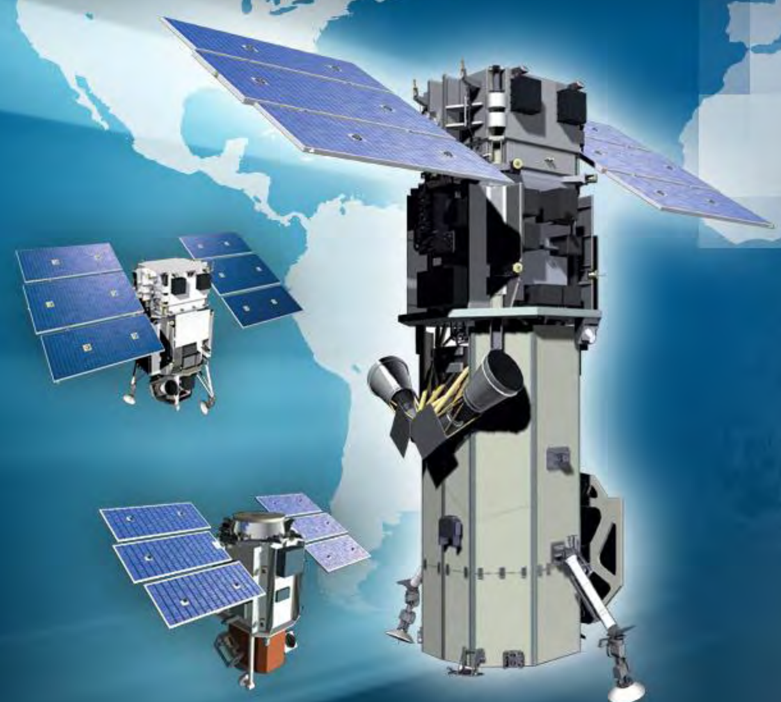
Ride on the Geospatial Revolution

ASPRS 2011 Annual Conference
Milwaukee, Wisconsin, May 1- 5

Evidence of Improved Vegetation Discrimination and Urban Mapping Using WorldView-2 Multi-Spectral Imagery

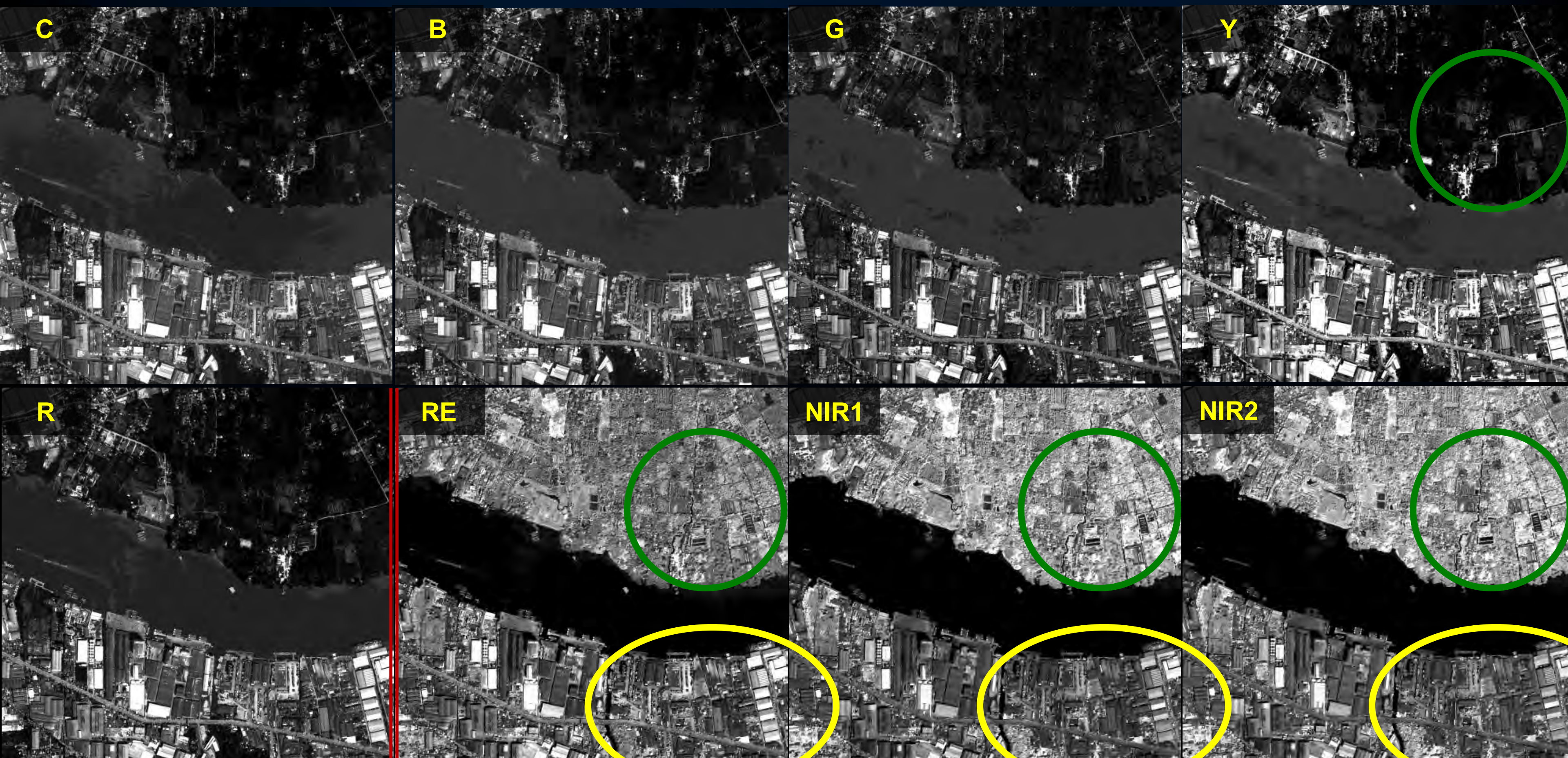


G. Marchisio, C. Padwick, F. Pacifici

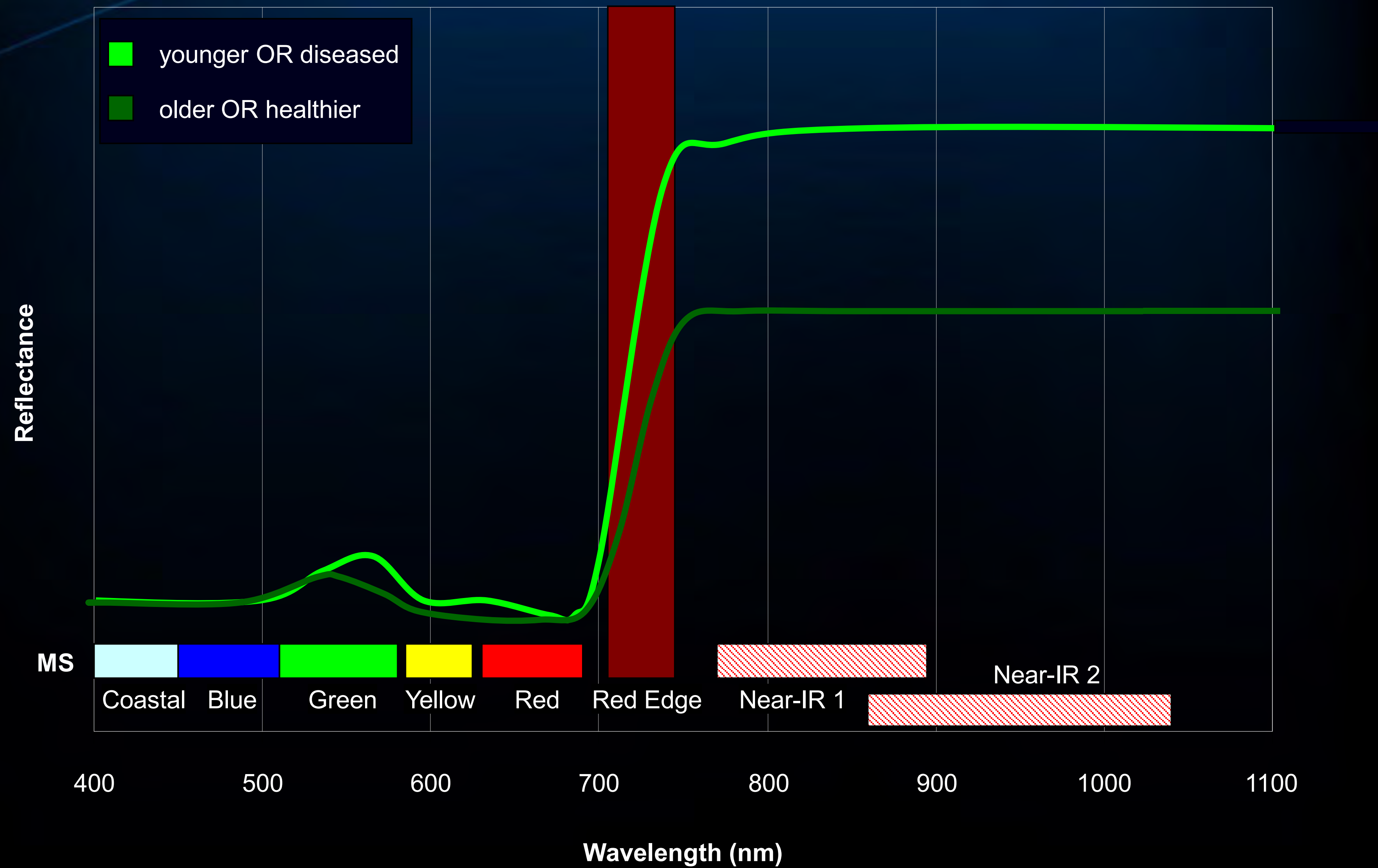
Overview

- How information content of new WV-2 bands may help vegetative analyses and discrimination of basic land covers
- Do the 8 band make a difference?
  - Description of Comparative Machine Learning Approach
  - Spectral predictor analysis
  - Validation of land cover separability
  - Improvement in accuracy
- Additional Vegetative Analyses
  - Mapping the effect of the Gulf oil spill on wetlands
  - Mapping of Phytoplankton and algal blooms
  - Potential for crop discrimination
- Conclusions

WV-2 Spectral Response

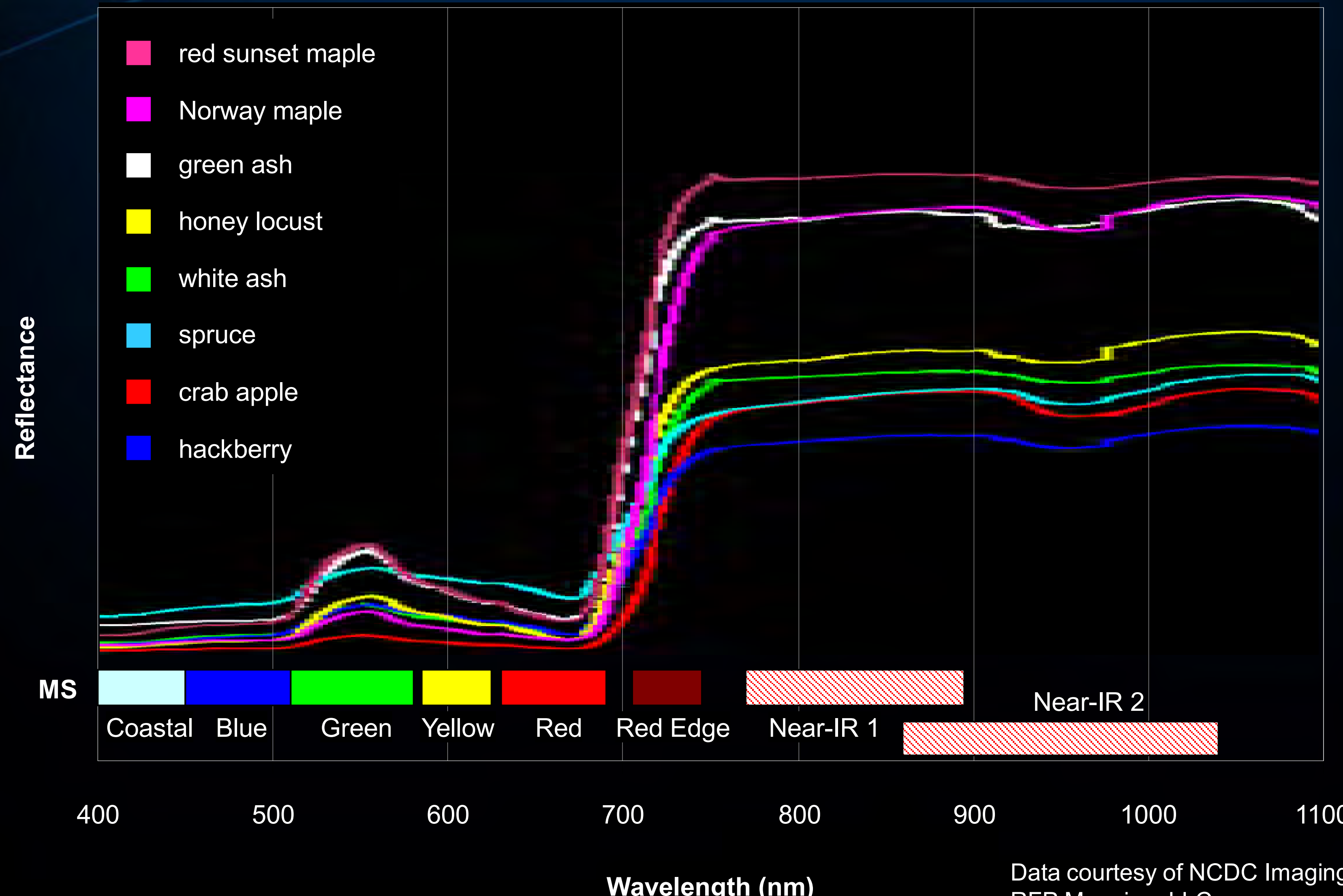


Red Edge and WV-2 Bands



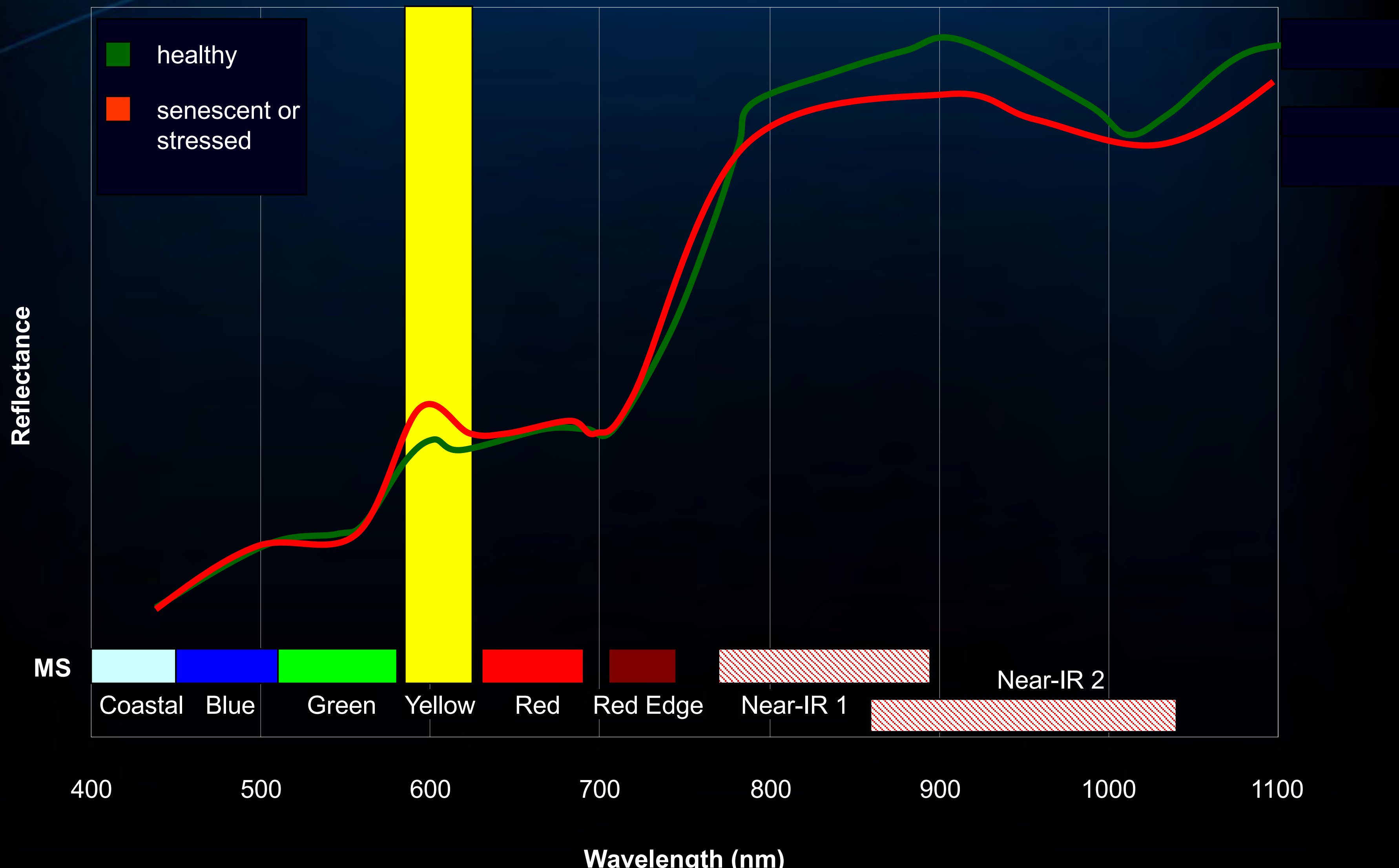
Vegetation Species and WV-2 Bands

(from Mapping the Future for Emerald Ash Borer Readiness and Response Planning, David Sivyer, City of Milwaukee, 2009

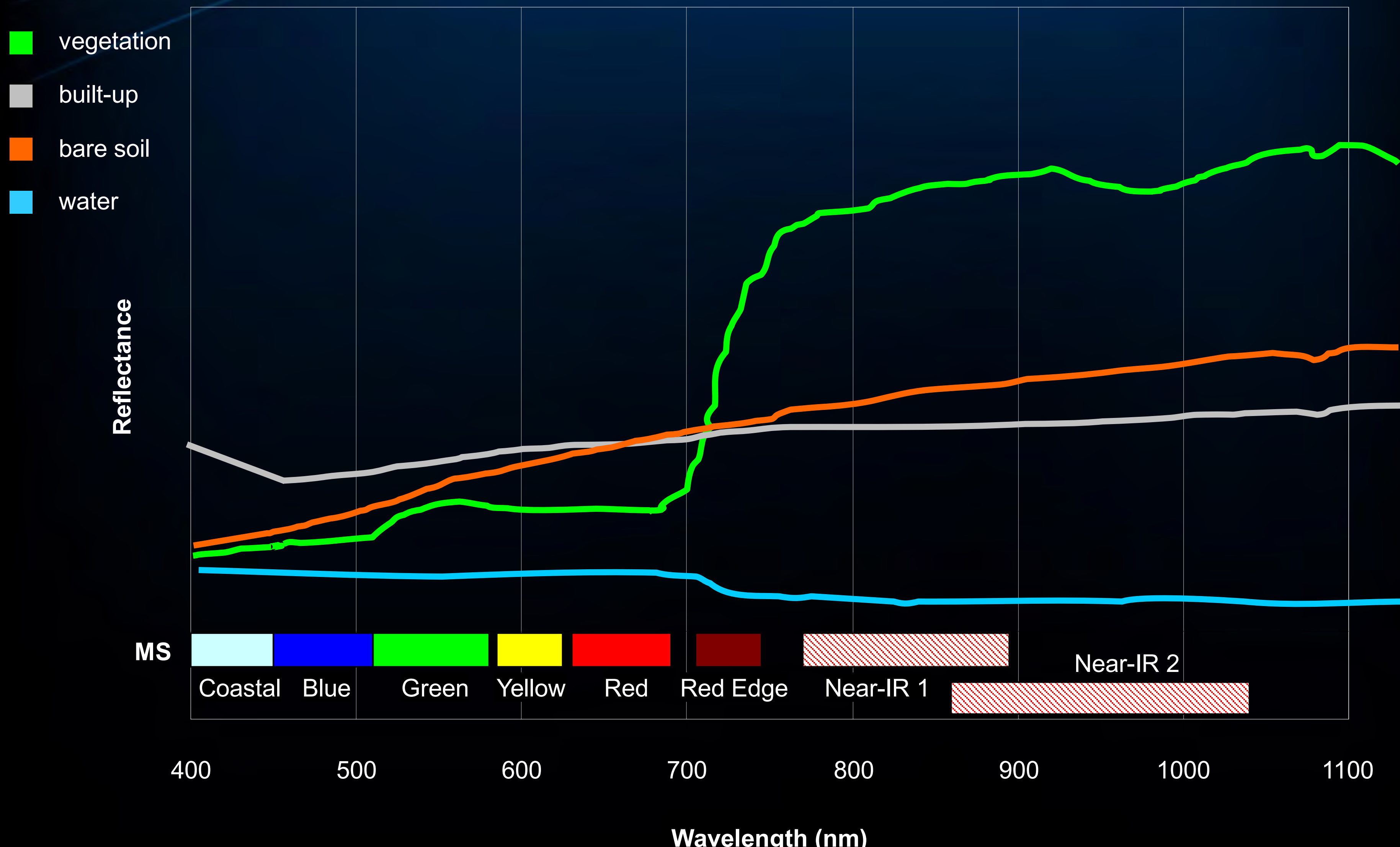


Data courtesy of NCDC Imaging and RFP Mapping, LLC

Yellow Edge and WV-2 Bands



Basic Land Covers and WV-2 Bands



Comparative Machine Learning Approach

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- Spectral features:
  - Reflectance values from the 8 WV-2 bands (b_i , i=1,8)
  - 28 unique pairs of NDVI-style band ratios computed from the above

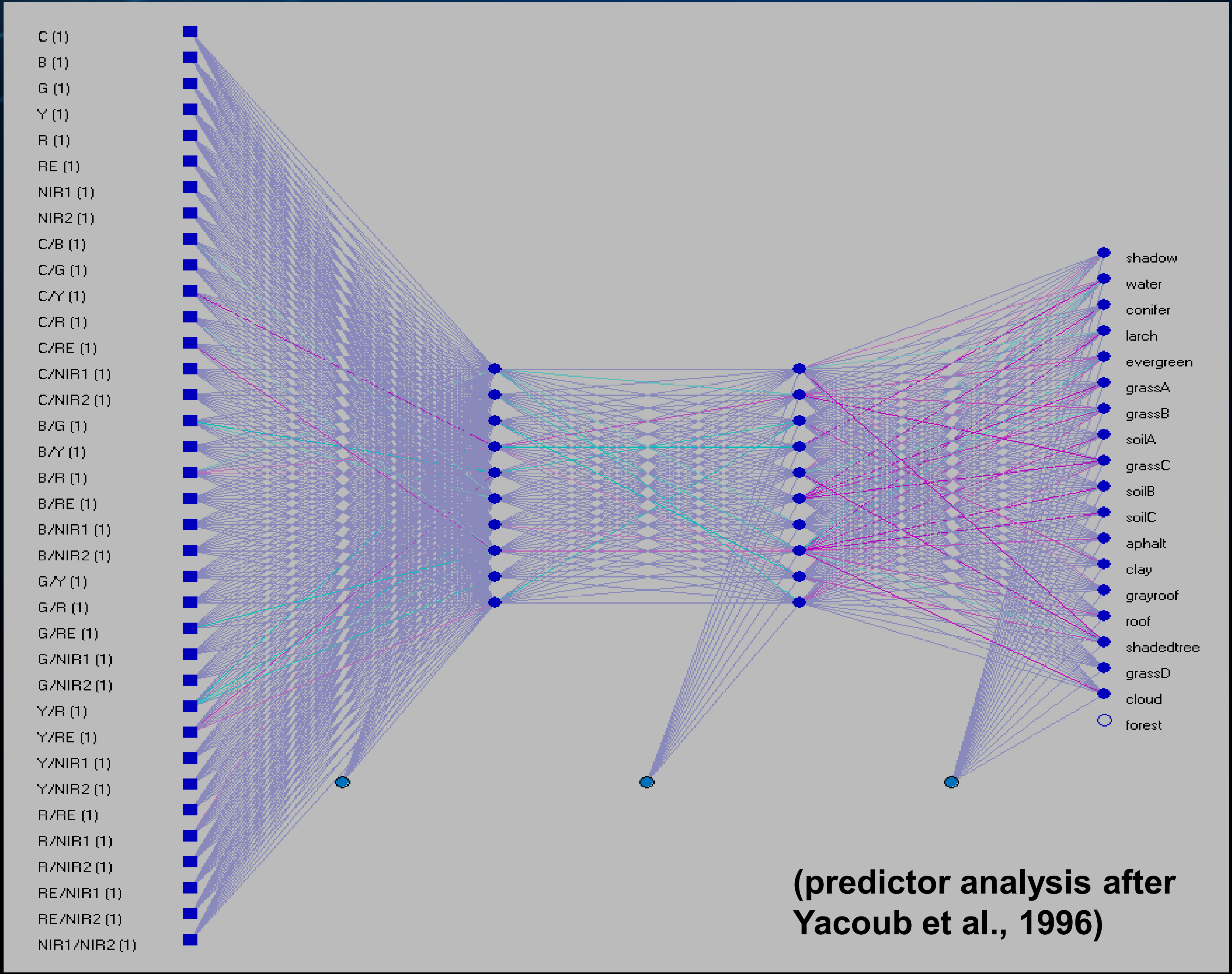
$$F(b_{ij}) = \frac{|b_i| - |b_j|}{|b_i| + |b_j|} \qquad N = \frac{n(n+1)}{2}$$

- Apply supervised machine learning methods:

  (PCA+Logistic Regression, Neural Networks, Classification Trees with k-fold cross-validation, Tree Ensembles)
- Produce confusion matrices
- Perform predictor analyses

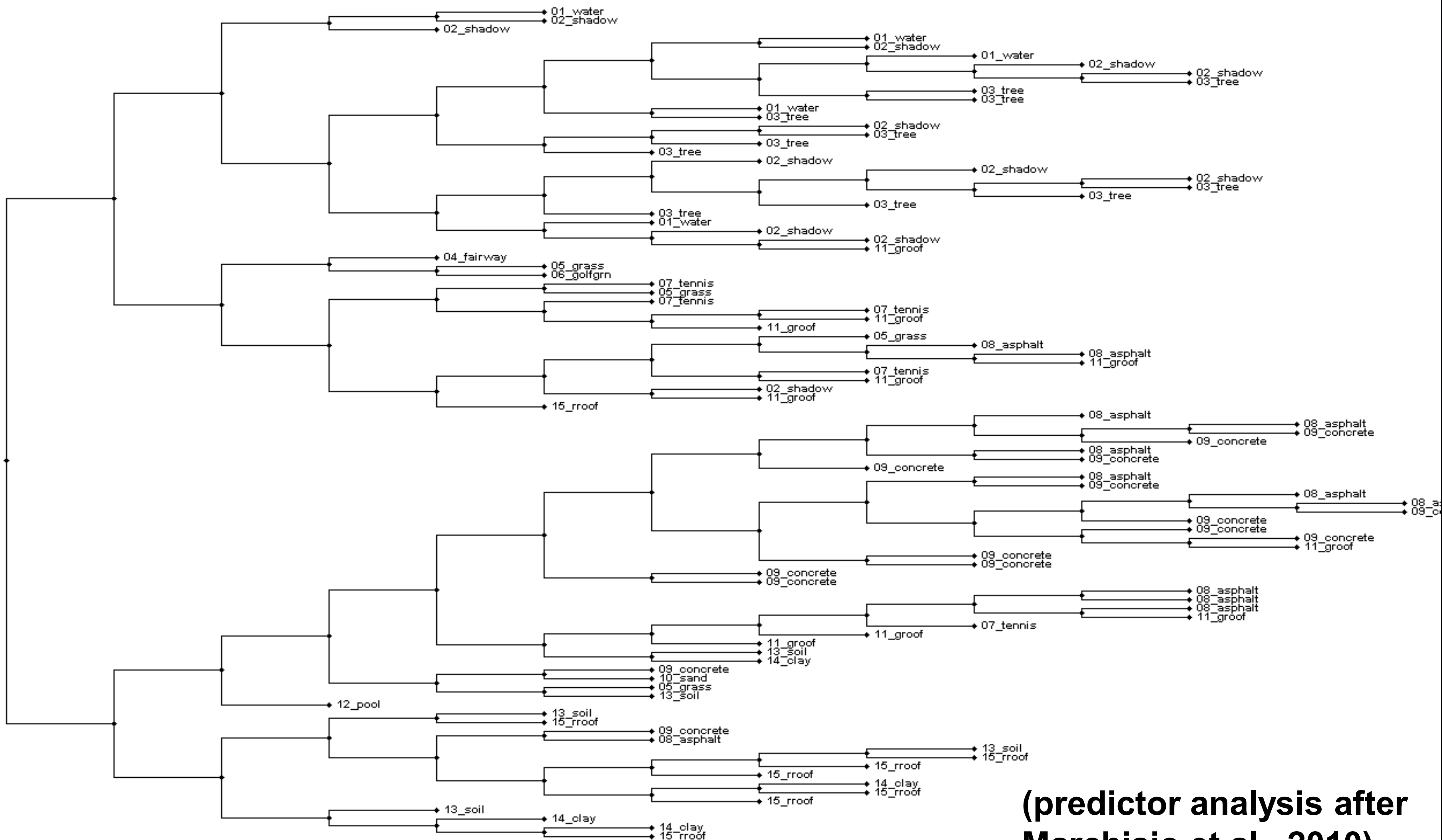
- Repeat using VNIR spectral features only:
  - Converted reflectance values from the 4 VNIR bands
  - 6 unique pairs of NDVI-style band ratios computed from the above

Topology of a Neural Network



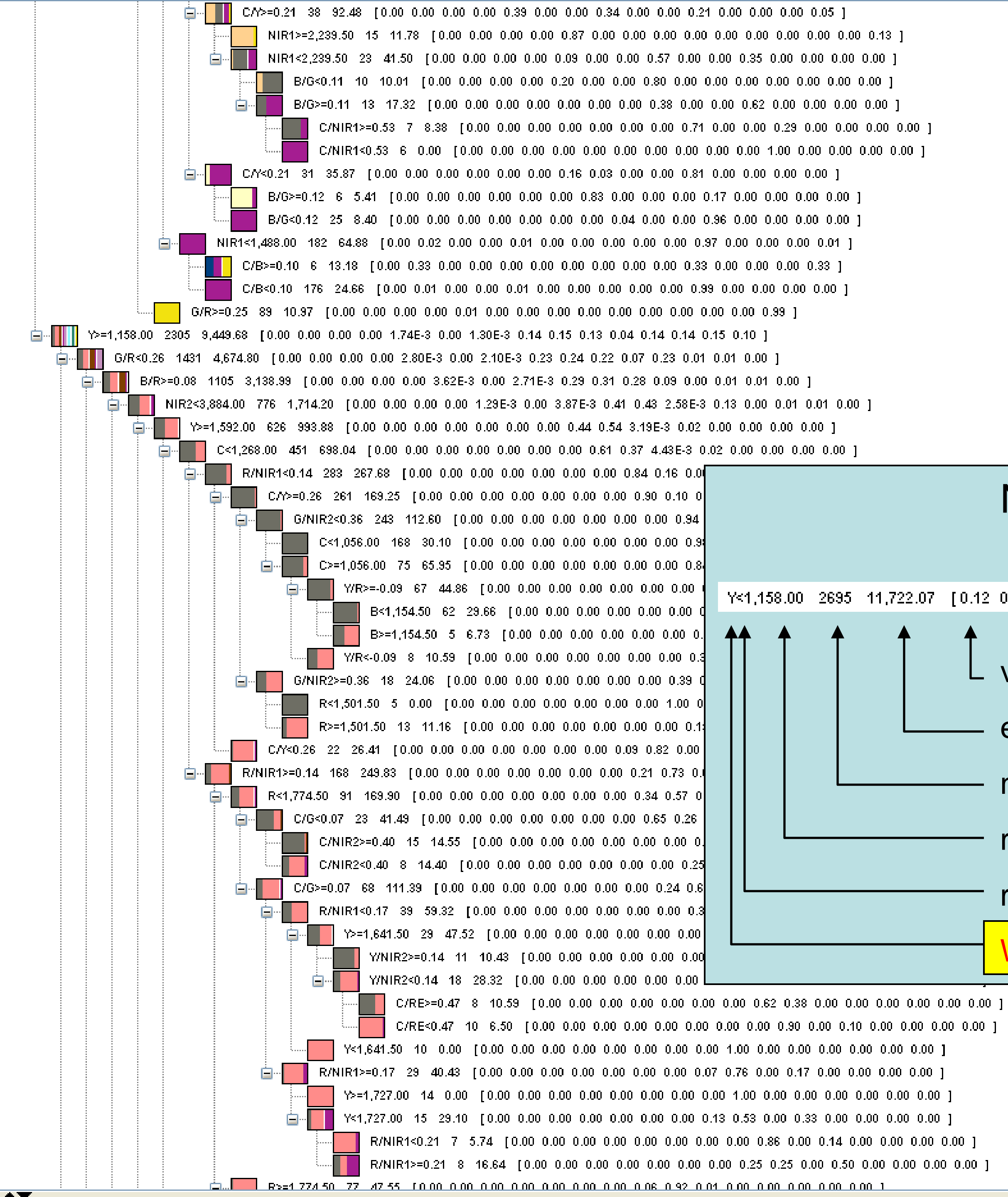
(predictor analysis after Yacoub et al., 1996)

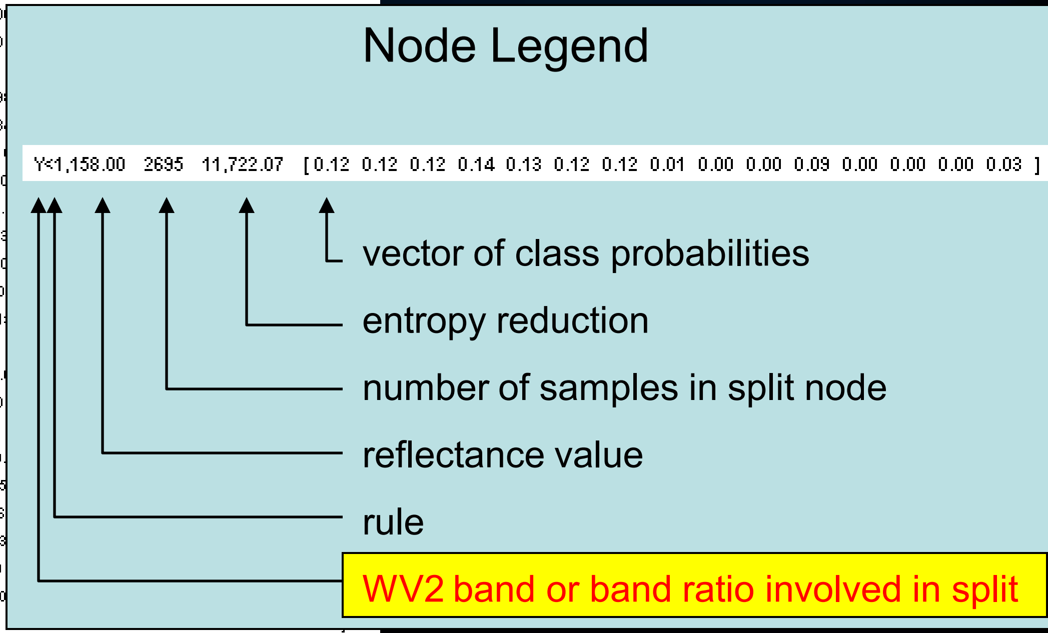
Topology of a Single Decision Tree



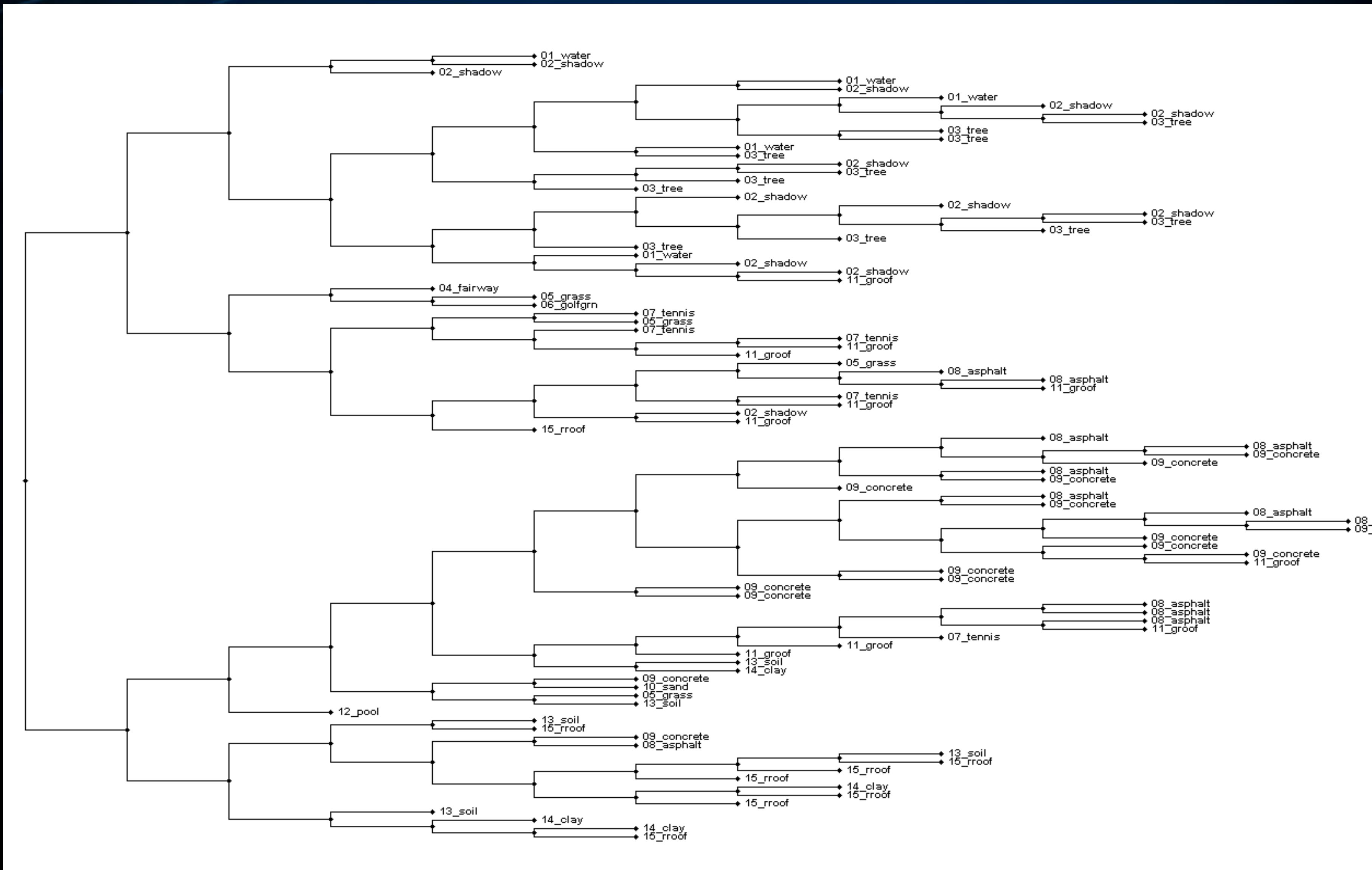
(predictor analysis after Marchisio et al., 2010)

Finding Which Bands Work Best (Marchisio et al., 2010)

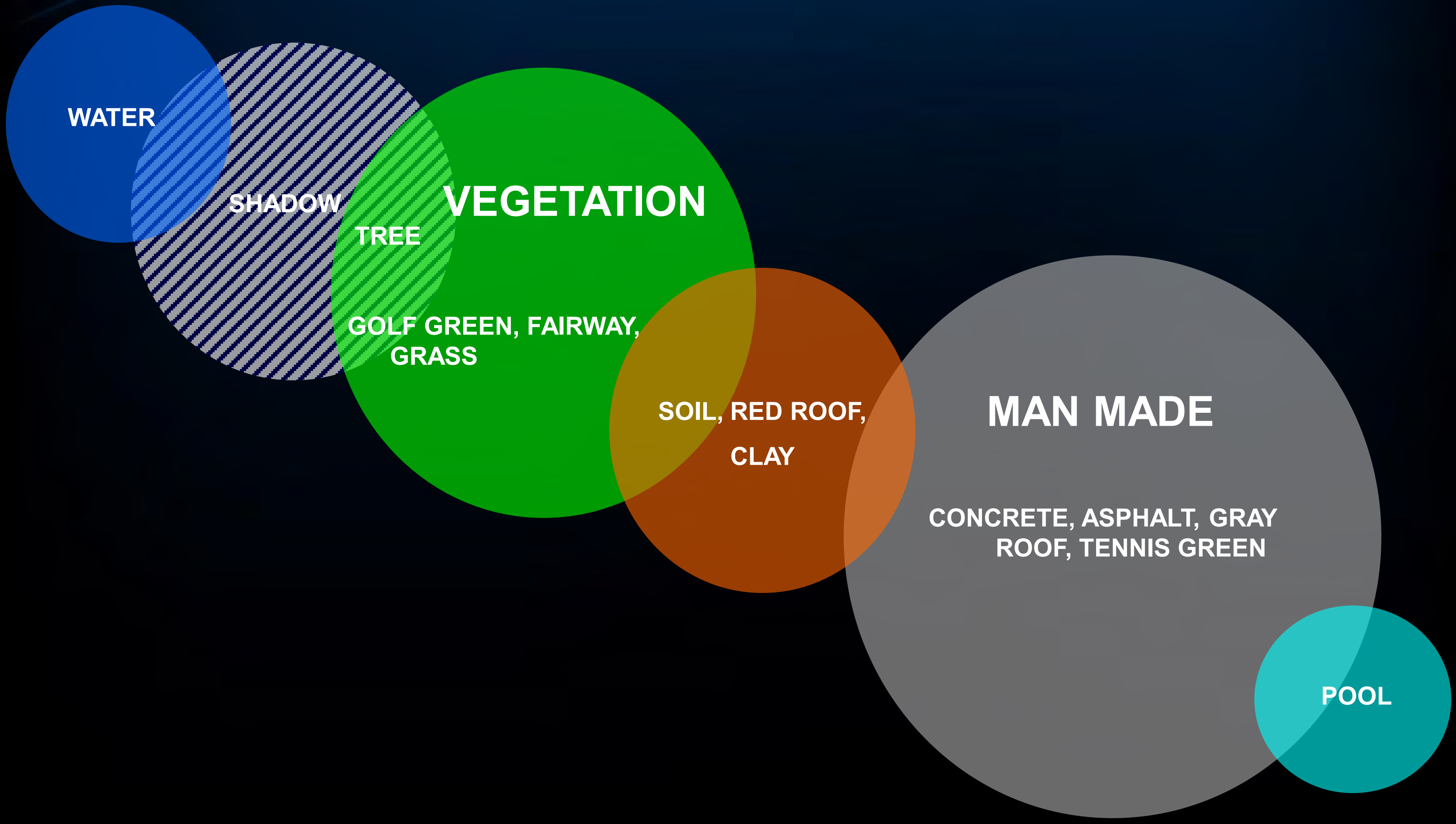




Natural Grouping of Land Cover Types Resulting from Predictor Analysis (Dallas)



Natural Grouping of Land Cover Types Resulting from Predictor Analysis (Dallas)



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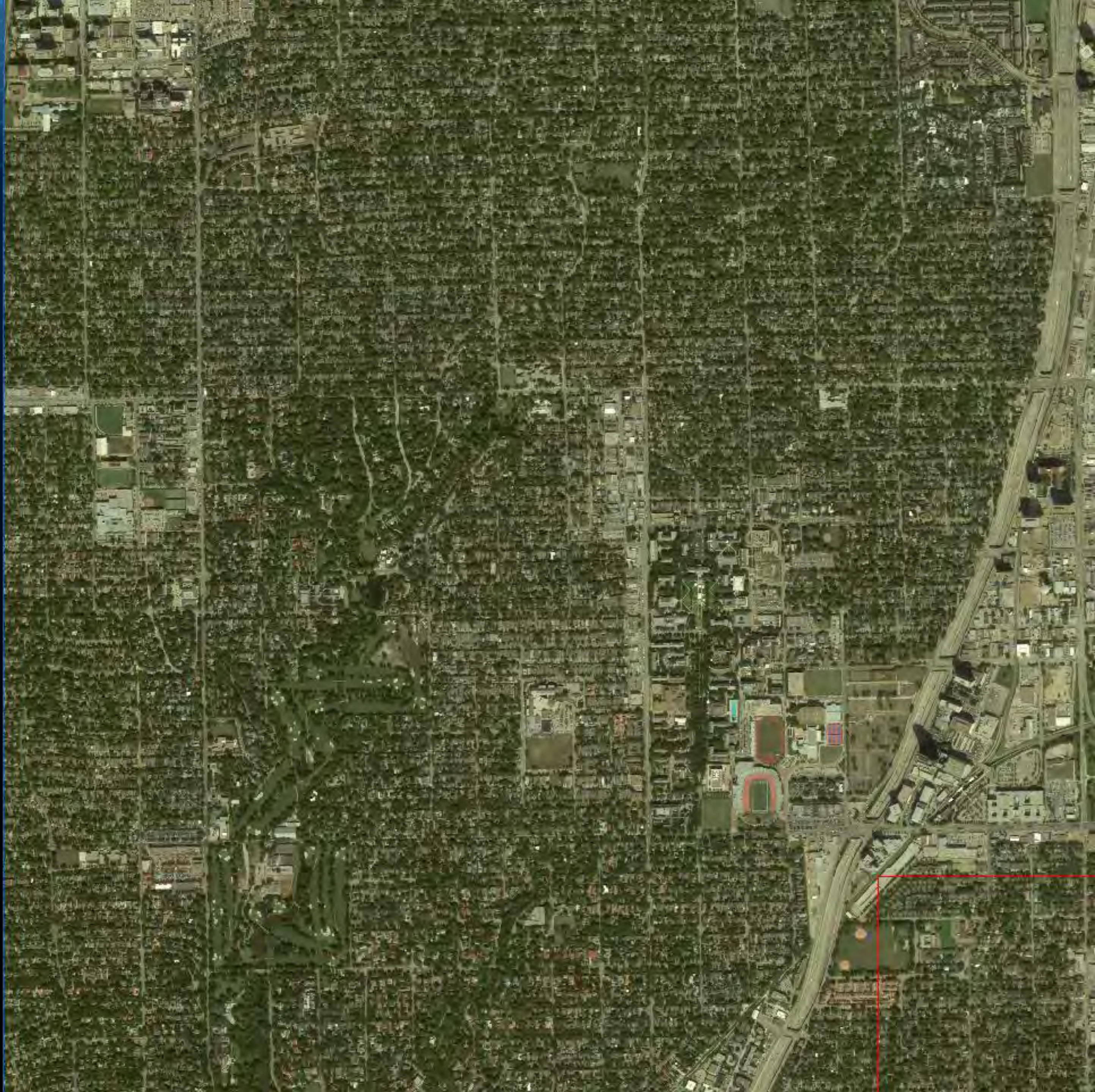
WorldView-2
First Images
Natural Color
2m Image

Dallas
Texas
Nov 20, 2009



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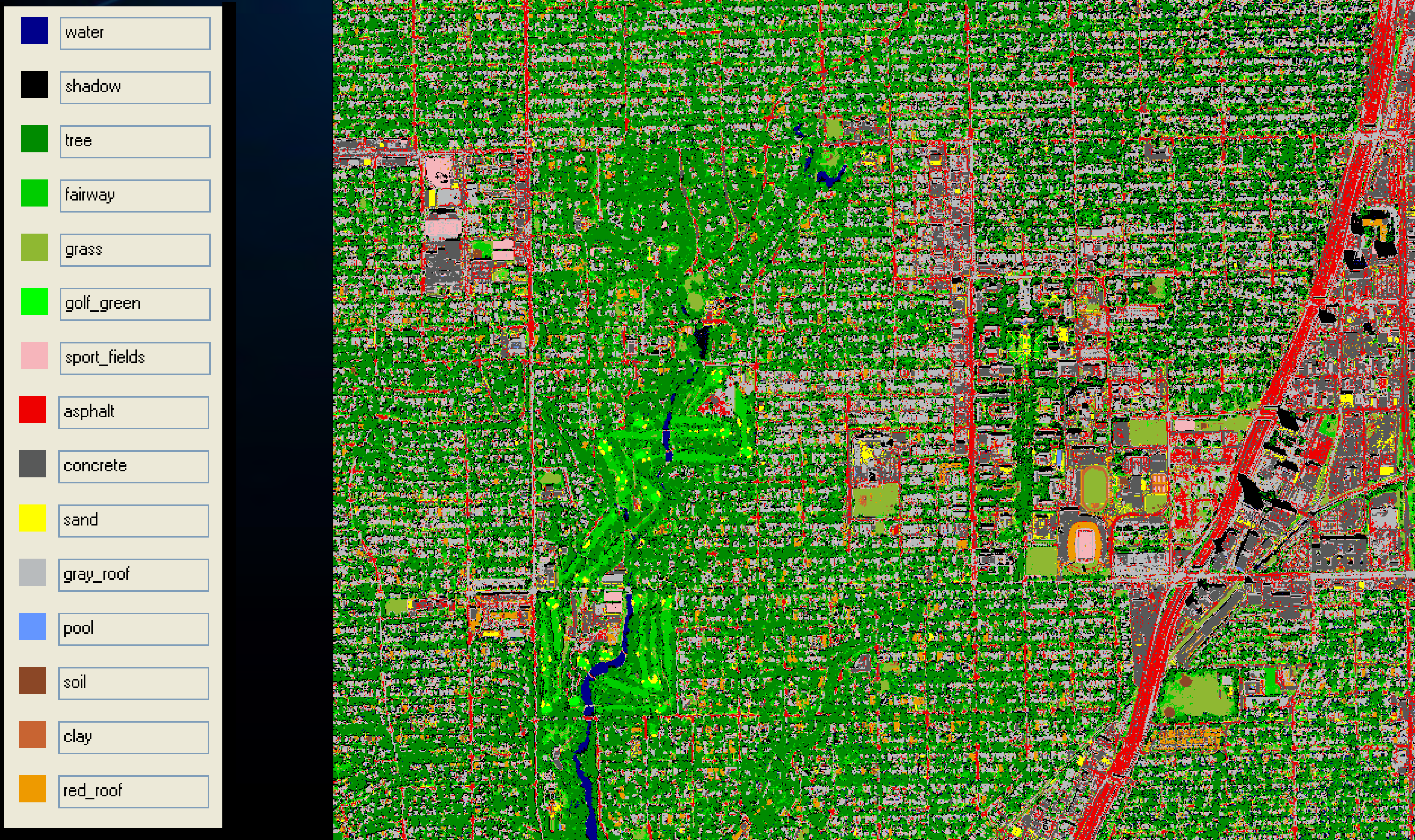
WorldView-2

15 Land Covers



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Classification Agreement for 15 Land Cover Types (Dallas) - Ensemble Method Technique

Input Node - Read Text File (793)

		Predicted															Totals
		01_water	02_shadow	03_tree	04_fairway	05_grass	06_golfgrn	07_tennis	08_asphalt	09_concrete	10_sand	11_groof	12_pool	13_soil	14_clay	15_rroof	
Observed	01_water	1639	28	79	5	1	0	2	0	0	0	1	0	0	0	0	1755
	02_shadow	139	12215	966	20	0	0	52	0	0	0	70	0	0	0	2	13464
	03_tree	162	1235	27791	0	0	0	0	0	0	0	0	0	0	0	0	29188
	04_fairway	0	0	0	4726	0	0	4	0	0	0	0	0	0	0	0	4730
	05_grass	0	0	0	0	12343	68	129	53	0	1	212	1	58	13	17	12895
	06_golfgrn	0	0	0	0	9	1695	0	0	0	0	0	0	0	0	0	1704
	07_tennis	0	4	0	0	1	0	1747	1	0	0	19	0	0	0	0	1772
	08_asphalt	0	7	0	7	91	0	6	11373	900	39	525	0	30	7	87	13072
	09_concrete	0	0	0	0	0	0	0	965	13834	132	1	72	135	0	229	15368
	10_sand	0	0	0	0	0	0	0	0	10	1274	0	1	4	0	0	1289
	11_groof	1	56	1	6	24	0	72	97	91	6	2665	0	6	1	2	3028
	12_pool	0	0	0	0	0	0	0	0	0	0	0	216	0	0	0	216
	13_soil	0	0	0	0	1	0	0	0	1	0	0	0	931	1	13	947
	14_clay	0	0	0	0	0	0	0	1	0	0	0	0	2	1049	10	1062
	15_rroof	0	3	0	0	4	0	0	4	1	0	9	0	14	11	1017	1063
Totals		1941	13548	28837	4764	12474	1763	2012	12494	14837	1452	3502	290	1180	1082	1377	101553

	Observed															Overall
	01_water	02_shadow	03_tree	04_fairway	05_grass	06_golfgrn	07_tennis	08_asphalt	09_concrete	10_sand	11_groof	12_pool	13_soil	14_clay	15_rroof	
% Agree	93.4%	90.7%	95.2%	99.9%	95.7%	99.5%	98.6%	87.0%	90.0%	98.8%	88.0%	100.0%	98.3%	98.8%	95.7%	93.1%

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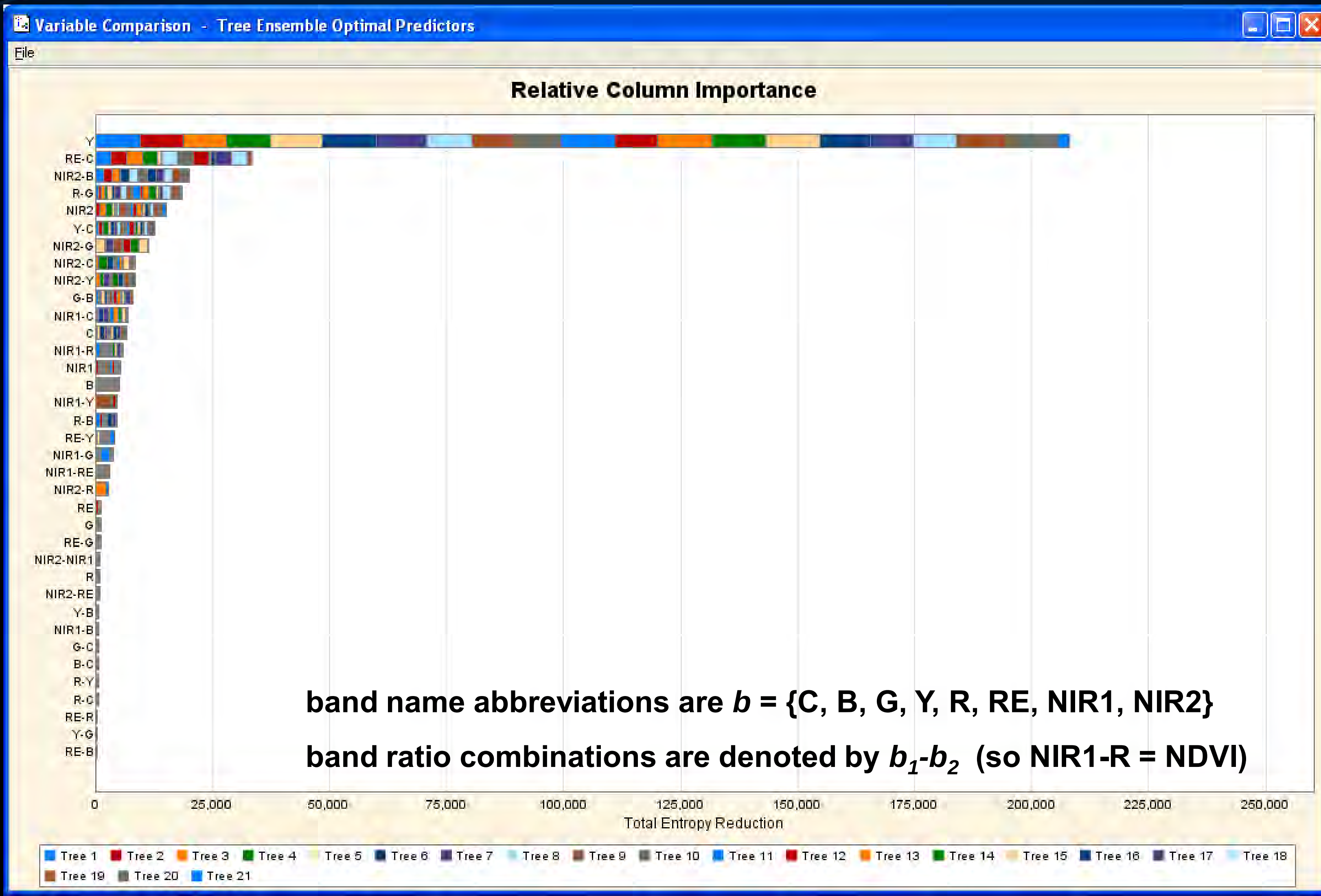
Top Predictors for Resolving all 15 Land Covers Types at Once (Dallas)

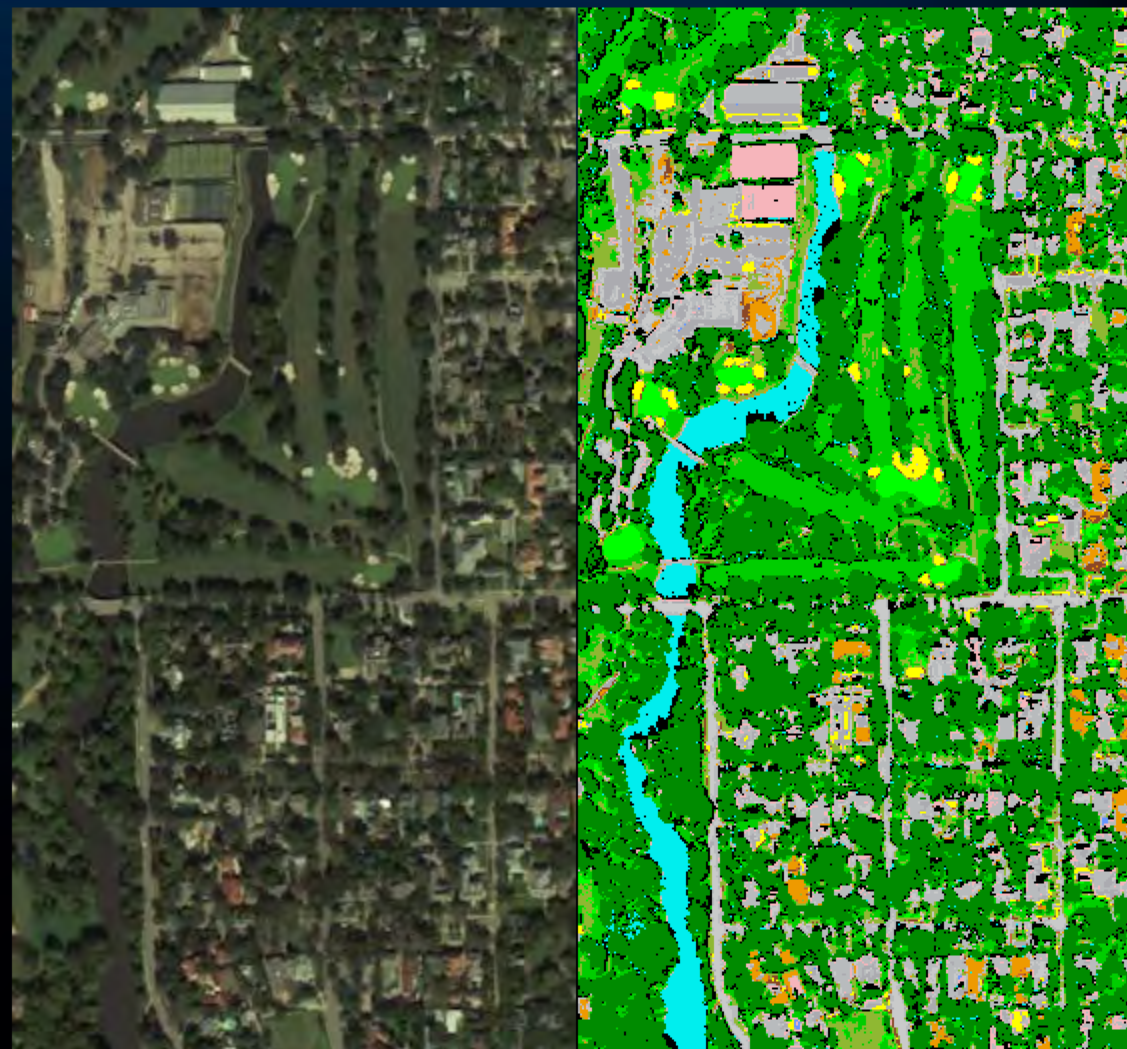


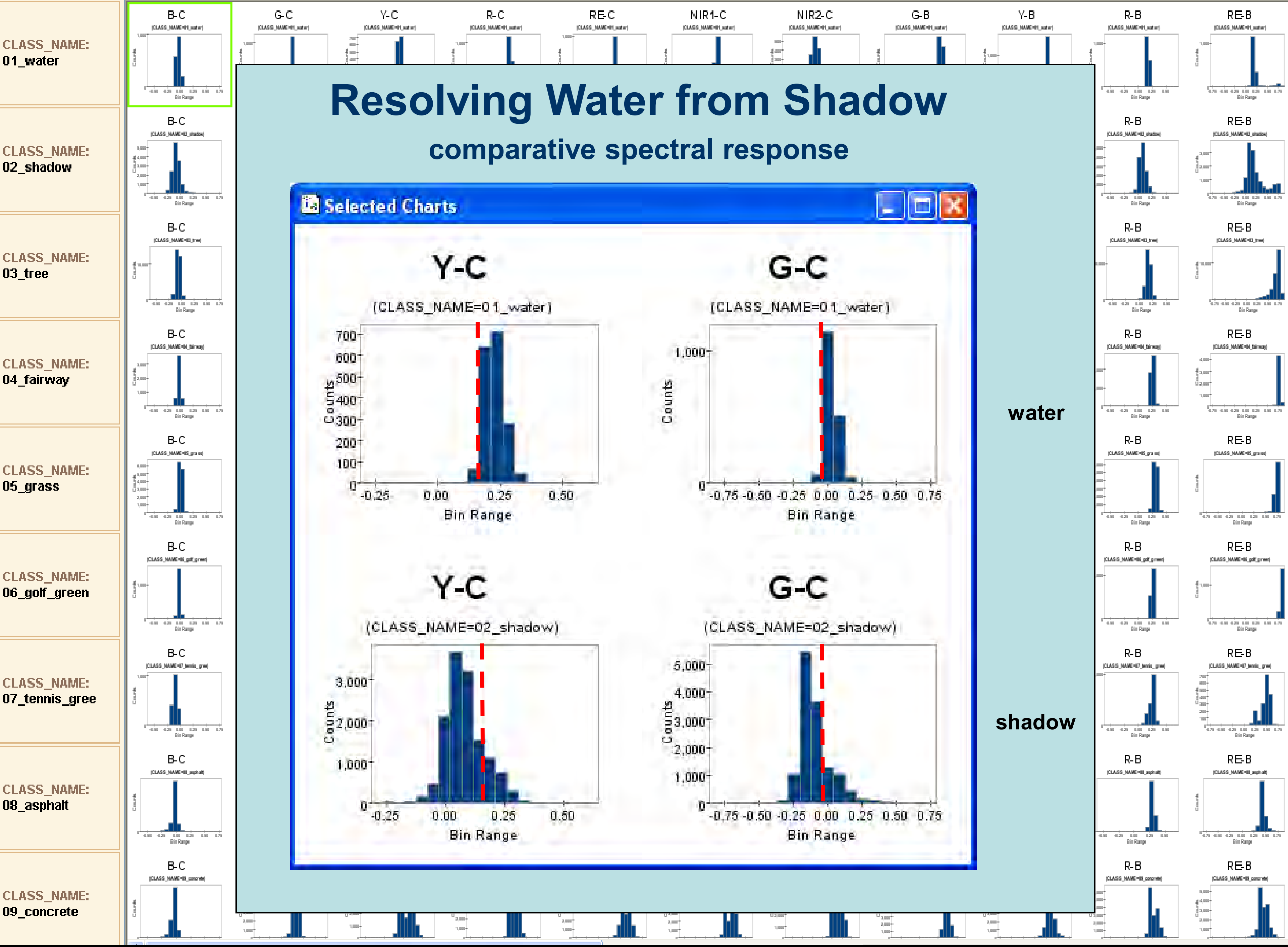
band name abbreviations are *b* = {C, B, G, Y, R, RE, NIR1, NIR2}

band ratio combinations are denoted by b_1-b_2 (so NIR1-R = NDVI)

Sharp Resolution of Shadows

shadow in water




Resolving Water from Shadow
comparative spectral response
Selected Charts
Y-C
(CLASS_NAME=01_water)
G-C
(CLASS_NAME=01_water)
Counts
Bin Range
water
Y-C
(CLASS_NAME=02_shadow)
G-C
(CLASS_NAME=02_shadow)
Counts
Bin Range
shadow
CLASS_NAME:
01_water
CLASS_NAME:
02_shadow
CLASS_NAME:
03_tree
CLASS_NAME:
04_fairway
CLASS_NAME:
05_grass
CLASS_NAME:
06_golf_green
CLASS_NAME:
07_tennis_gree
CLASS_NAME:
08_asphalt
CLASS_NAME:
09_concrete
B-C
G-C
Y-C
R-C
RE-C
NIR1-C
NIR2-C
G-B
Y-B
R-B
RE-B

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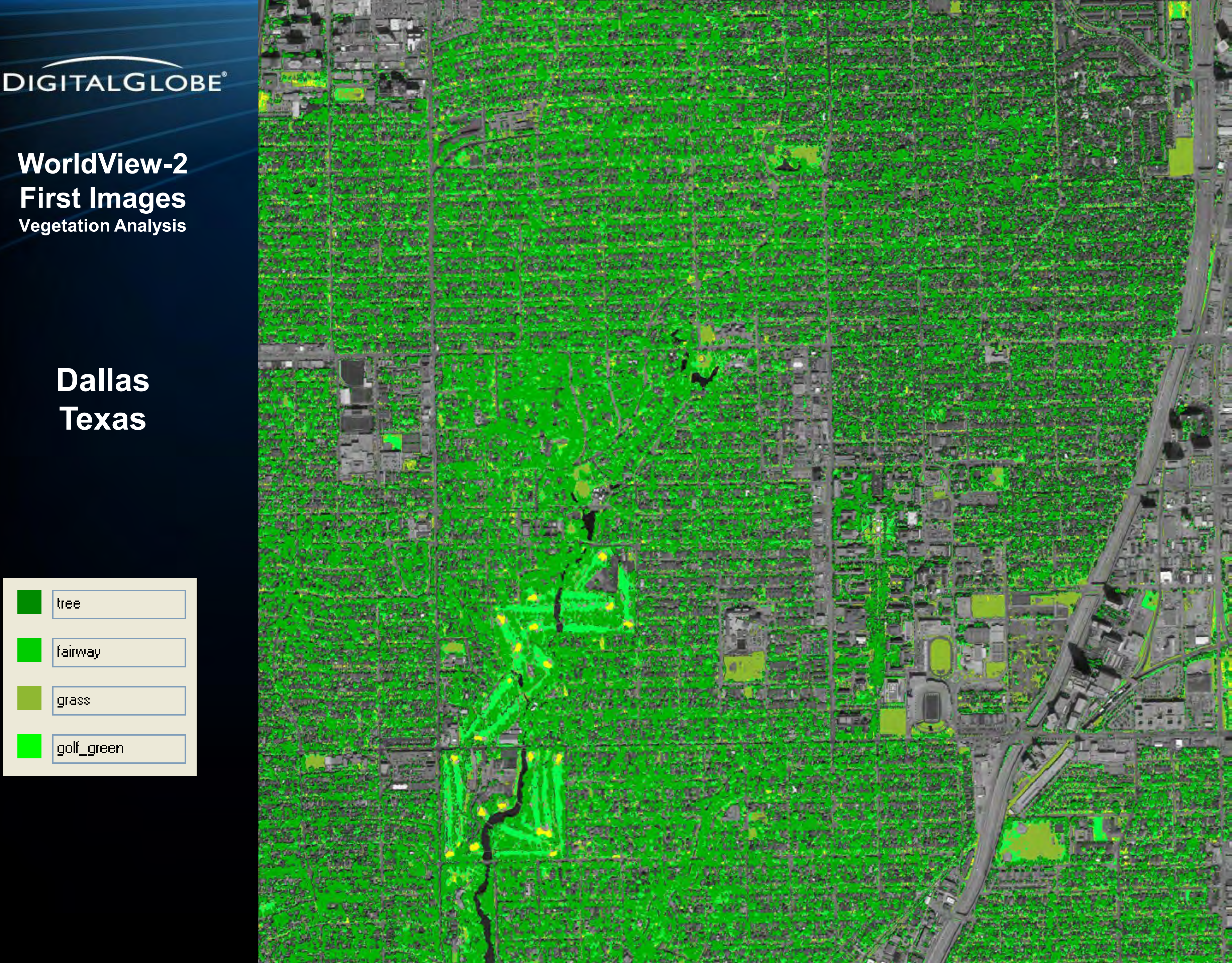
WorldView-2 First Images

Vegetation Analysis

Dallas Texas



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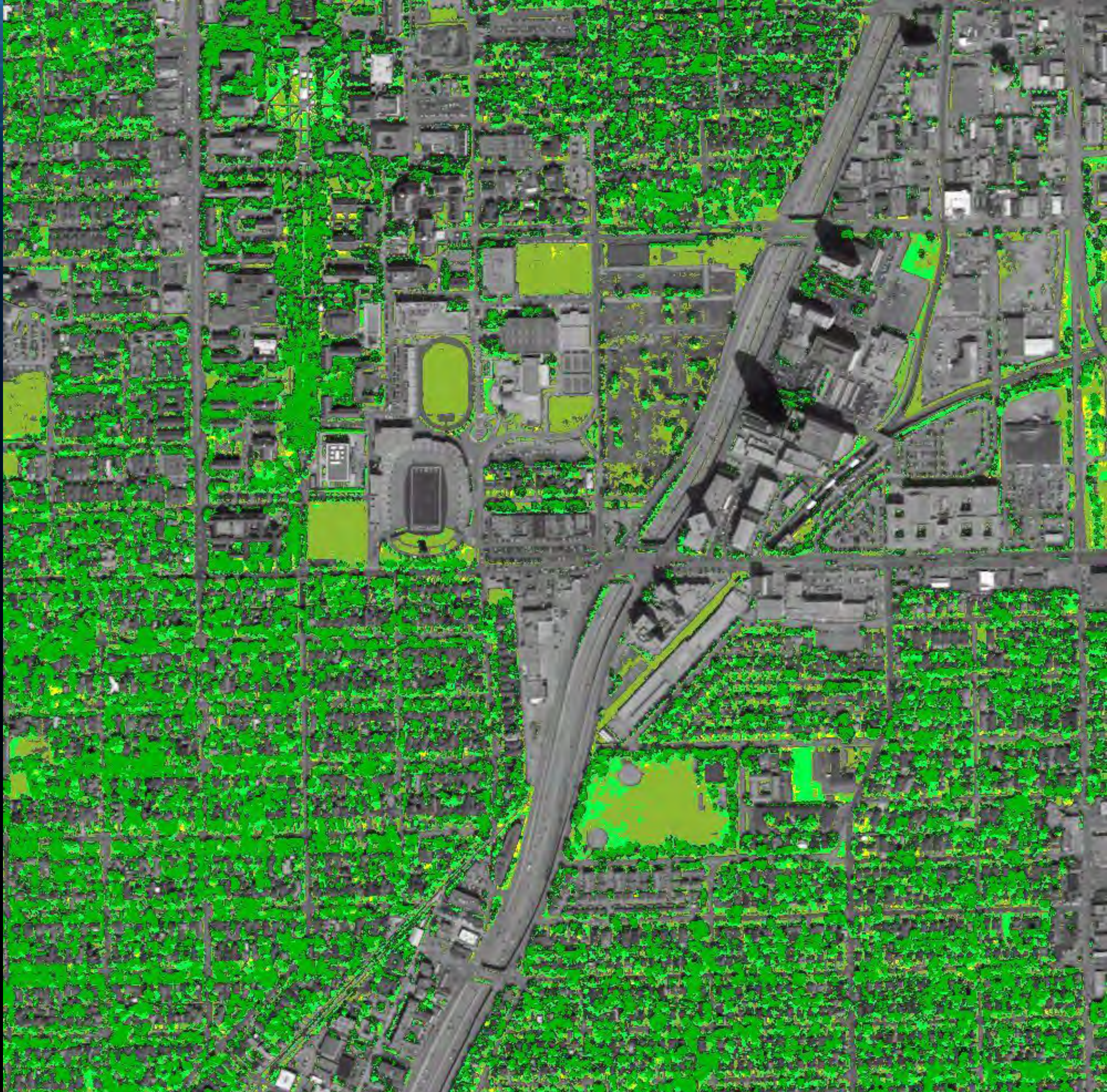
WorldView-2 First Images

Vegetation Analysis

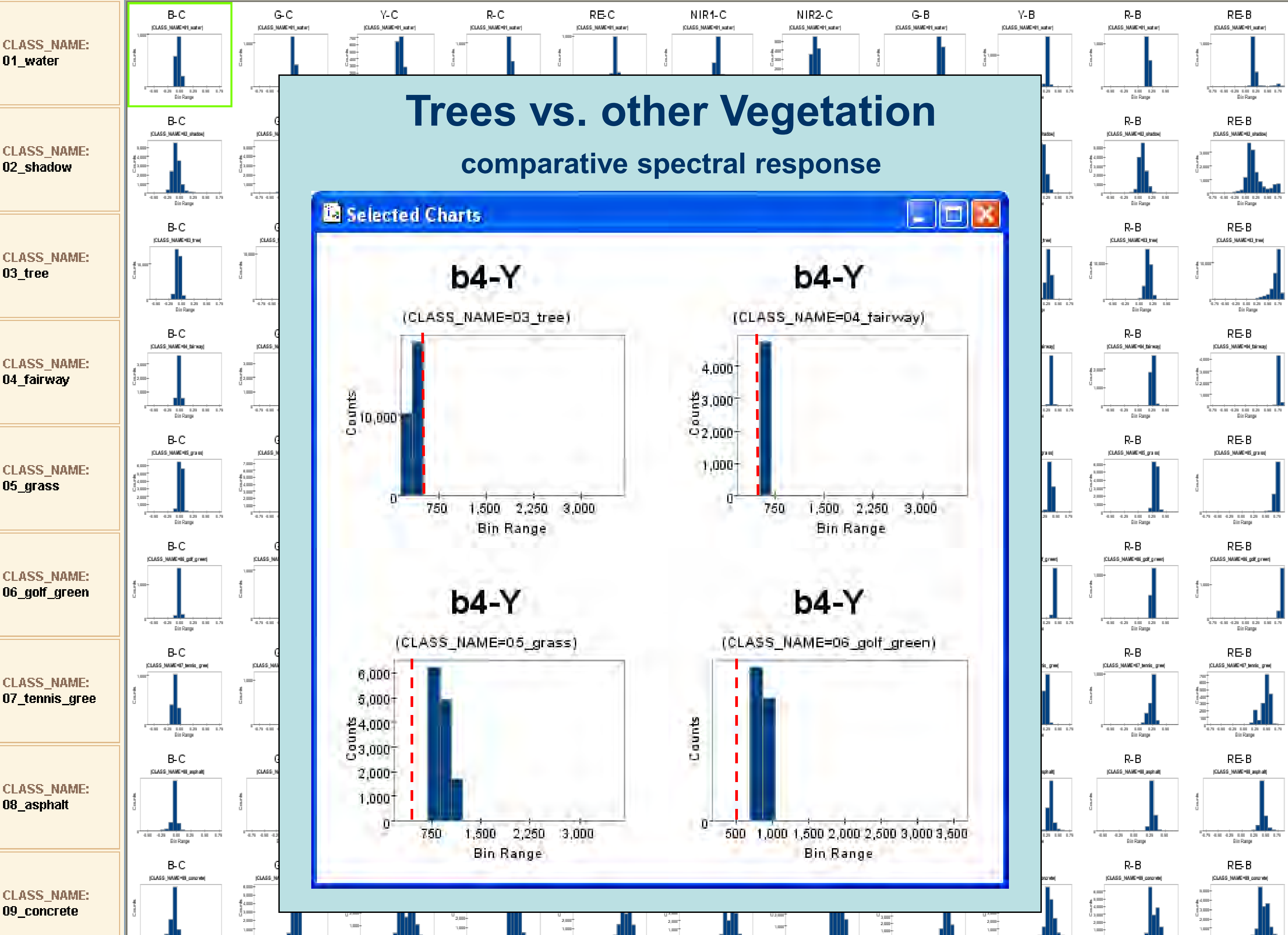
Dallas Texas

- tree
- fairway
- grass
- golf_green



Trees vs. other Vegetation

comparative spectral response



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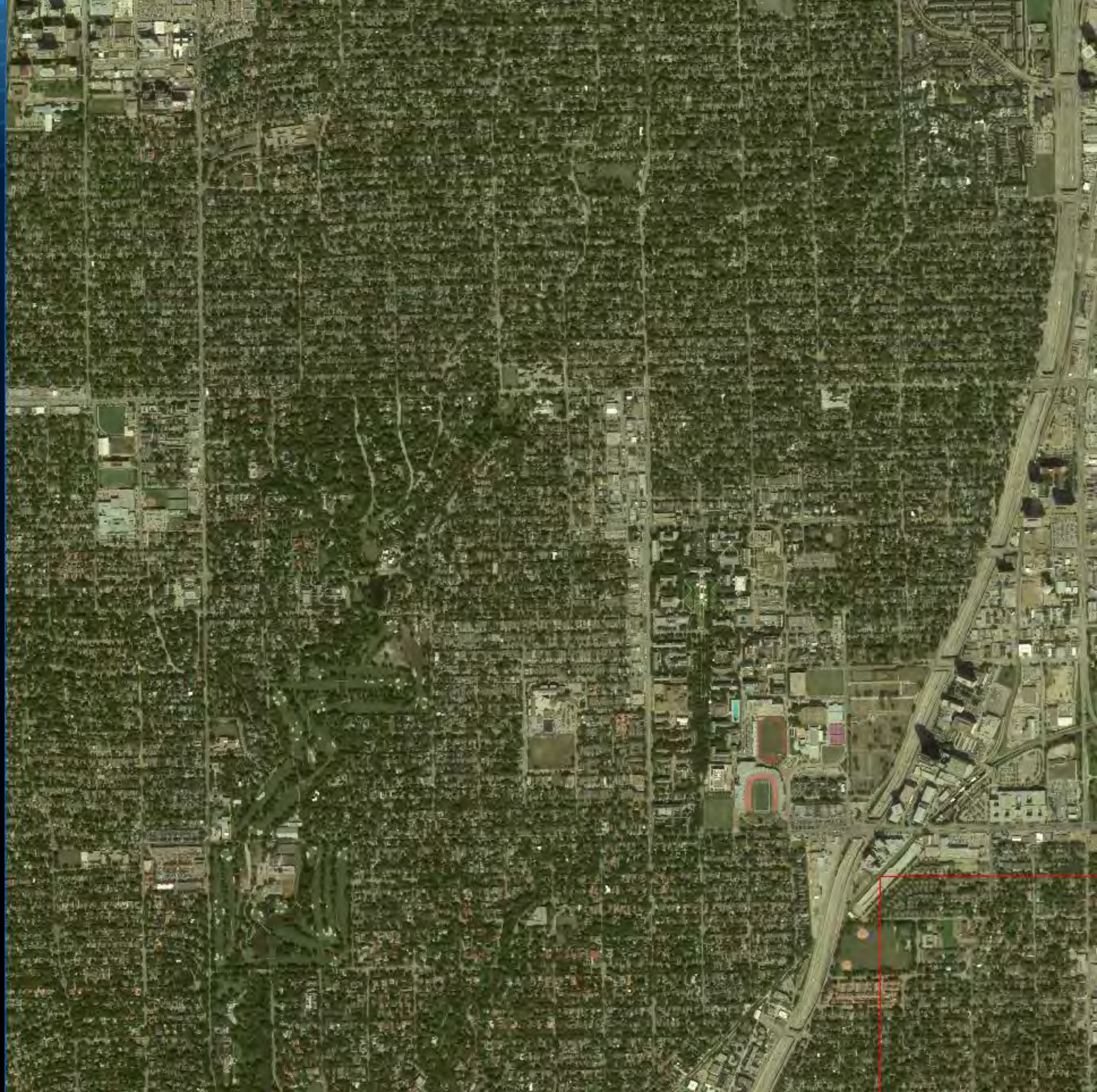
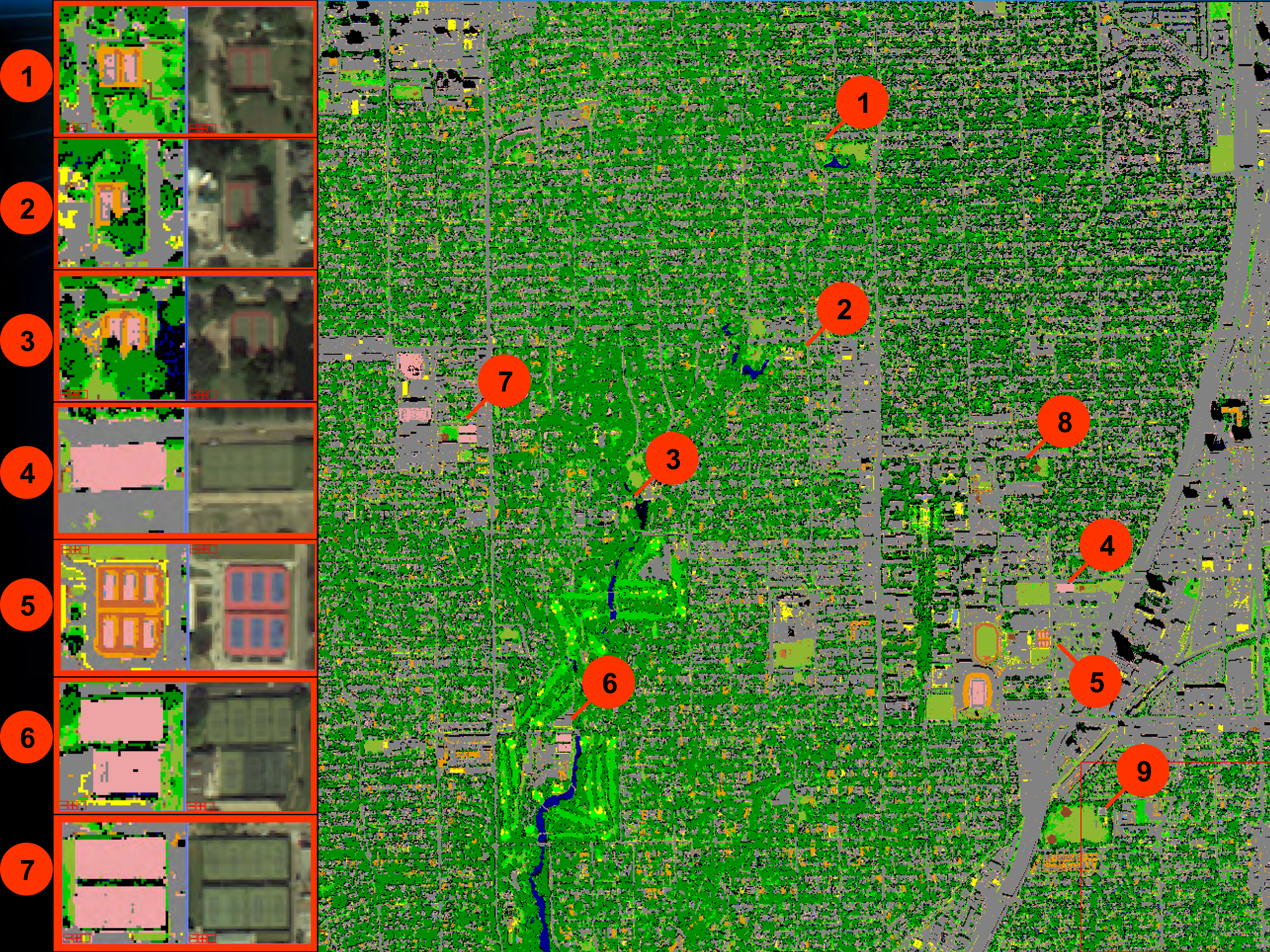
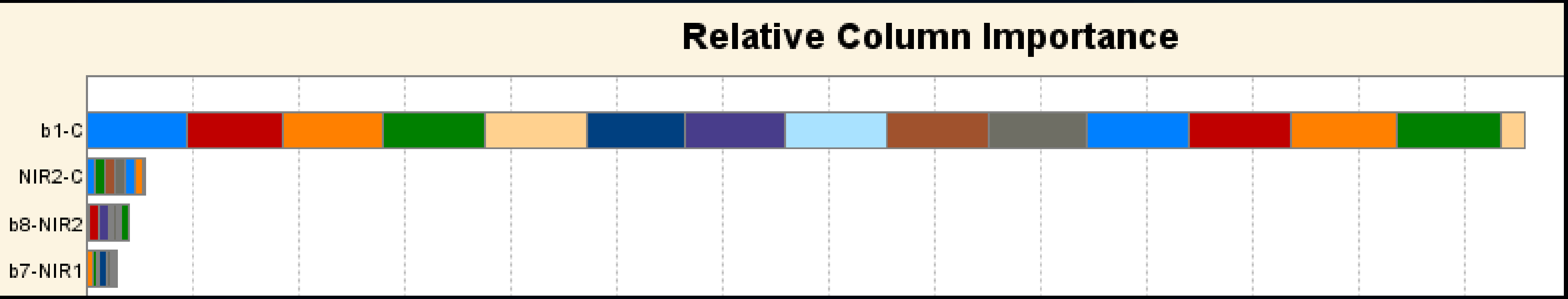
WorldView-2
First Images
Natural Color
2m Image

Dallas
Texas
Nov 20, 2009




1
2
3
4
5
6
7
1
2
3
4
5
6
7
8
9

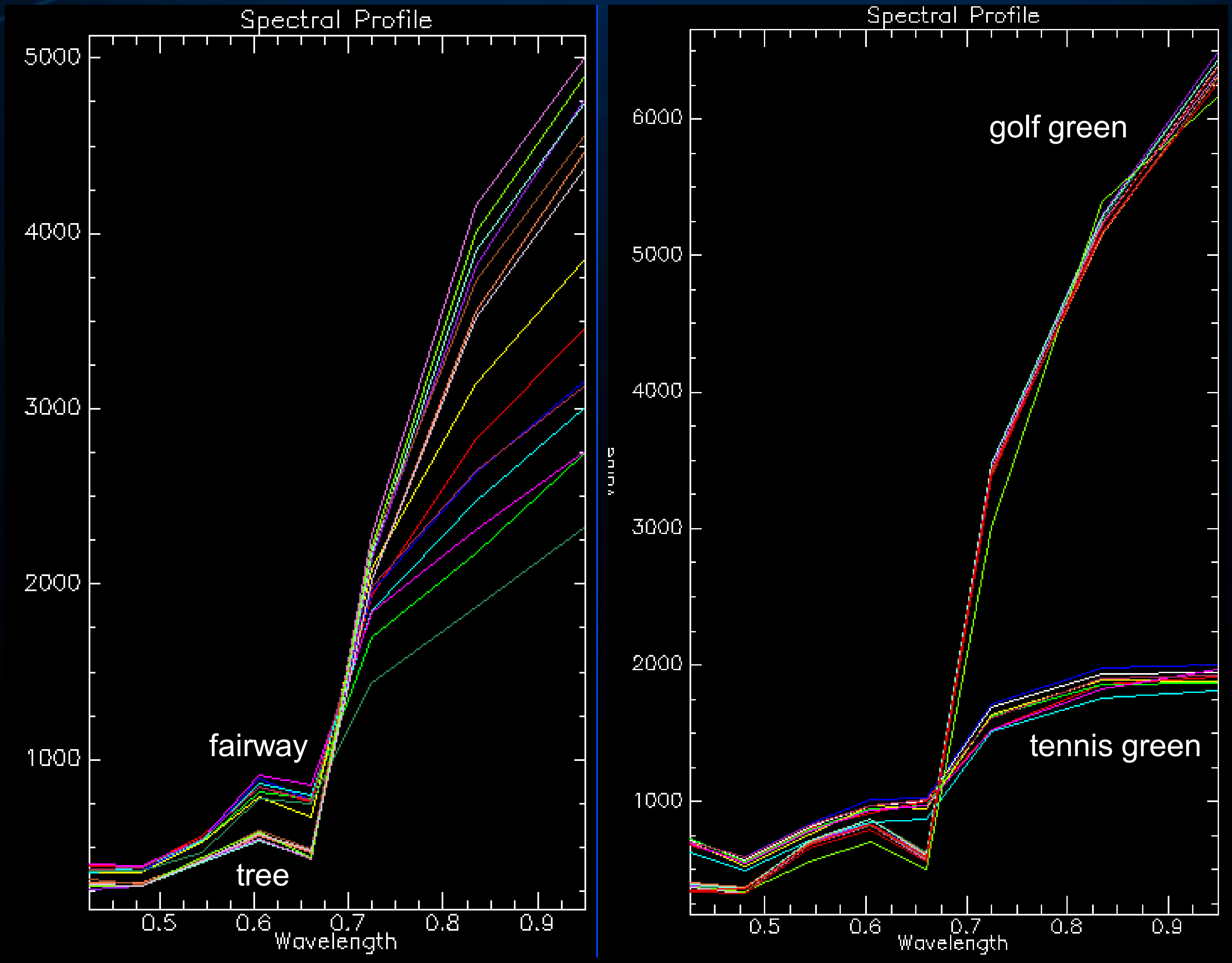
Top Predictors for Man-made Features (Dallas Scene)



band name abbreviations are b1-C, b2-B, b3-G, b4-Y, b5-R, b6-RE, b7-NIR1, b8-NIR2

band ratio combinations are denoted by b_1-b_2 (so NIR1-R = NDVI)

Validating Land Cover Separability



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WorldView-2
4 band
2m Image
November 7, 2009

Bangkok
Thailand

DIGITALGLOBE

WV2

13 land covers

Bangkok Thailand

- water
- shadow
- tree1
- tree2
- tree3
- grass A
- grass B
- asphalt
- concrete
- blue roof
- red roof
- gray roof
- metal roof
- soil

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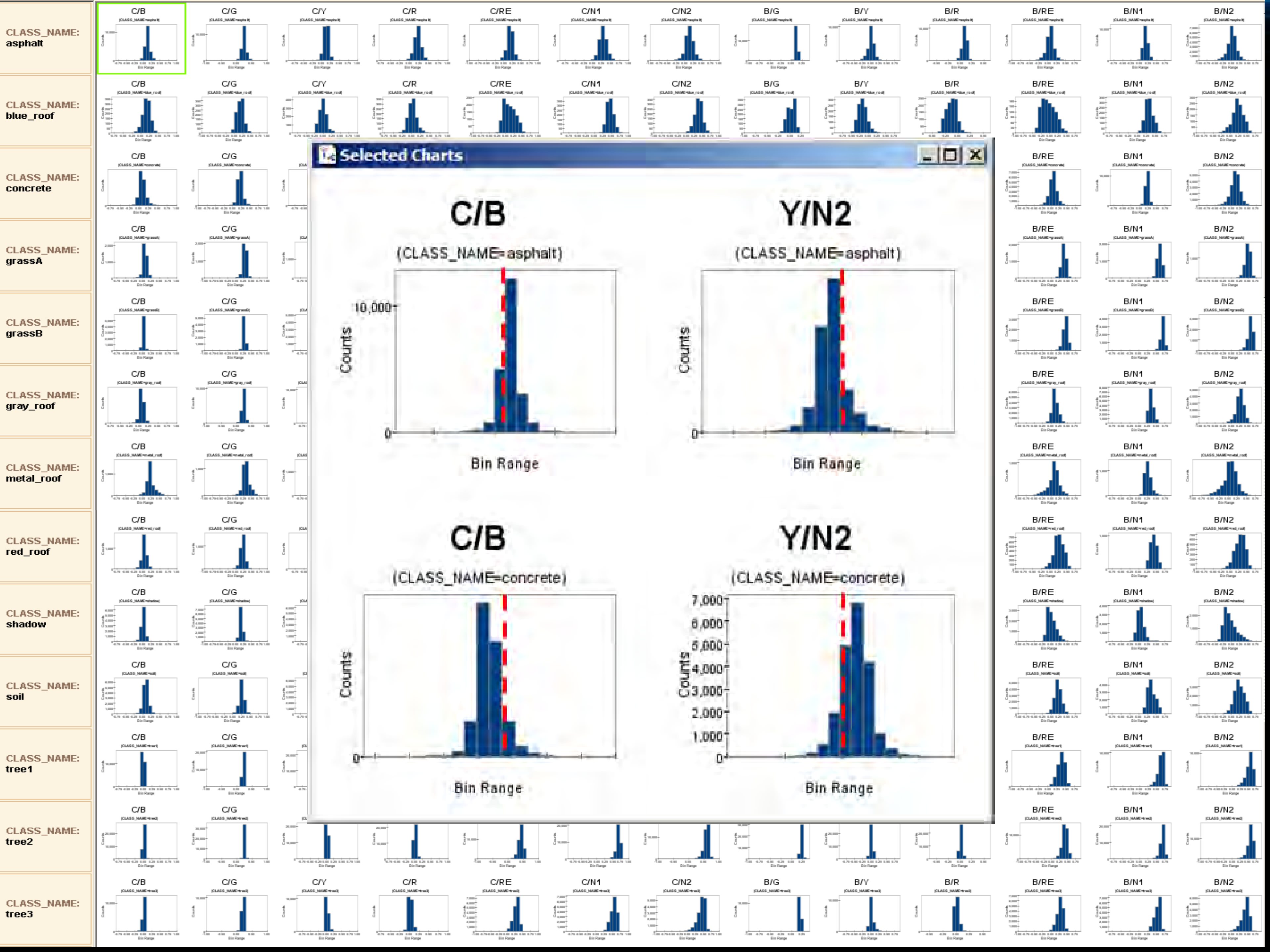
Classification Agreement for 14 Land Cover Types (Bangkok) – Tree Ensembles

Input Node - Predict: Tree Ensemble (8)

		Predicted														Totals
		water	shadow	tree1	tree2	tree3	grassA	grassB	asphalt	concrete	blue_roof	red_roof	gray_roof	metal_roof	soil	
Observed	water	9388	19	0	0	0	0	0	7	4	0	0	0	1	0	9419
	shadow	36	2899	20	10	16	0	0	70	75	0	1	0	0	4	3131
	tree1	0	3	7685	8	1	0	0	0	0	0	0	0	0	0	7697
	tree2	0	0	0	10431	149	2	67	0	0	0	0	0	0	1	10650
	tree3	0	0	0	112	4878	0	36	0	0	0	0	17	0	12	5055
	grassA	0	0	0	0	0	1077	29	2	0	0	0	7	0	62	1177
	grassB	0	0	0	74	61	16	1824	0	0	0	0	12	0	23	2010
	asphalt	14	21	0	0	0	6	2	6214	171	0	8	22	3	155	6616
	concrete	18	73	0	0	0	0	0	177	5464	1	5	132	20	80	5970
	blue_roof	0	1	3	0	3	2	3	0	1	278	0	20	0	1	312
	red_roof	5	2	0	0	0	0	0	8	4	0	823	1	4	89	936
	gray_roof	0	0	0	4	20	11	0	12	135	11	2	4223	0	74	4492
	metal_roof	5	0	0	0	0	0	0	2	33	0	0	0	968	3	1011
	soil	3	0	0	1	51	49	18	109	109	1	57	125	0	3916	4439
Totals		9469	3018	7708	10640	5179	1163	1979	6601	5996	291	896	4559	996	4420	62915

	Observed														Overall
	water	shadow	tree1	tree2	tree3	grassA	grassB	asphalt	concrete	blue_roof	red_roof	gray_roof	metal_roof	soil	
% Agree	99.7%	92.6%	99.8%	97.9%	96.5%	91.5%	90.7%	93.9%	91.5%	89.1%	87.9%	94.0%	95.7%	88.2%	95.5%


C/B
C/G
C/Y
C/R
C/RE
C/N1
C/N2
B/G
B/Y
B/R
B/RE
B/N1
B/N2
CLASS_NAME: asphalt
CLASS_NAME: blue_roof
CLASS_NAME: concrete
CLASS_NAME: grassA
CLASS_NAME: grassB
CLASS_NAME: gray_roof
CLASS_NAME: metal_roof
CLASS_NAME: red_roof
CLASS_NAME: shadow
CLASS_NAME: soil
CLASS_NAME: tree1
CLASS_NAME: tree2
CLASS_NAME: tree3
Selected Charts
C/B
(CLASS_NAME=asphalt)
10,000
0
Counts
Bin Range
Y/N2
(CLASS_NAME=asphalt)
0
Counts
Bin Range
C/B
(CLASS_NAME=concrete)
0
Counts
Bin Range
Y/N2
(CLASS_NAME=concrete)
7,000
6,000
5,000
4,000
3,000
2,000
1,000
0
Counts
Bin Range

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Urban Classification

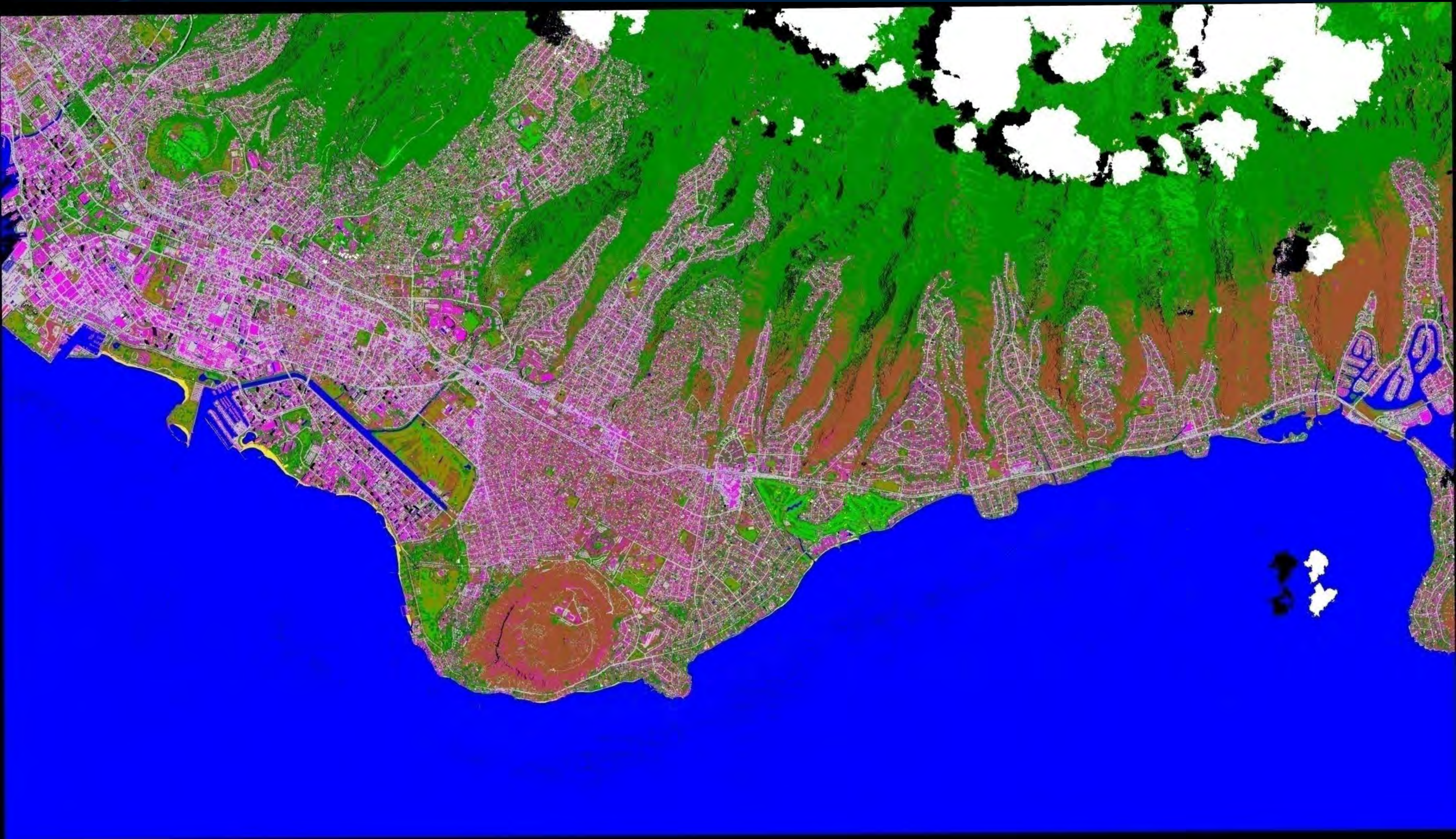
WorldView-2

Honolulu, HI
Apr 25, 2010

Urban Classification

WorldView-2

Honolulu, HI
Apr 25, 2010



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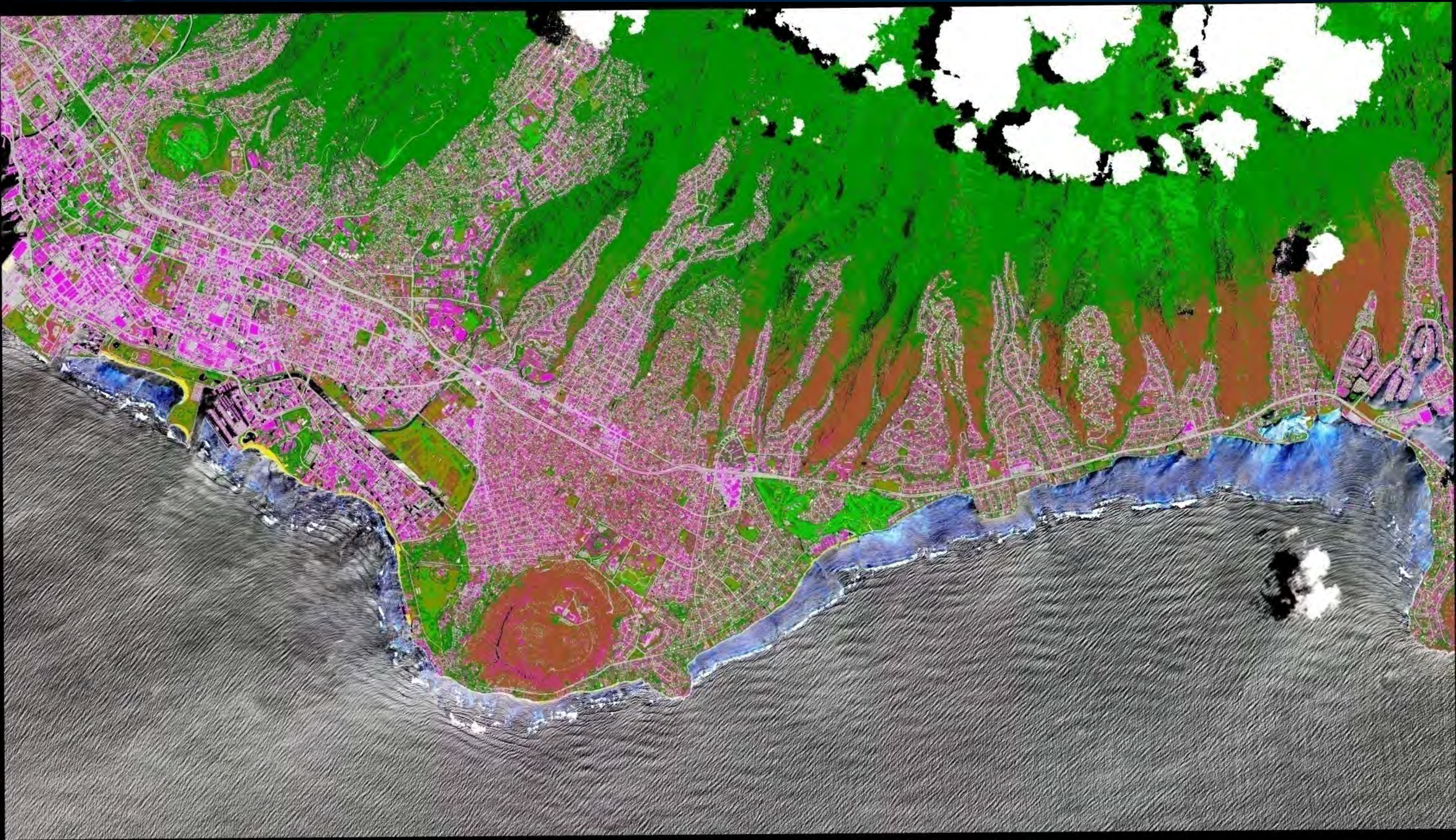
Urban Classification with RE, NIR1, NIR2 Wave Layer

WorldView-2

Honolulu, HI
Apr 25, 2010

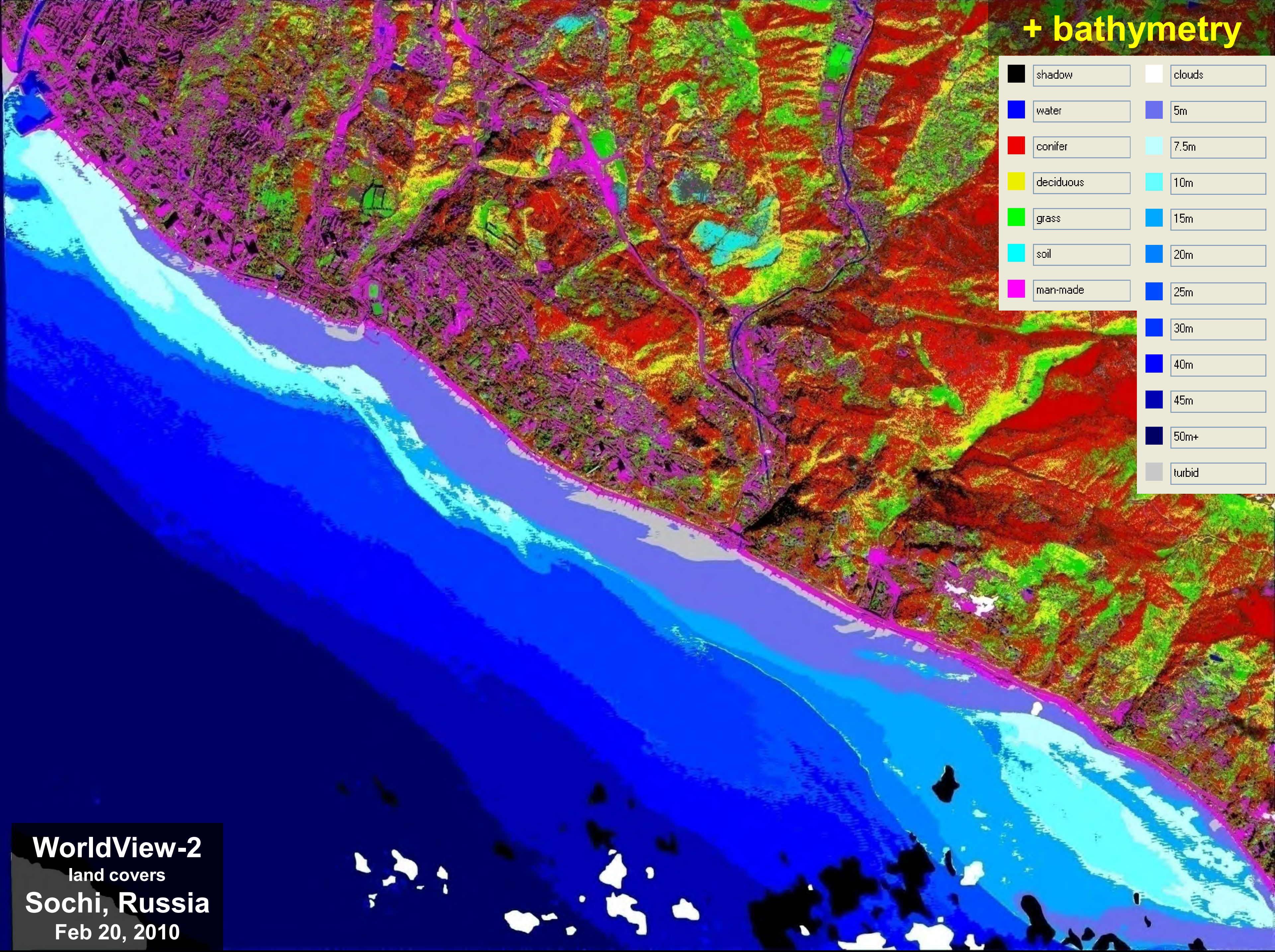


Urban Classification

WorldView-2

Honolulu, HI
Apr 25, 2010


WorldView-2
true color image
Sochi, Russia
Feb 20, 2010


+ bathymetry
shadow
water
conifer
deciduous
grass
soil
man-made
clouds
5m
7.5m
10m
15m
20m
25m
30m
40m
45m
50m+
turbid
WorldView-2
land covers
Sochi, Russia
Feb 20, 2010

Comparison in Classification Accuracy for 34 Land Covers (QB vs. WV2)

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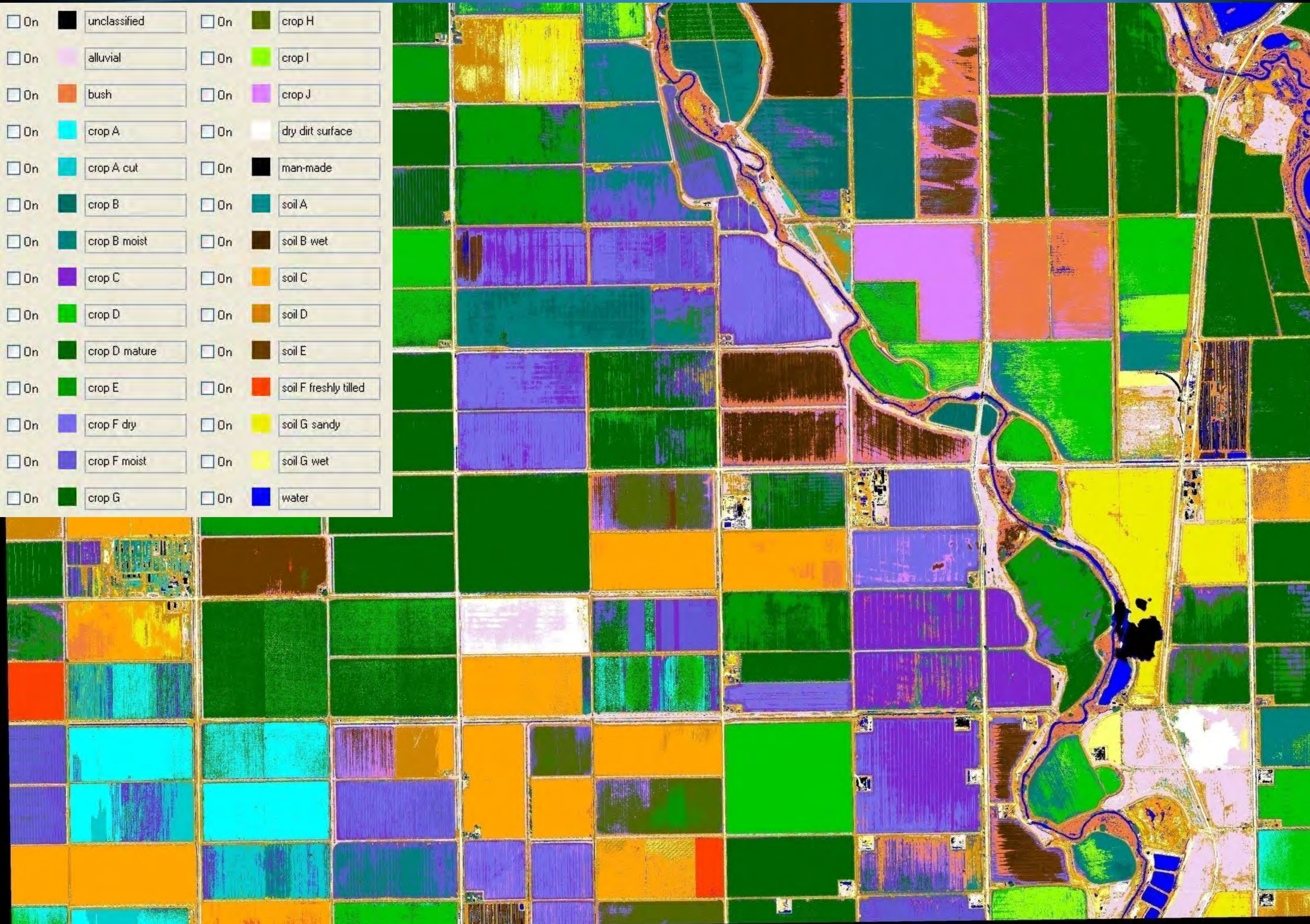
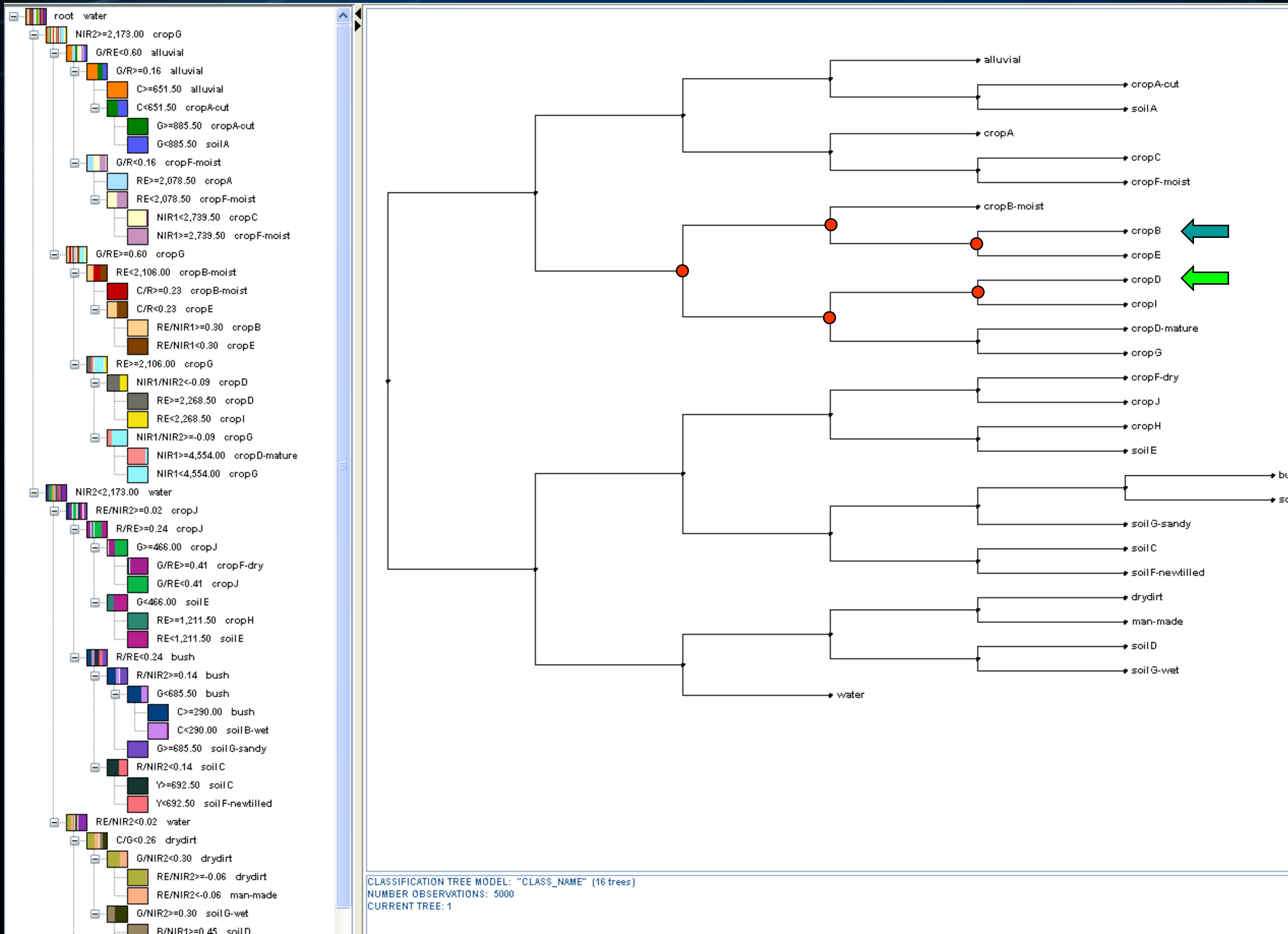
	LC	CLASSIFICATION ACCURACY								IMPROVEMENT					TOP PREDICTORS (best 4 out of 8 bands)							
		VNIR				WV2																
		LR	CT	TE	NN	LR	CT	TE	NN	LR	CT	TE	NN	AVE	C	B	G	Y	R	RE	N1	N2
SCENE 1	water	86.7	89.5	90.0	86.5	87.8	90.5	91.1	90.6	1.1	1.0	1.1	4.1	1.8	■	■	■	■				
	shadow	77.8	72.4	75.6	74.0	87.5	83.8	83.0	78.1	9.7	11.4	7.4	4.1	8.2	■	■		■				■
	tree	95.4	95.0	93.4	89.8	96.9	95.2	95.0	94.6	1.5	0.2	1.6	4.8	2.0		■	■	■				■
	grass A	95.5	88.6	91.5	89.5	97.2	89.6	91.7	92.9	1.7	1.0	0.2	3.4	1.6	■			■			■	■
	grass B	83.4	88.9	91.5	87.7	95.7	99.9	99.9	94.5	12.3	11.0	8.4	6.8	9.6	■			■		■		■
	grass C	96.9	98.2	95.8	96.2	97.0	98.4	98.7	97.5	0.1	0.2	2.9	1.3	1.1		■	■	■				■
	tennis	64.8	79.5	78.9	82.6	90.9	89.5	92.9	93.3	26.1	10.0	14.0	10.7	15.2	■		■	■				■
	asphalt	84.8	72.1	72.9	61.7	89.2	75.3	77.6	81.3	4.4	3.2	4.7	19.6	8.0	■			■	■			■
	concrete	76.6	87.9	82.1	74.2	82.5	93.0	88.0	84.1	5.9	5.1	5.9	9.9	6.7	■			■			■	■
	sand	93.7	91.5	93.5	96.5	97.7	98.4	98.3	98.7	4.0	6.9	4.8	2.2	4.5				■	■		■	■
	gray roof	35.1	70.0	68.5	72.8	59.3	82.6	74.3	76.2	24.2	12.6	5.8	3.4	11.5	■			■	■			■
	pool	91.8	95.2	96.3	99.0	91.9	96.3	97.2	99.1	0.1	1.1	0.9	0.1	0.6	■			■			■	■
	soil	86.4	90.3	83.2	85.8	91.8	96.0	91.3	92.9	5.4	5.7	8.1	7.1	6.6	■			■	■		■	
	clay	92.2	89.5	91.8	96.2	95.9	92.5	96.0	98.5	3.7	3.0	4.2	2.3	3.3			■	■	■	■		
	red roof	46.6	89.2	83.2	83.8	81.4	93.2	86.3	88.5	34.8	4.0	3.1	4.7	11.7			■	■		■		■
SCENE 2	water	96.2	96.1	95.5	96.5	98.7	96.1	96.4	98.1	2.5	0.0	0.9	1.6	1.3	■	■	■			■		
	turbidity	79.5	78.5	81.6	79.3	84.7	82.1	87.9	83.5	5.2	3.6	6.3	4.2	4.8	■	■		■		■		
	shadow	91.7	95.2	95.3	83.0	98.2	97.1	97.1	85.9	6.5	1.9	1.8	2.9	3.3	■	■		■				■
	conifer	93.5	91.3	93.6	95.1	97.9	93.9	94.0	96.1	4.4	2.6	0.4	1.0	2.1	■	■				■		■
	conifer #	92.8	96.2	94.1	94.2	100.0	99.4	99.4	97.6	7.2	3.2	5.3	3.4	4.8		■	■			■	■	
	deciduous	96.0	95.3	89.8	93.6	97.4	95.8	93.7	94.8	1.4	0.5	3.9	1.2	1.8	■			■	■			■
	grass	89.1	86.2	90.7	91.8	96.6	94.2	94.5	92.7	7.5	8.0	3.8	0.9	5.1			■		■	■		■
	soil	88.7	88.1	86.6	84.5	89.1	89.8	89.4	89.6	0.4	1.7	2.8	5.1	2.5	■			■	■			■
	asphalt	90.4	85.8	90.0	90.9	91.5	88.8	90.0	92.0	1.1	3.0	0.0	1.1	1.3	■		■		■			■
	gray roof	76.3	79.9	80.1	82.4	80.5	90.2	81.2	84.5	4.2	10.3	1.1	2.1	4.4	■			■	■			■
SCENE 3	rice paddy	93.0	90.7	88.6	89.6	98.4	96.2	94.6	97.7	5.4	5.5	6.0	8.1	6.3			■	■	■	■		
	trees	90.8	88.0	89.1	94.2	91.6	88.4	89.6	94.6	0.8	0.4	0.5	0.4	0.5		■	■	■	■			
	water	99.5	99.7	99.6	99.0	99.9	99.9	100.0	100.0	0.4	0.2	0.4	1.0	0.5		■	■	■				■
	soil	96.3	89.2	86.4	73.6	96.4	89.5	88.6	88.5	0.1	0.3	2.2	14.9	4.4			■	■		■	■	
	asphalt	88.9	93.8	92.3	93.2	90.4	95.7	96.8	95.6	1.5	1.9	4.5	2.4	2.6	■			■	■			■
	dirt	96.0	96.0	95.9	95.9	96.8	96.8	96.9	97.6	0.8	0.8	1.0	1.7	1.1	■		■	■				■
	gray roof	0.0	61.6	59.6	65.2	81.3	84.3	78.4	82.1	81.3	22.7	18.8	16.9	34.9			■	■	■			■
	red roof	95.1	87.8	90.2	93.5	98.4	96.7	96.7	96.7	3.3	8.9	6.5	3.2	5.5			■	■		■		■
	bush	82.8	78.0	97.9	79.5	86.2	86.7	98.6	86.0	3.4	8.7	0.7	6.5	4.8			■	■	■	■		


WorldView-2
true color image
Salton Sea
Feb 20, 2010


unclassified
alluvial
bush
crop A
crop A cut
crop B
crop B moist
crop C
crop D
crop D mature
crop E
crop F dry
crop F moist
crop G
crop H
crop I
crop J
dry dirt surface
man-made
soil A
soil B wet
soil C
soil D
soil E
soil F freshly tilled
soil G sandy
soil G wet
water

Spectral Predictors and LC Separability



Spectral Distance Estimation – I
(Single Tree Regression Model)

The partition in a Regression Tree is given by the leaves of the tree. Each sample in a training set is assigned to a leaf. The deviance for the regression model at each node *j* is defined as

$$D = \sum_{cases\ j} (y_j - \mu_{[j]})^2$$

Where y_j is the class probability label. We should estimate the constant μ_i for leaf *i* by mean of the value of the training set assigned to that node.

Then the deviance is the sum over leaves of D_i and the entropy reduction of a split is the reduction in the residual sum of the squares.

The obvious probability model is to take a normal $N(\mu_i, \sigma^2)$ distribution within each leaf, so *D* is the usual scaled deviance for a Gaussian GLM. However, the distribution at internal nodes of the tree is then a mixture of distributions, and so D_j is only appropriate at the node.

The tree-construction process has to be seen as a hierarchical refinement of probability models.

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Spectral Distance Estimation II
(A More Refined Model of Deviance)

At each node *j* of a classification tree we have a probability distribution p_{ik} over the classes. At each leaf we have a random sample n_{ik} from the multinomial distribution specified by p_{ik}.

The conditional likelihood is then proportional to:

$$\prod_{cases\ j} p_{[j]y_j} = \prod_{leaves\ i} \prod_{classes\ k} p_{ik}^{n_{ik}}$$

Where *[j]* denotes the leaf assigned to sample *j*. This allows us to define a deviance for the tree as a sum over leaves

$$D = \sum_i D_i, \qquad D_i = -2\sum_k n_{ik} \log p_{ik}$$

Spectral Distance Estimation IV
(A More Refined Model of Deviance)

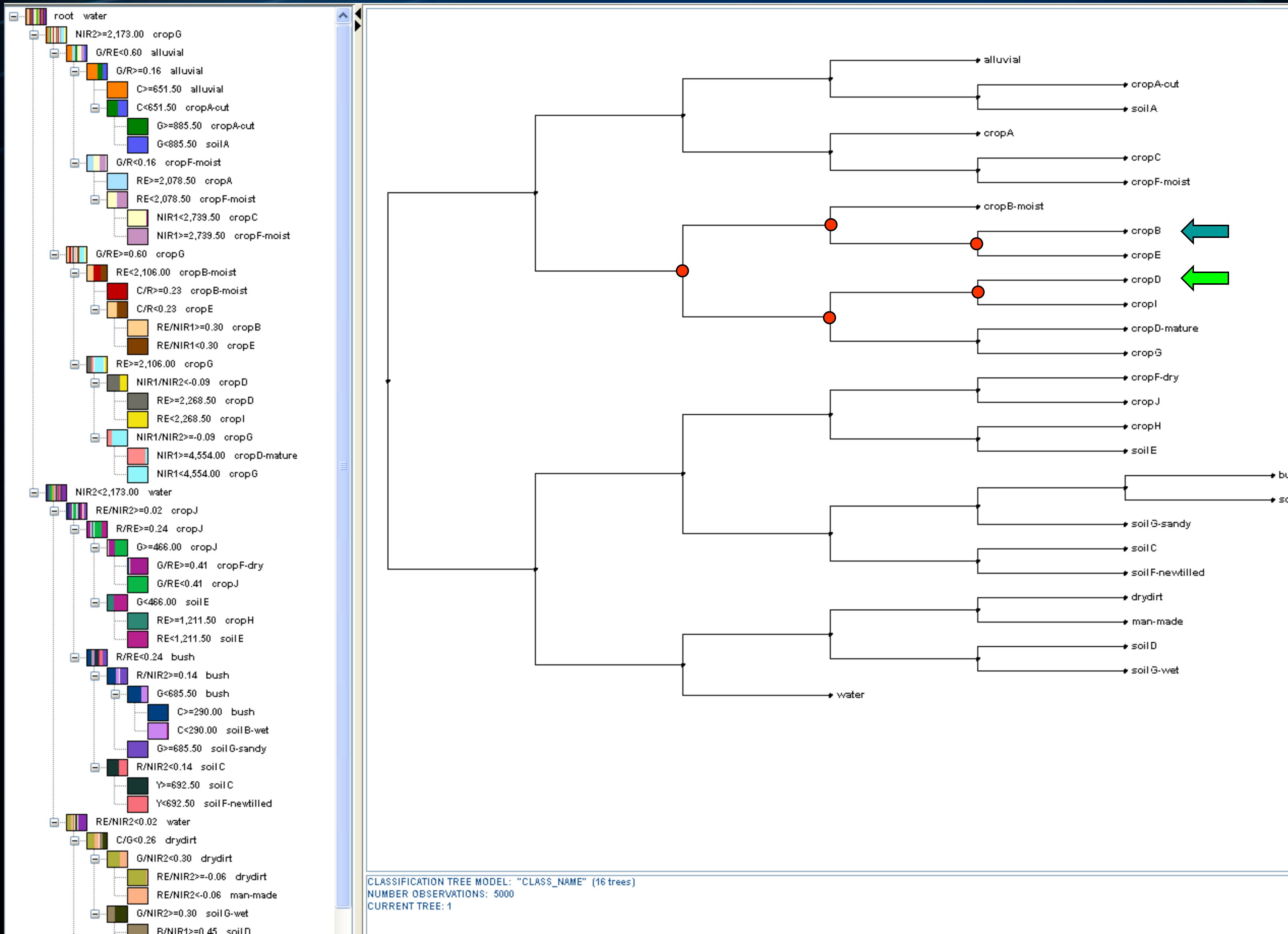
Consider splitting node s into nodes t and u. This changes the probability model within node s, so the reduction in deviance for the tree is

$$D_s - D_t - D_u = 2\sum_k \left[n_{tk} \log \frac{p_{tk}}{p_{sk}} + n_{uk} \log \frac{p_{uk}}{p_{sk}} \right]$$

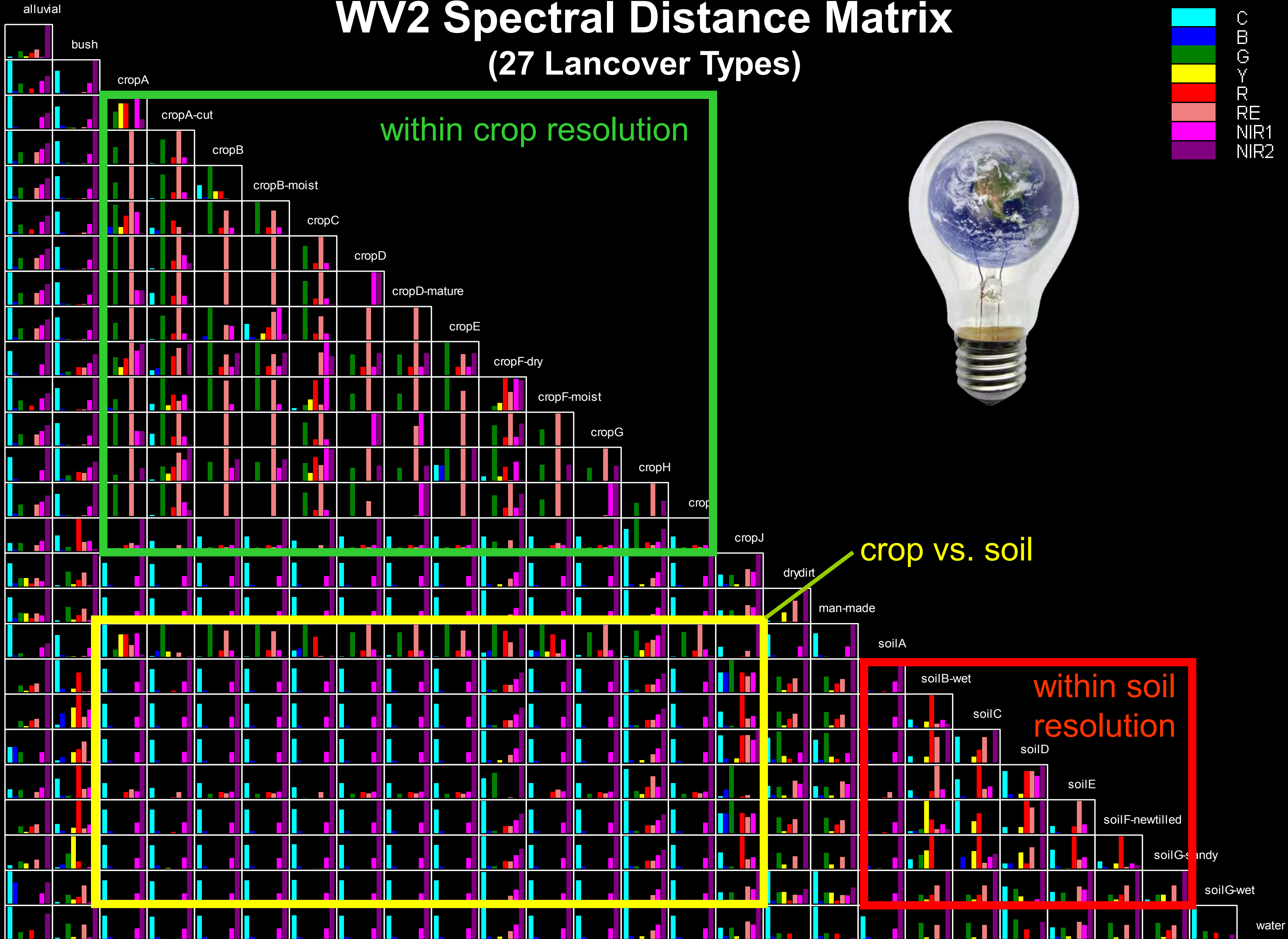
or, in the terms of the sample proportions in the split node

$$D_s - D_t - D_u = 2\sum_k \left[n_{tk} \log \frac{n_{tk} n_s}{n_{sk} n_t} + n_{uk} \log \frac{n_{uk} n_s}{n_{sk} n_u} \right]$$

Spectral Predictors and LC Separability



WV2 Spectral Distance Matrix
(27 Lancover Types)



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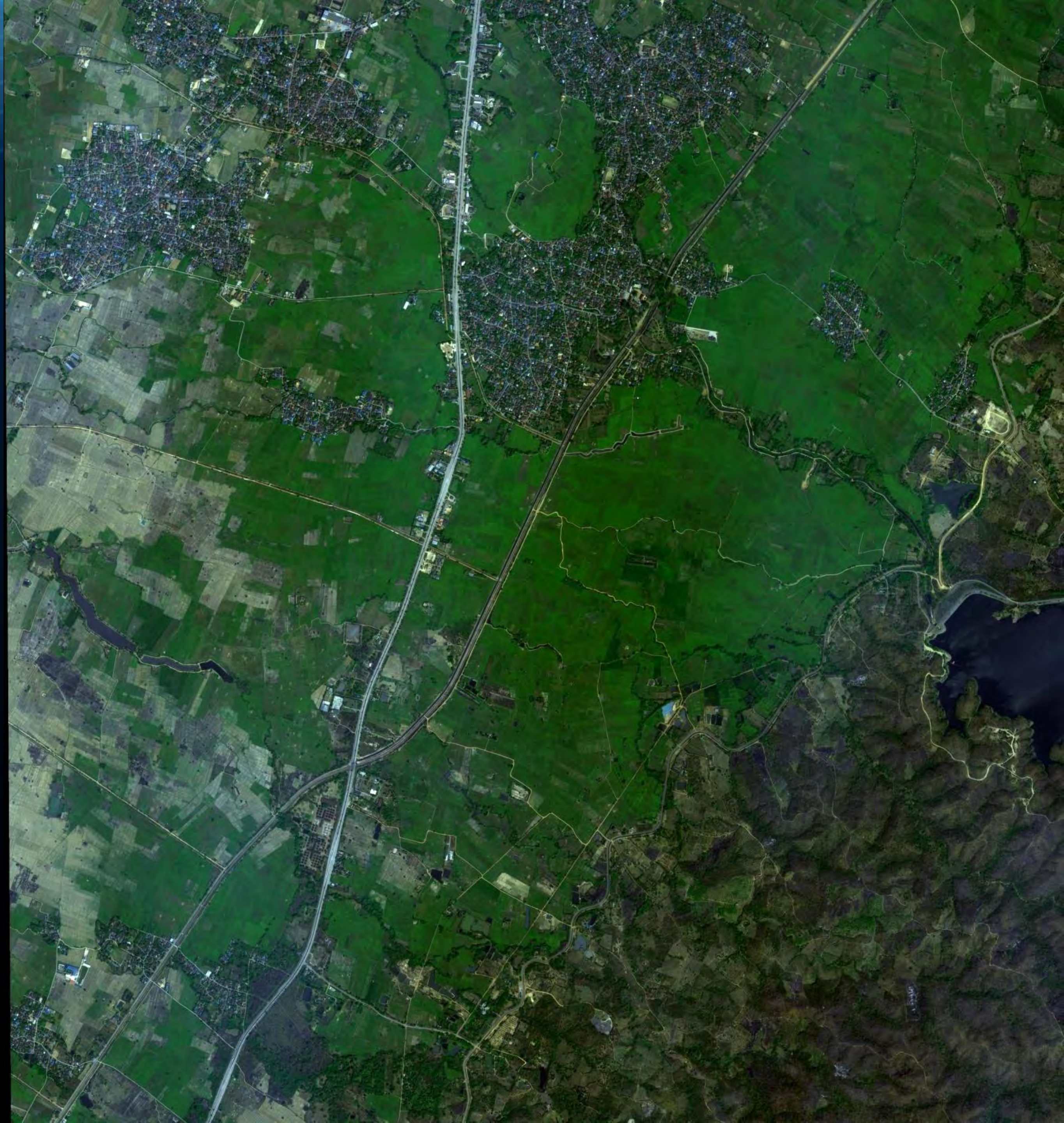
WorldView-2
natural color
2m image
March 13, 2010



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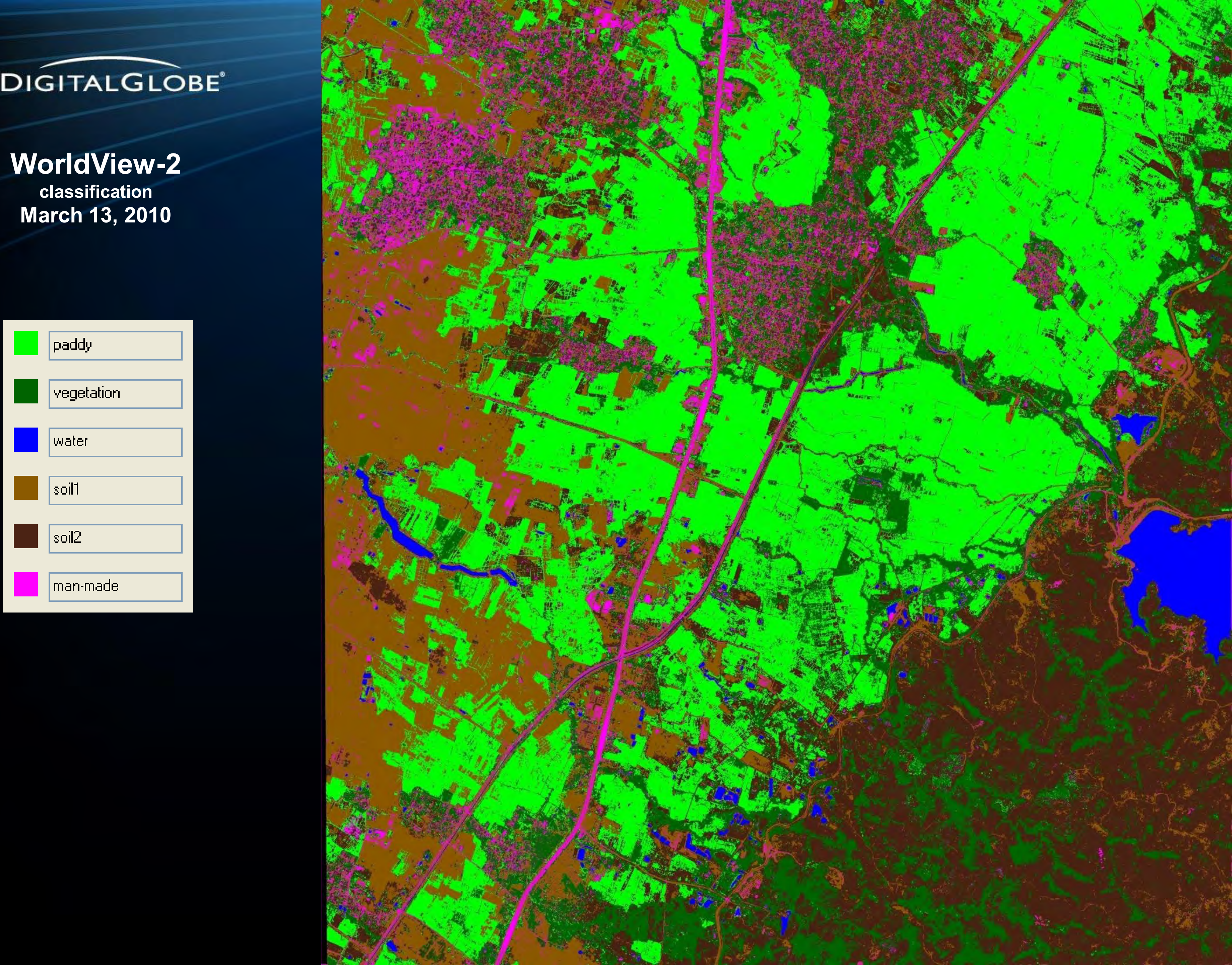
WorldView-2

classification

March 13, 2010



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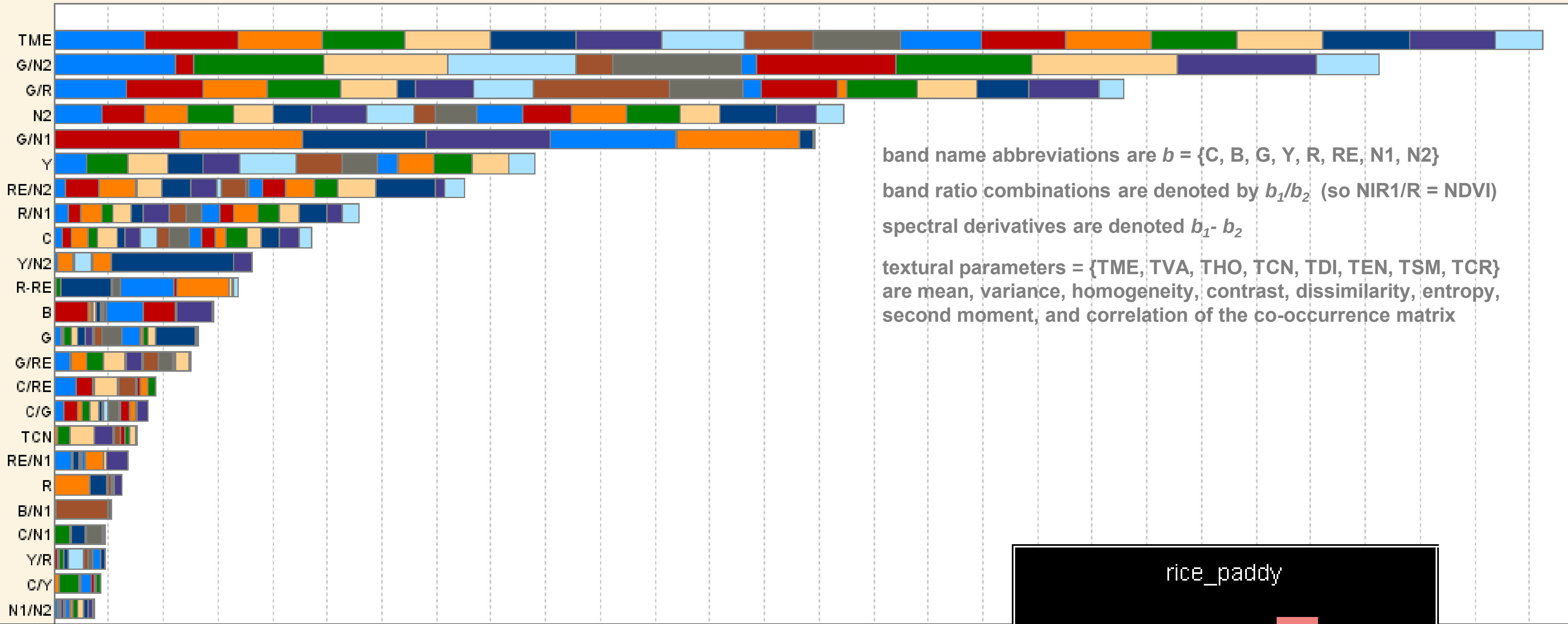
Best Predictors

Overall Scene - **Relative Column Importance**

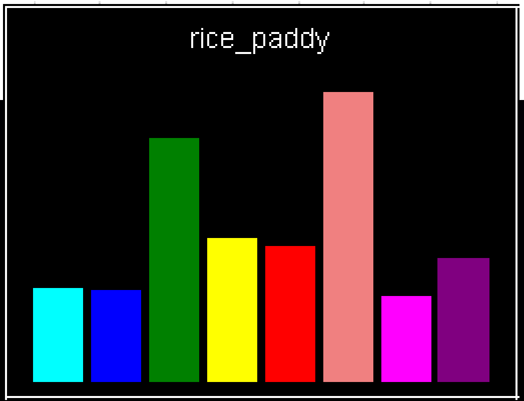


band name abbreviations are *b* = {C, B, G, Y, R, RE, N1, N2}

band ratio combinations are denoted by b_1/b_2 (so NIR1/R = NDVI)

spectral derivatives are denoted $b_1 - b_2$

textural parameters = {TME, TVA, THO, TCN, TDI, TEN, TSM, TCR} are mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment, and correlation of the co-occurrence matrix



relative importance of WV-2 spectral bands for rice paddies

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WorldView-2

natural color

2m Image

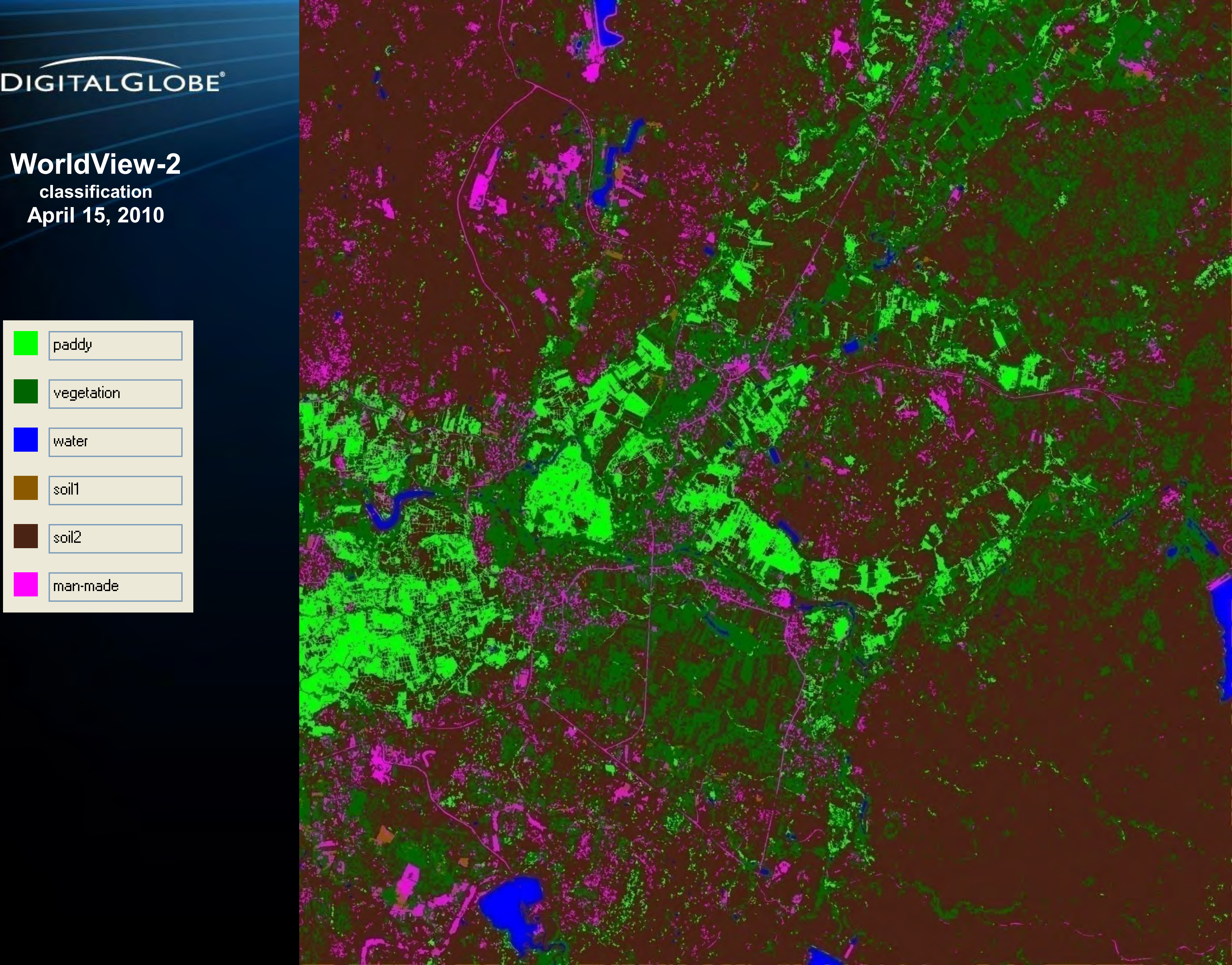
April 15, 2010

DIGITALGLOBE

WorldView-2

classification

April 15, 2010



Mapping Wetlands Health after the Spill

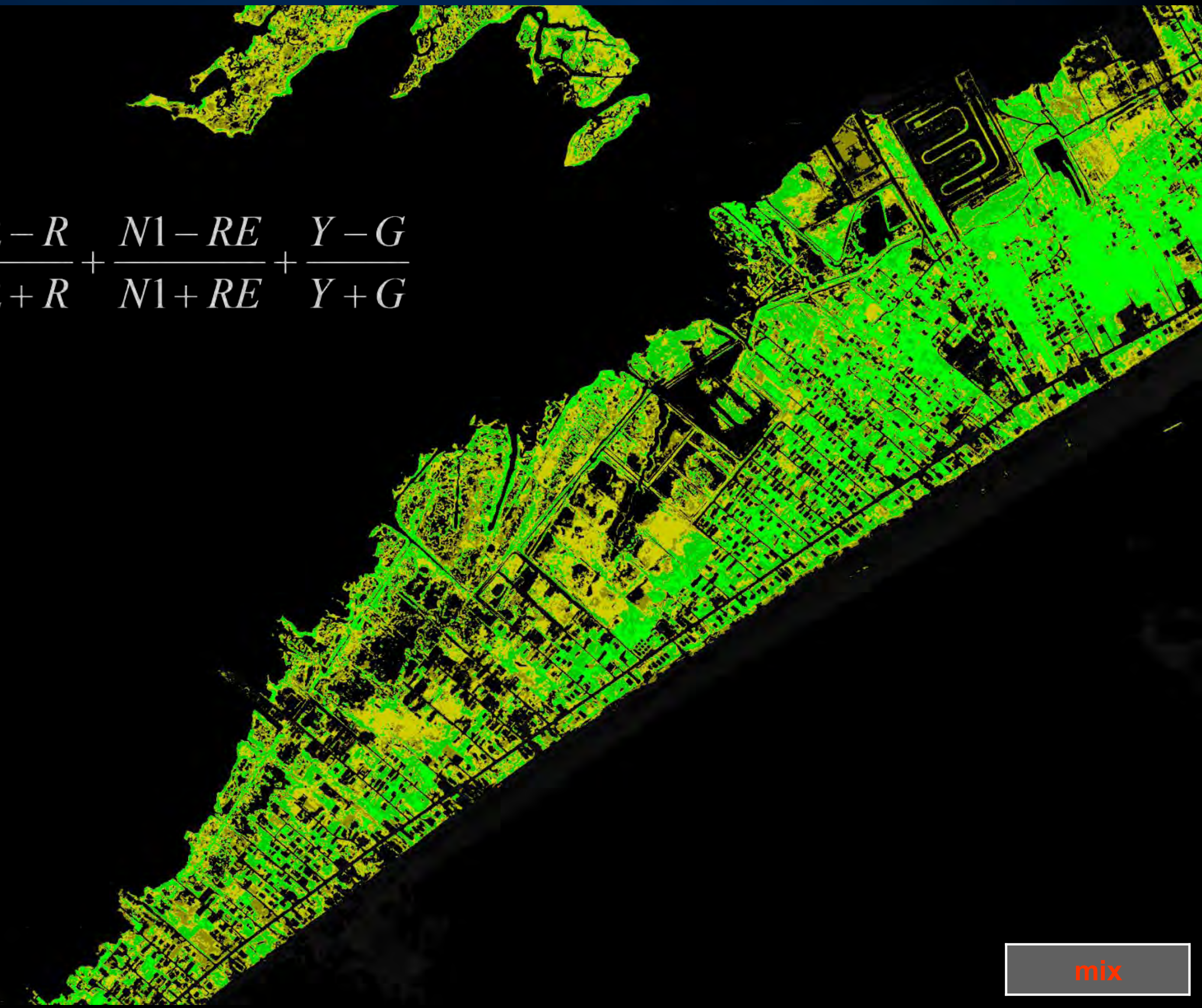
healthy vegetation

normal vegetation

stressed vegetation

dead vegetation

$$\text{Mix} = \frac{N2-R}{N2+R} + \frac{N1-RE}{N1+RE} + \frac{Y-G}{Y+G}$$



Mapping Wetlands Health after the Spill

DIGITALGLOBE

healthy vegetation

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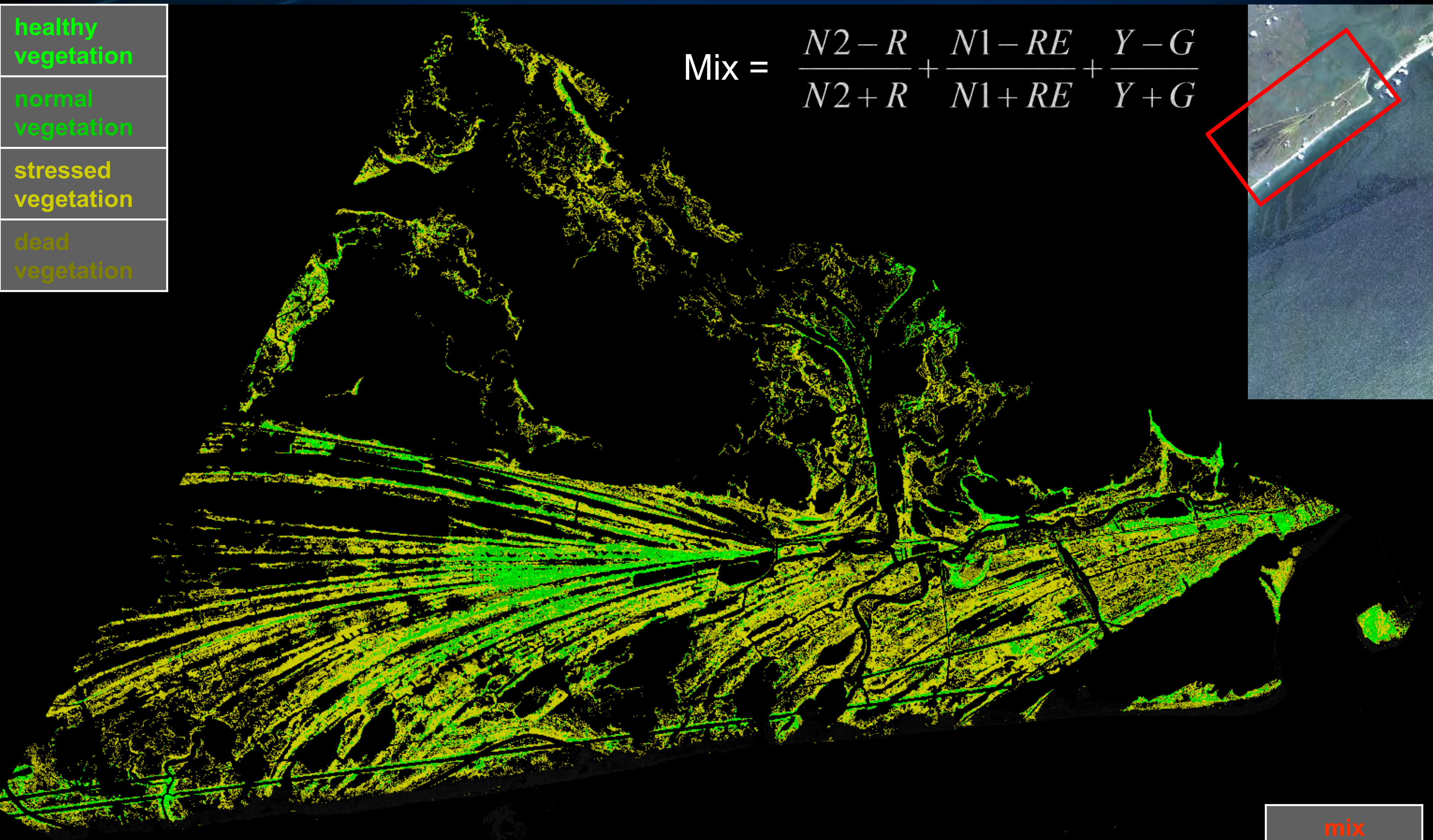

mix

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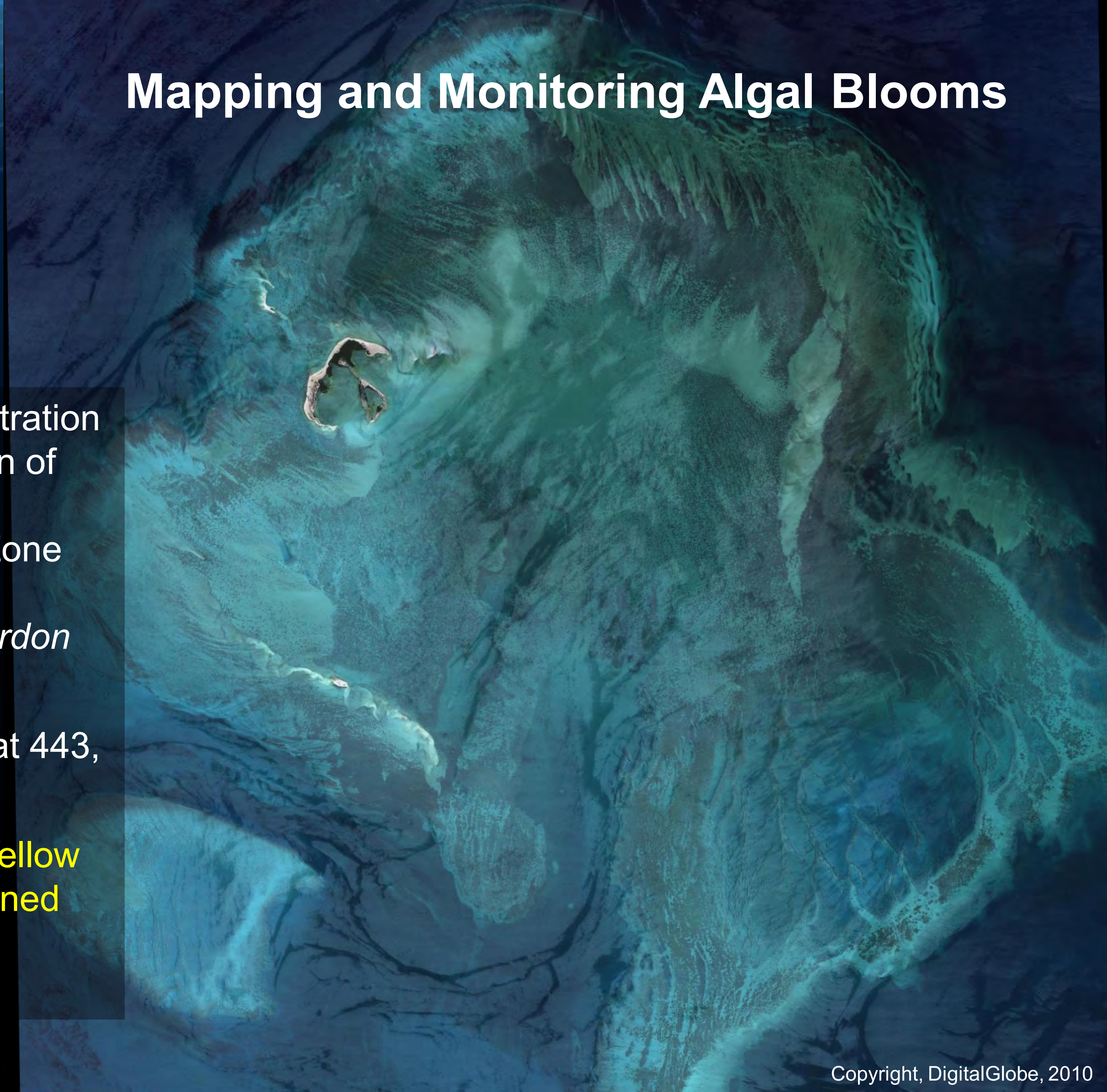
Mapping and Monitoring Algal Blooms

WorldView-2
true color image
Bu Tinah Island
Abu Dhabi
Mar 13, 2010



Chlorophyll concentration based on estimation of upwelling radiance, similar to Coastal Zone Color Scanner & SeaWiFS *(after Gordon et al., 1983)*

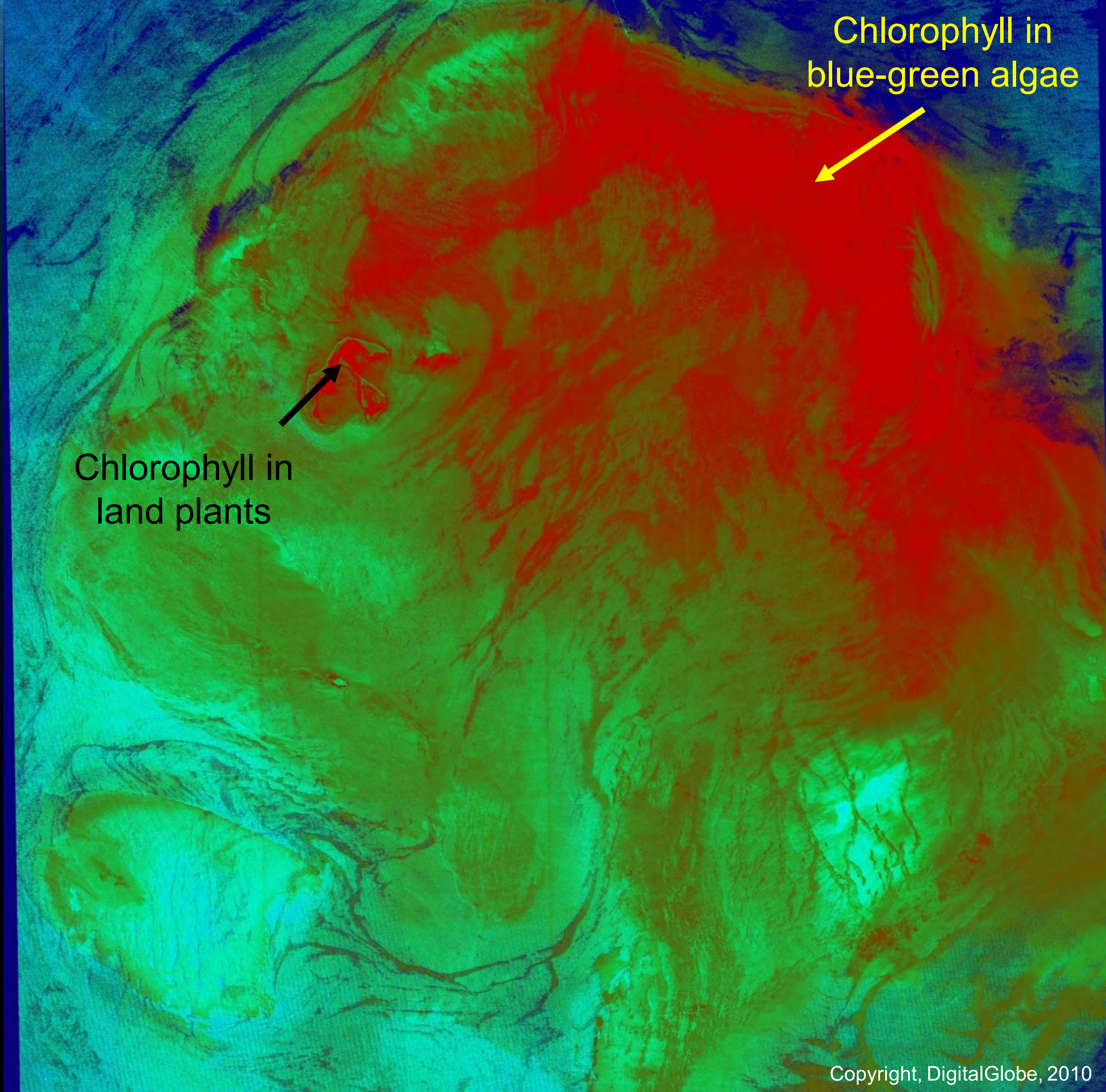
Employ radiances at 443, 520, 550 nm.

In addition, WV-2 Yellow band ideally positioned for cyanobacteria detection.

DIGITALGLOBE

WorldView-2
chlorophyll map
Bu Tinah Island
Abu Dhabi
Mar 13, 2010

Cyanobacteria monitoring from space a reality with WV-2!



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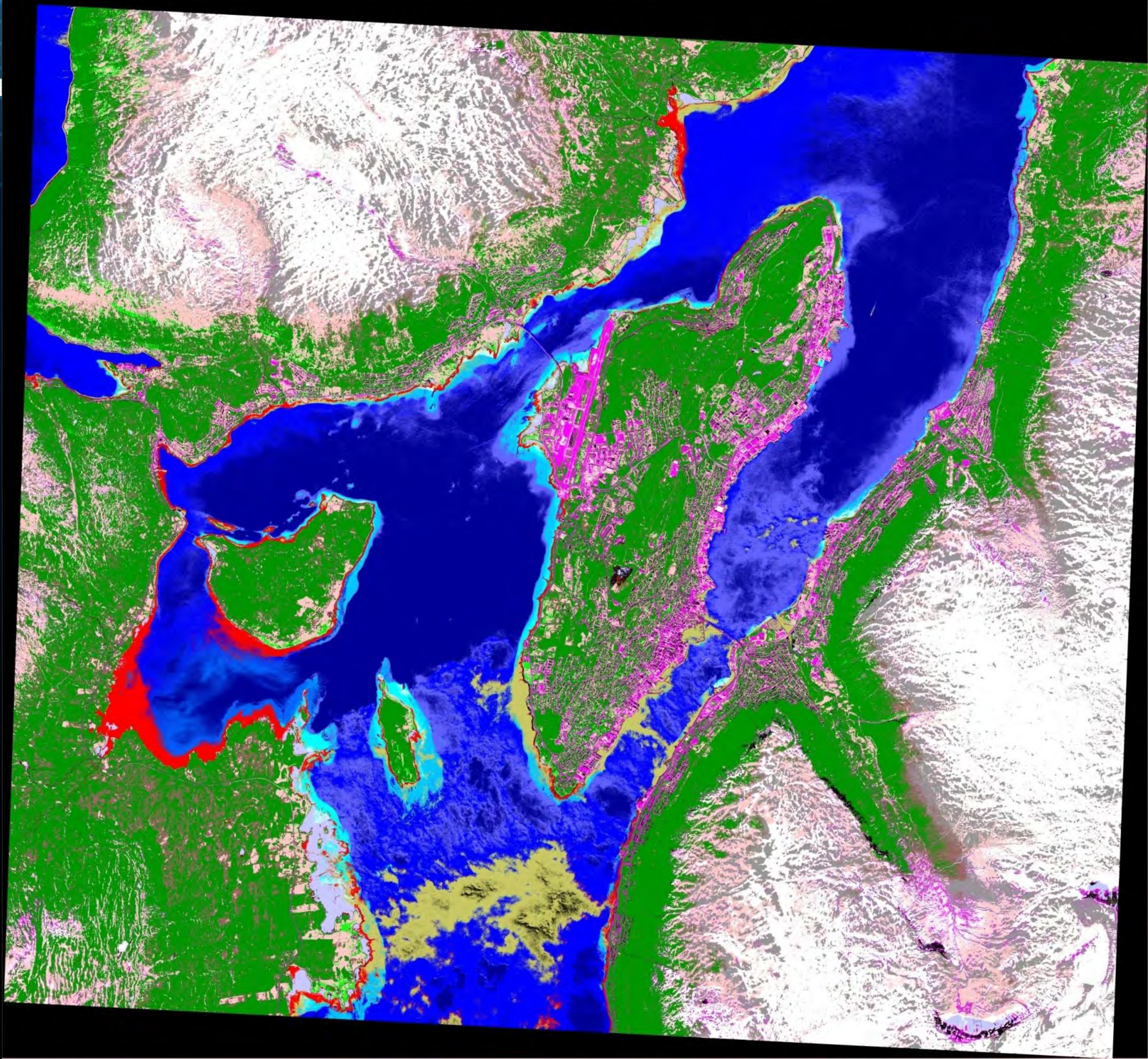
WorldView-2
true color image
Tromsö
Norway
May 26, 2010

DIGITALGLO

WorldView-2
land covers
Tromsö
Norway
May 26, 2010



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Conclusions

- The added spectral dimensions in WV-2 improve classification accuracy as much as 5-20% over ordinary VNIR imagery for certain land cover types.
- The C and NIR2 bands, by extending the usable range of the spectrum, provide more discriminatory power for man-made surfaces, such as gray roofs, red roofs, asphalt, concrete and sport fields. Our ability to resolve shadow greatly increases
- The Y and RE bands target vegetation phenomenology with applications in agriculture, forestry and coastal studies
- The more detailed WV2 spectral signature in conjunction with textural attributes from the 50 cm panchromatic band allow us to produce more accurate classifiers for certain crop types.