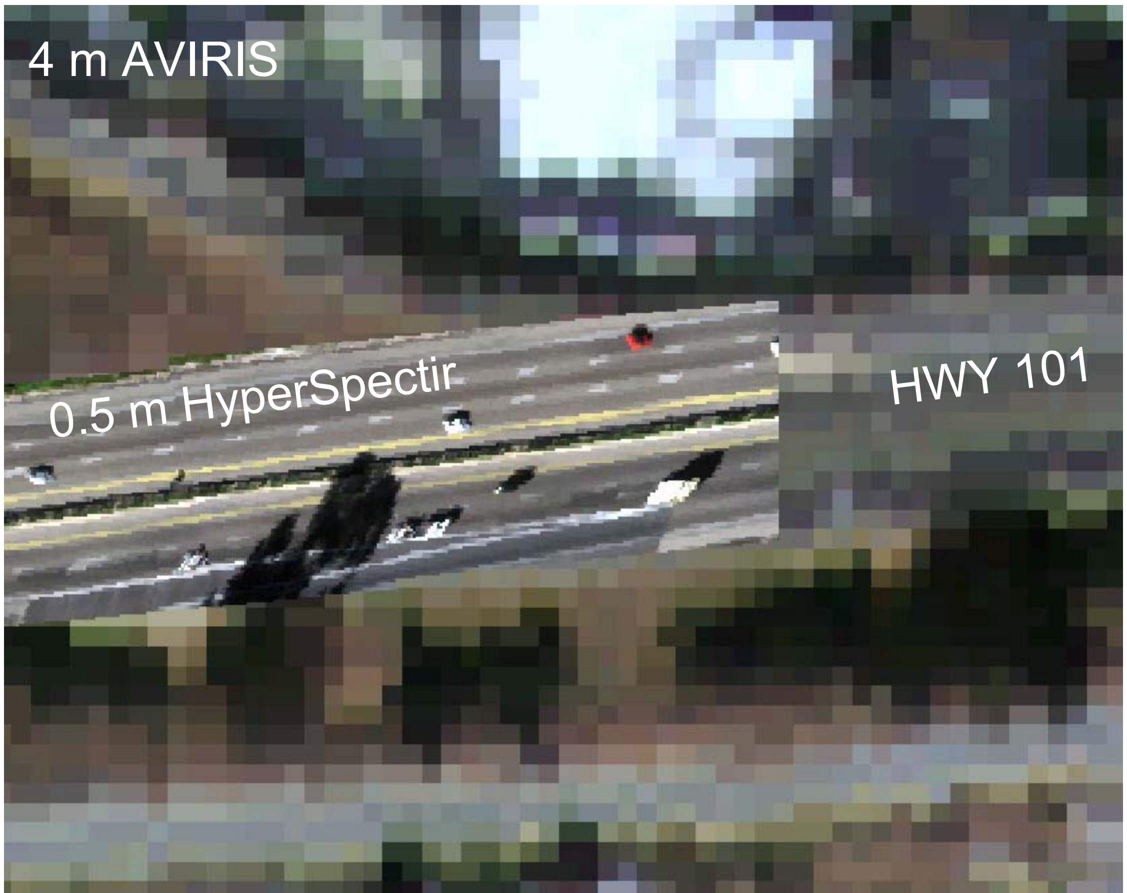


VIS2 Difference= (830nm-490nm)

SWIR Difference = (2120nm-2340nm)

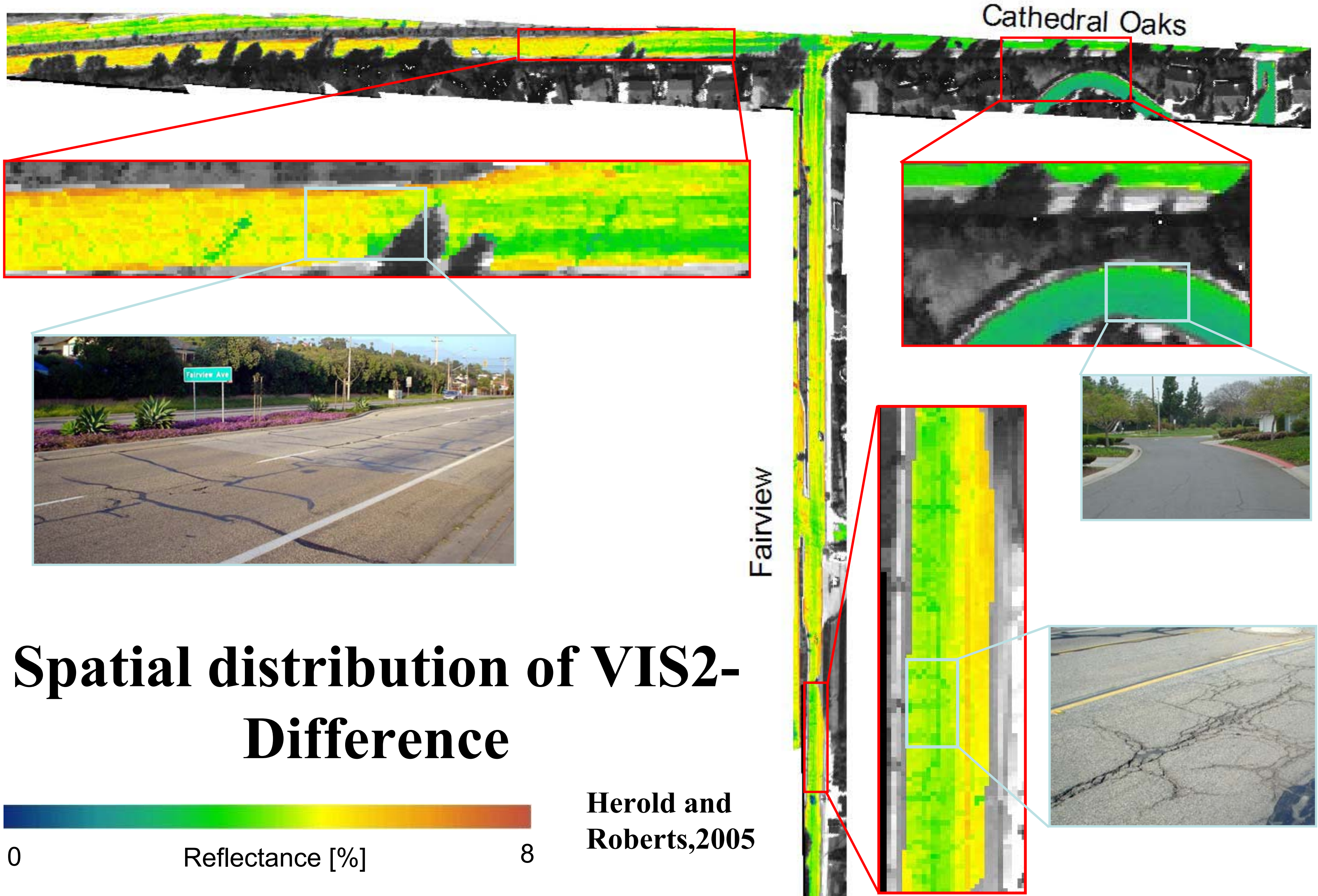
Herold and Roberts,2005

HyperSpectir (HSI) data
Ultra-fine spatial resolution is needed for mapping road quality



- **Goleta, CA**
- **www.spectir.com**
- **HSI-1 data**
- **spatial res. ++**
- **0.5 m / 40 m swath**
- **spectral cal. --**
- **Only VIS/VNIR use**
- **Improv. sensor now**

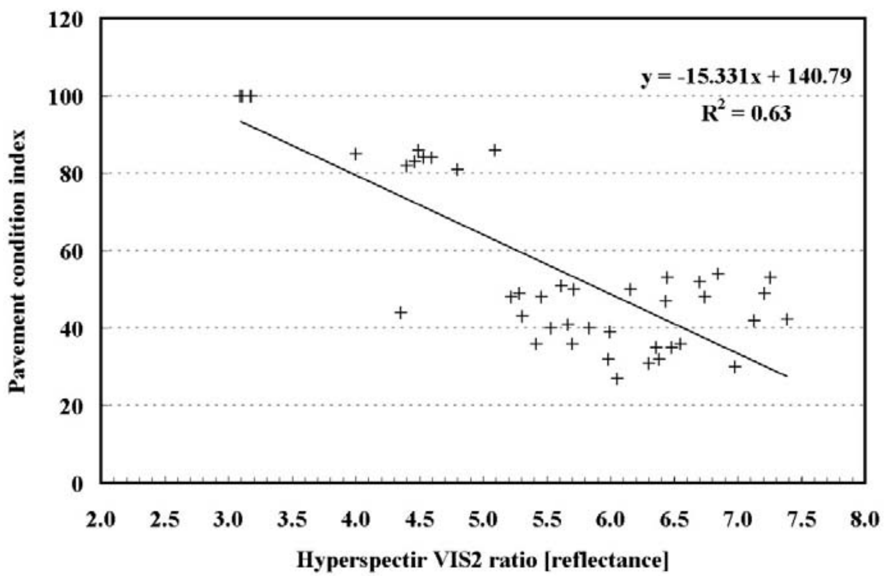
Herold and Roberts,2005

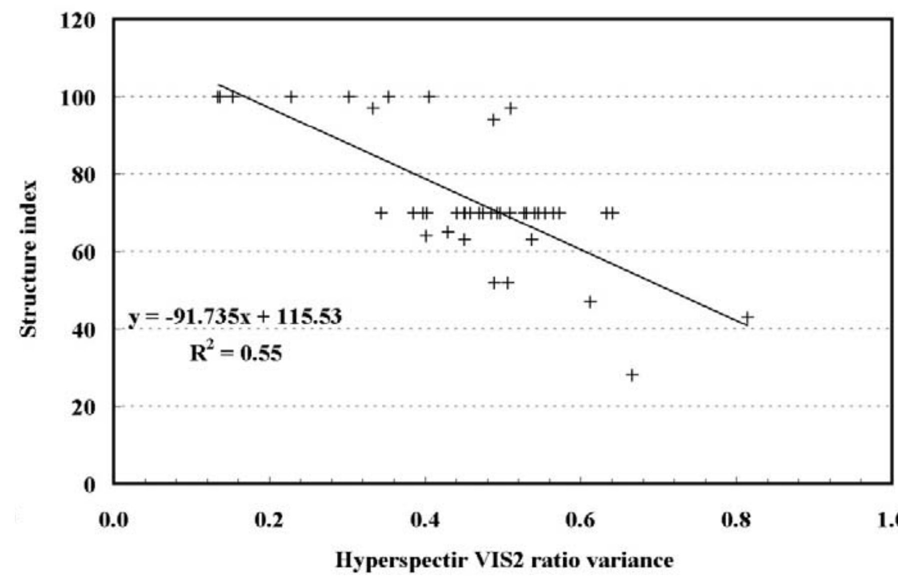


Spatial distribution of VIS2-Difference

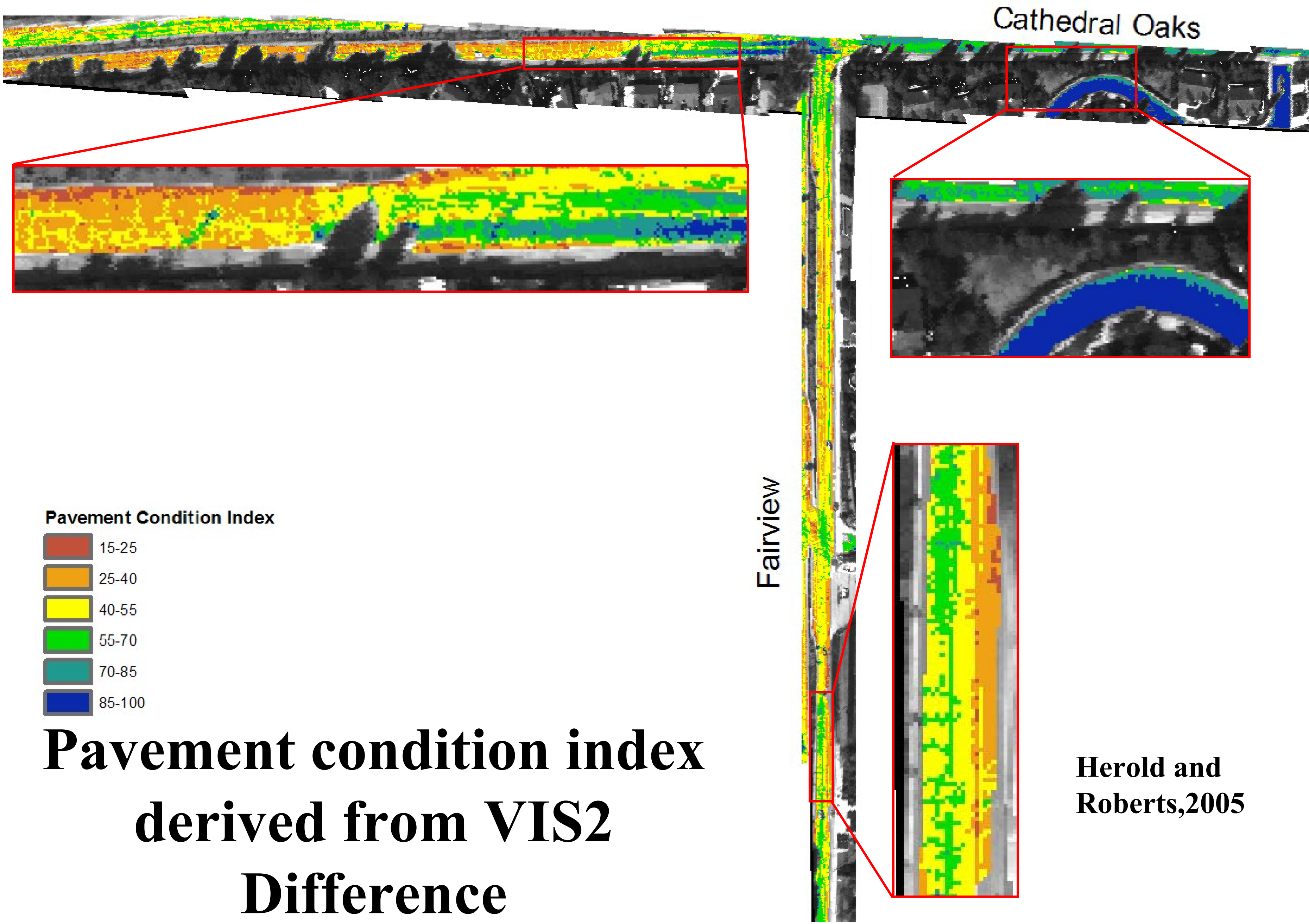
Herold and Roberts,2005

HSI signal versus Roadware data





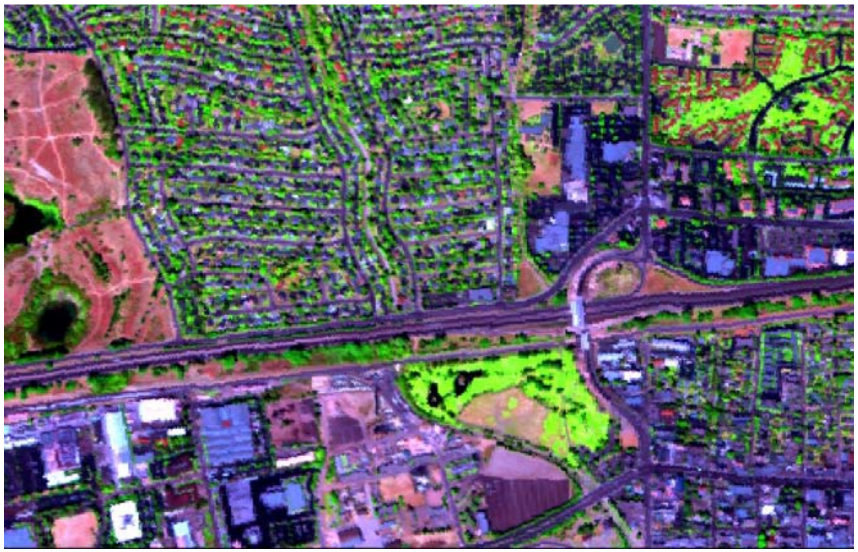
Herold and Roberts,2005



Pavement condition index derived from VIS2 Difference

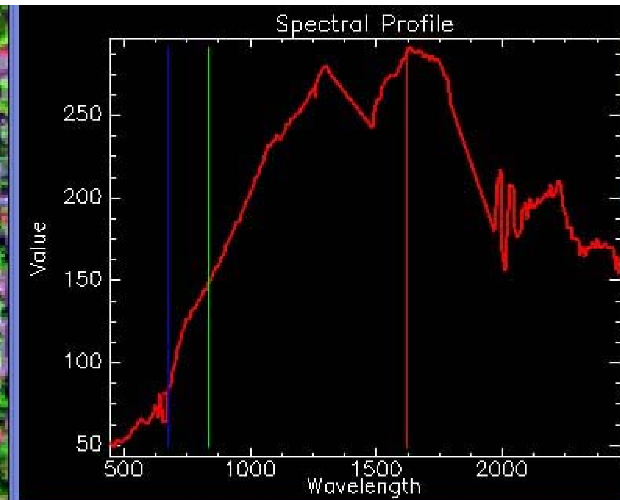
Herold and Roberts,2005

Mapping Impervious Surfaces and Vegetation Cover in an Urban area using MESMA



- **Objective**
  - Identify optimal spectra for discriminating impervious and pervious surfaces
  - Accurately estimate subpixel vegetation cover with variable backgrounds
- **Approach**
  - Multiple Endmember Spectral Mixture Analysis
    - Allows number and types of endmembers to vary per pixel
    - Addresses challenges of spectral diversity in urban areas
- **Data**
  - Field spectral library of over 900 materials
  - AVIRIS high resolution image
  - 2000+ spectra for accuracy assessment

Building a Spectral Library

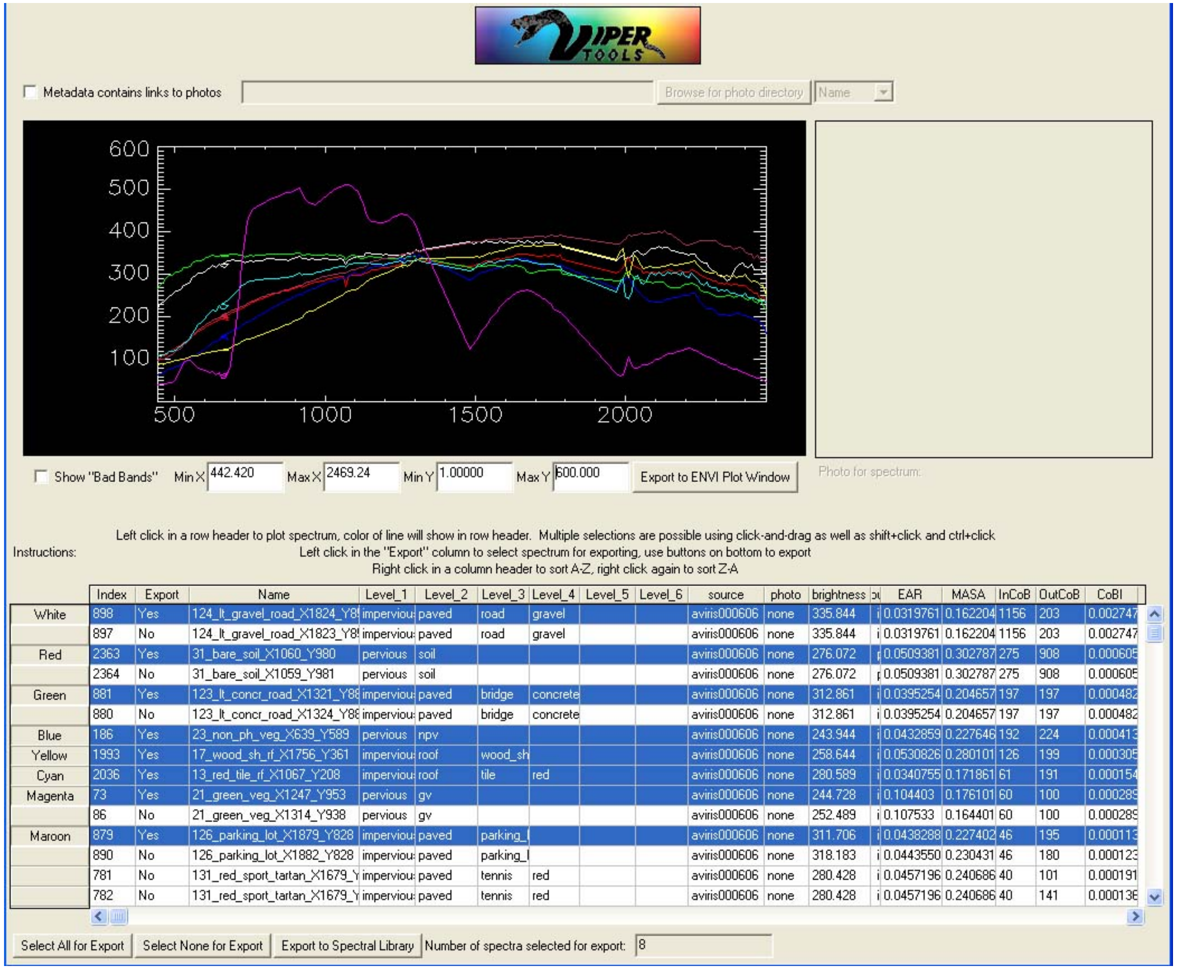


000606, 1650, 830, 645 nm RGB

Wood Shingle Roof

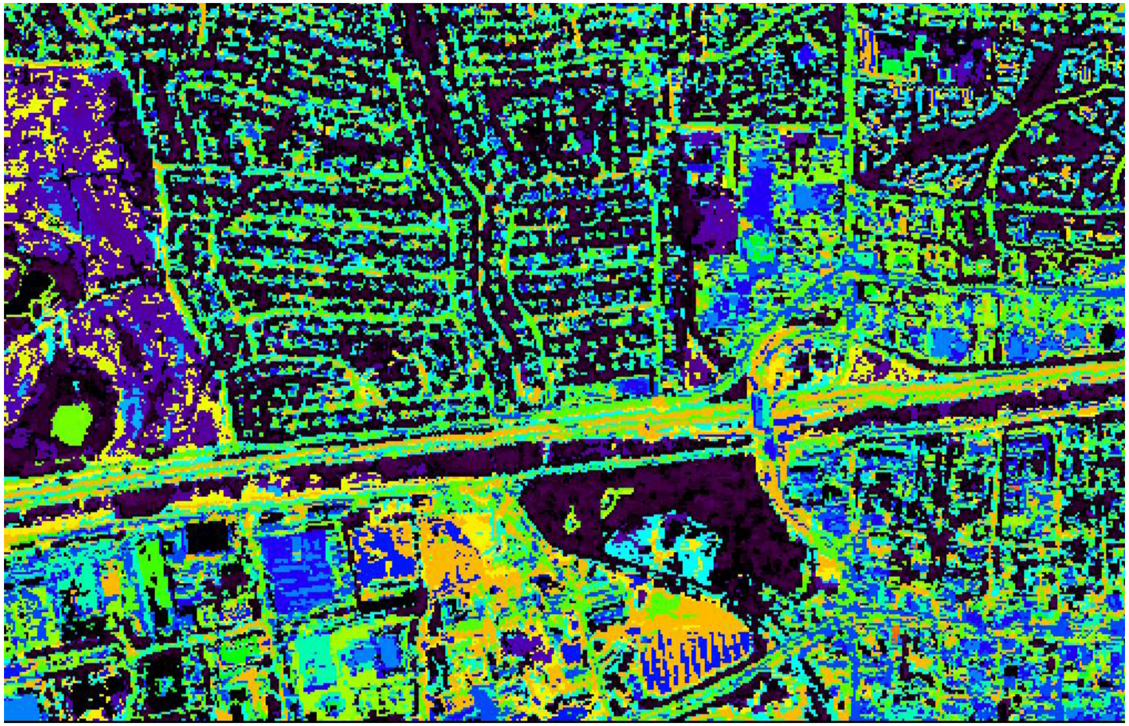
Selecting Impervious and Pervious Spectra Count Based Endmember Selection

- Objective
  - Identify spectra that best discriminate pervious and impervious surfaces
- Spectra sorted by two categories
- Optimum spectra selected from each category using CoB
- 51 spectra selected
  - 20 pervious
    - 4 GV
    - 4 NPV
    - 5 soils
    - 7 water
  - 31 impervious
    - 21 roofs
    - 10 roads



Model Selection: Two Endmembers

- **Legend**
  - Vegetation: Dark purple
  - Senesced Grass: light purple
  - Woodshingle roofs: Aquamarine
  - Parking lots: Dark blue
  - Roads and Streets; Green



Accuracy Assessment:

Unclassified: 156 (100 of water)

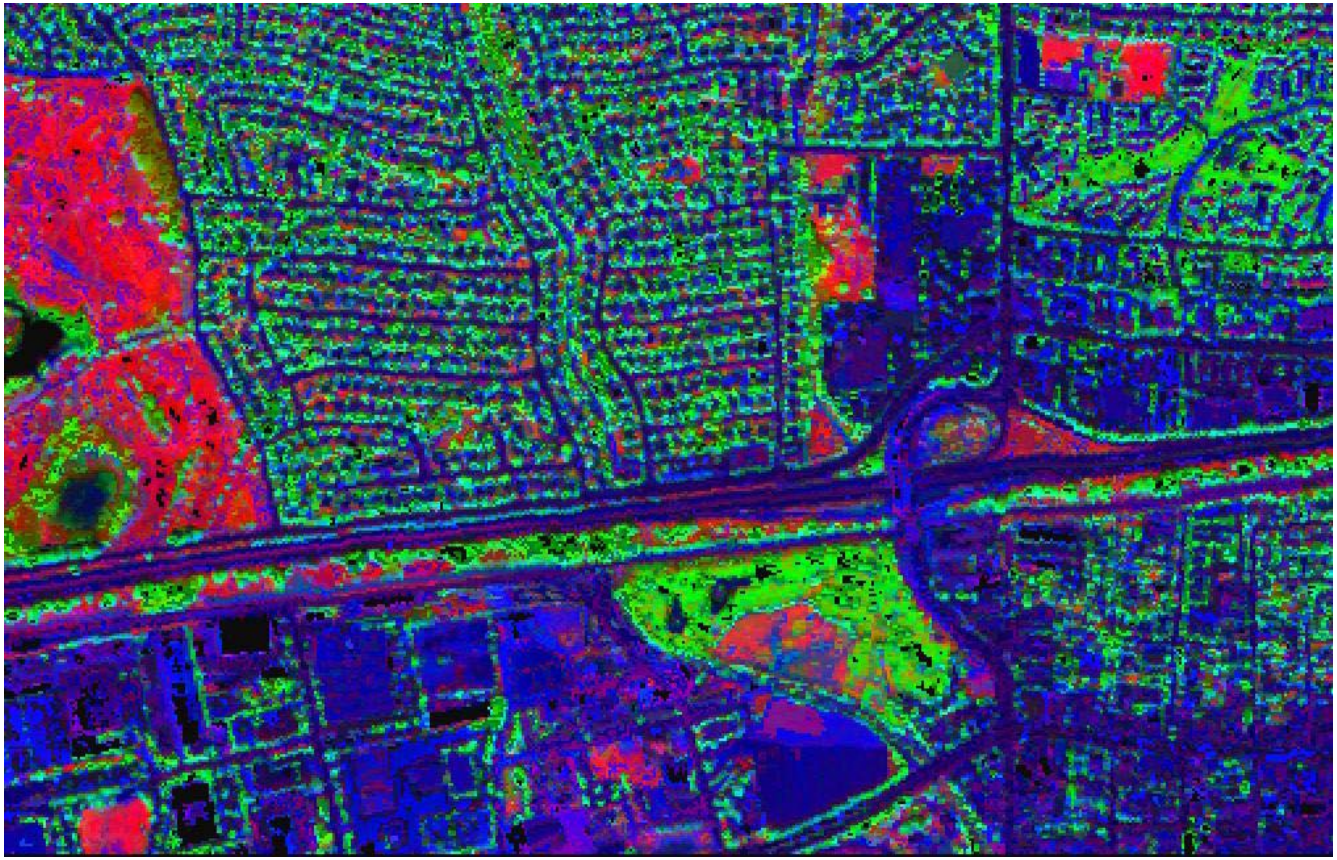
Overall: 86.3%

Pervious: 327/400 (81.8%)

72% Soil, 77% GV, 92% NPV

Impervious: 1720/1973 (87.2%)

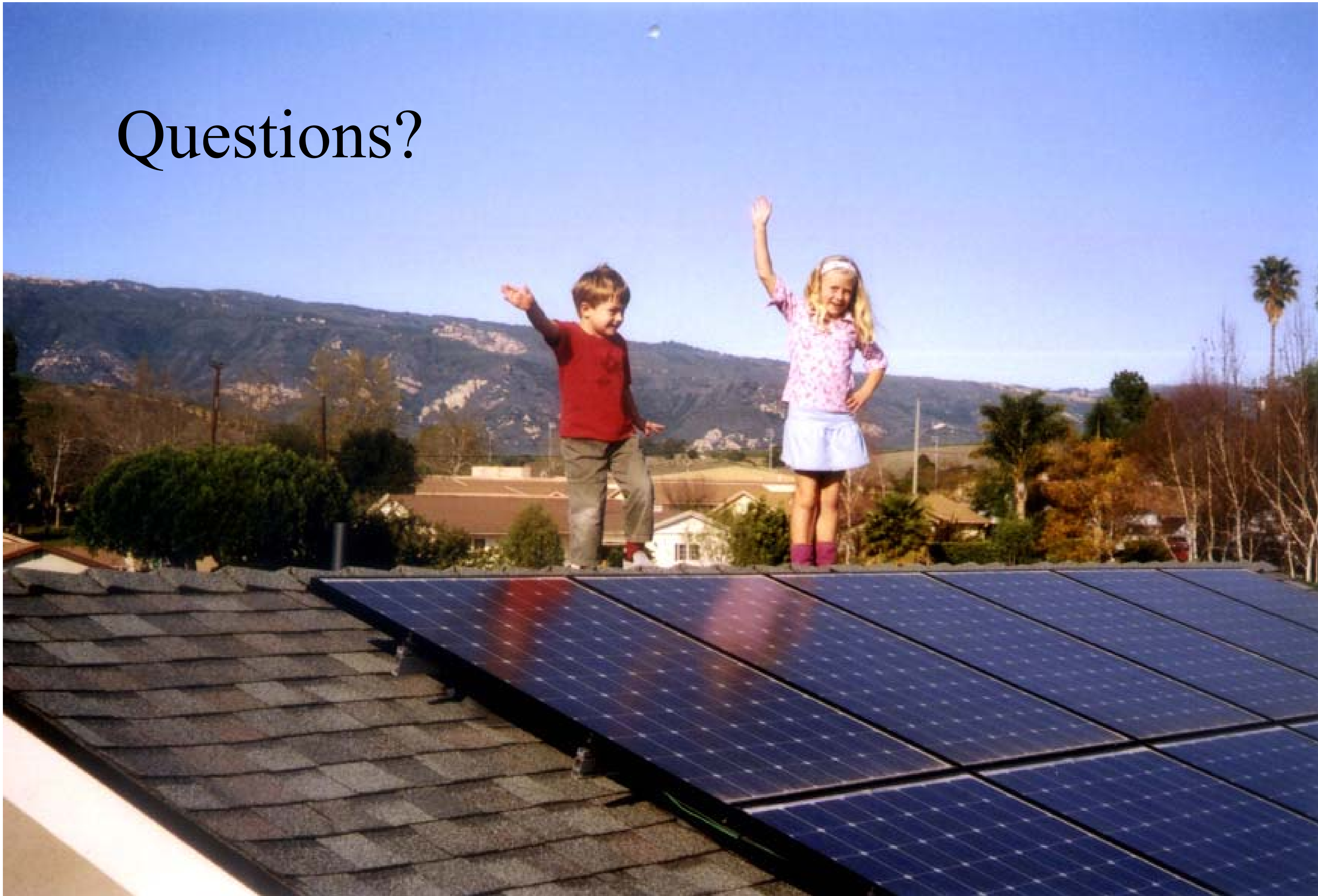
MESMA Fraction Images



- **4 Endmember Model**
- **NPV, GV, Soil/Impervious (RGB)**
- **Fractions highly accurate**
  - **Readily accounts for spectral variability in backgrounds**

Summary

- Urban environments are challenging due to fine spatial requirements and large spectral heterogeneity
- Imaging spectrometry is critical for improving our understanding of urban spectroscopy
- Imaging spectrometry provides improved spectral discrimination
  - Roofs and roads remain difficult to separate
  - Wood shingle is particularly easy to map
- Adding a vertical dimension vastly improves accuracy
- New tools, such as MESMA have considerable promise


Questions?