Remote Sensing and the Growth of “Big” Data in RIT’s Digital Image and Remote Sensing Lab:

Applications and Data Processing

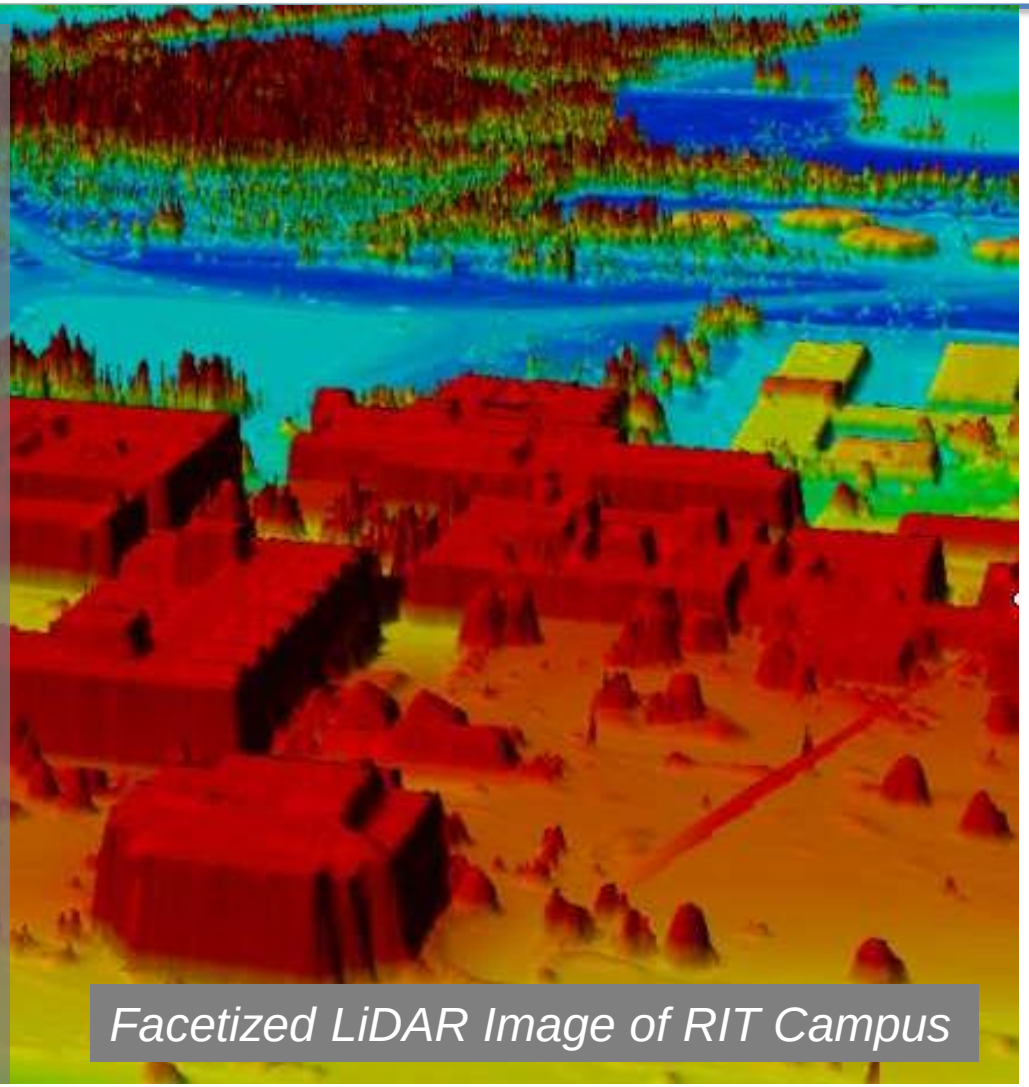
Emmett J. Ientilucci, Ph.D.

Digital Image and Remote Sensing (DIRS) Lab
Chester F. Carlson Center for Image Science (CIS)
Rochester Institute of Technology (RIT)

Rochester, NY, USA

Todays Talk

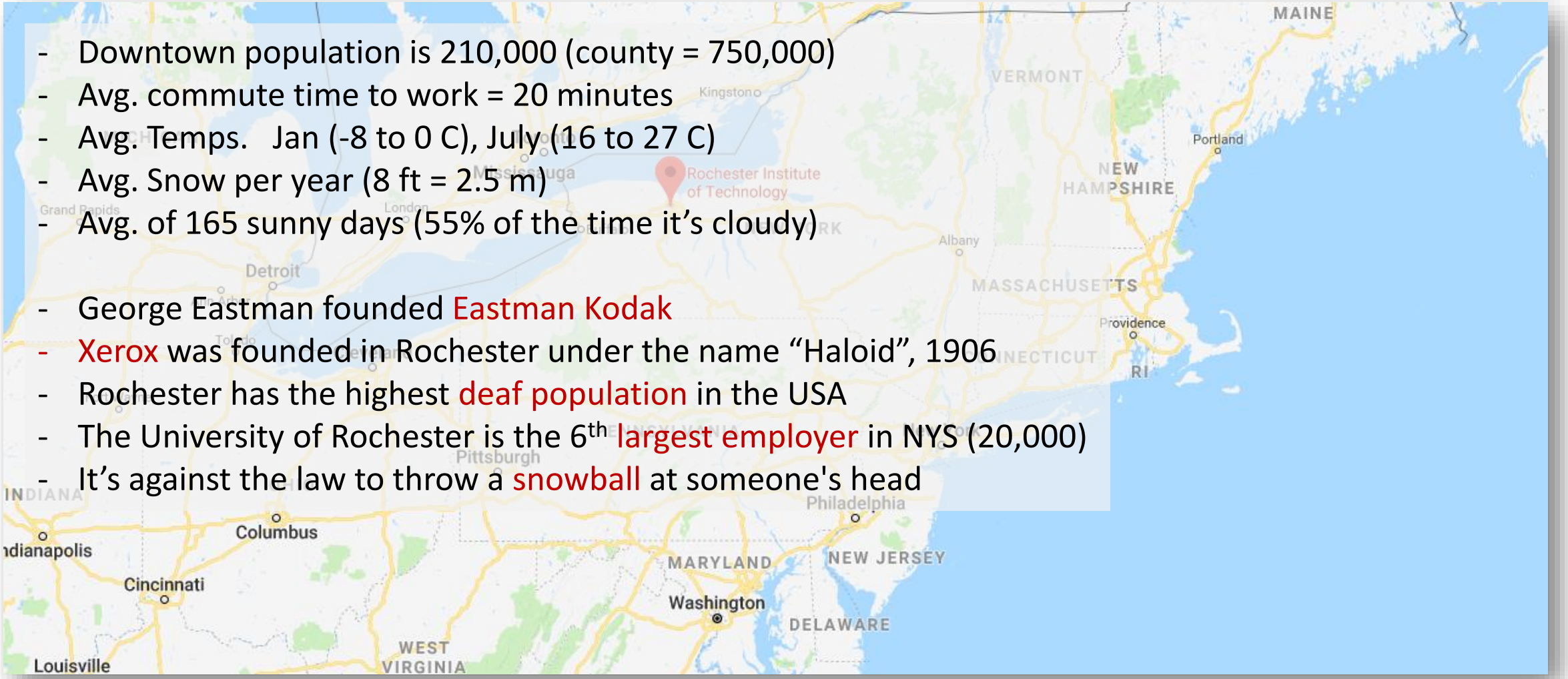
- PART I
  - Background on:
    - Rochester, RIT, CIS, DIRS
- PART II
  - DIRS Research Focus Areas
  - Growth and Management of Data
  - WNY GRSS
- PART III
  - Hyperspectral Imaging
  - Target Detection w/ HSI and LiDAR
  - Where do we go from hear?



Facetized LiDAR Image of RIT Campus

Rochester, NY

Rochester, NY - Fast Facts



- Downtown population is 210,000 (county = 750,000)
- Avg. commute time to work = 20 minutes
- Avg. Temps. Jan (-8 to 0 C), July (16 to 27 C)
- Avg. Snow per year (8 ft = 2.5 m)
- Avg. of 165 sunny days (55% of the time it's cloudy)

- George Eastman founded Eastman Kodak
- Xerox was founded in Rochester under the name "Haloid", 1906
- Rochester has the highest deaf population in the USA
- The University of Rochester is the 6th largest employer in NYS (20,000)
- It's against the law to throw a snowball at someone's head

Rochester Institute of Technology – Fast Facts

- Established in 1829
- 1,300 acres in suburban Rochester, NY
- 18,000 Students, 5,500 Co-ops
- 9 Colleges
  - including the National Technical Institute for the Deaf
- Over 200 degree granting programs
- 8 Interdisciplinary Ph.D. Programs
- > $50 M in Sponsored Research

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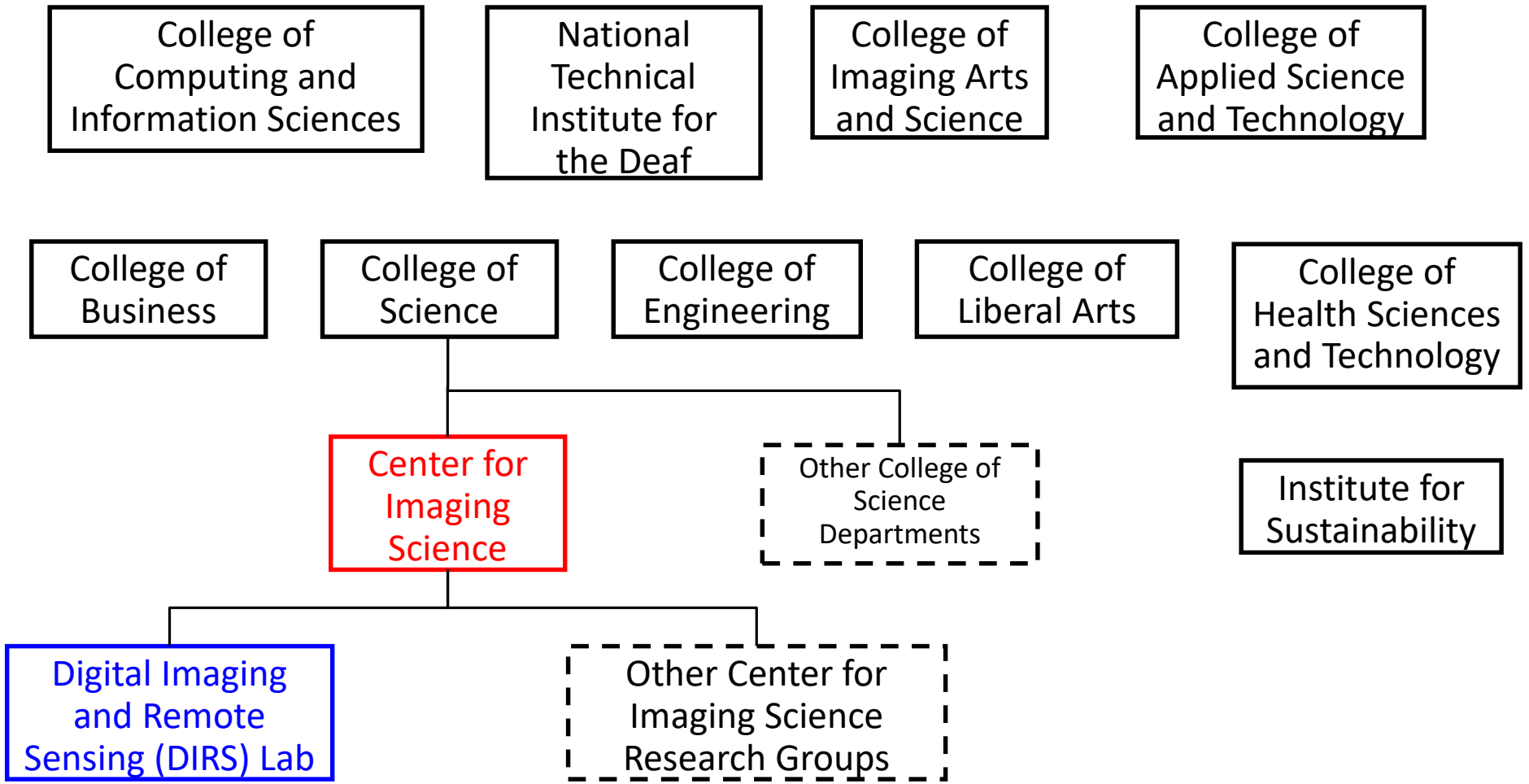
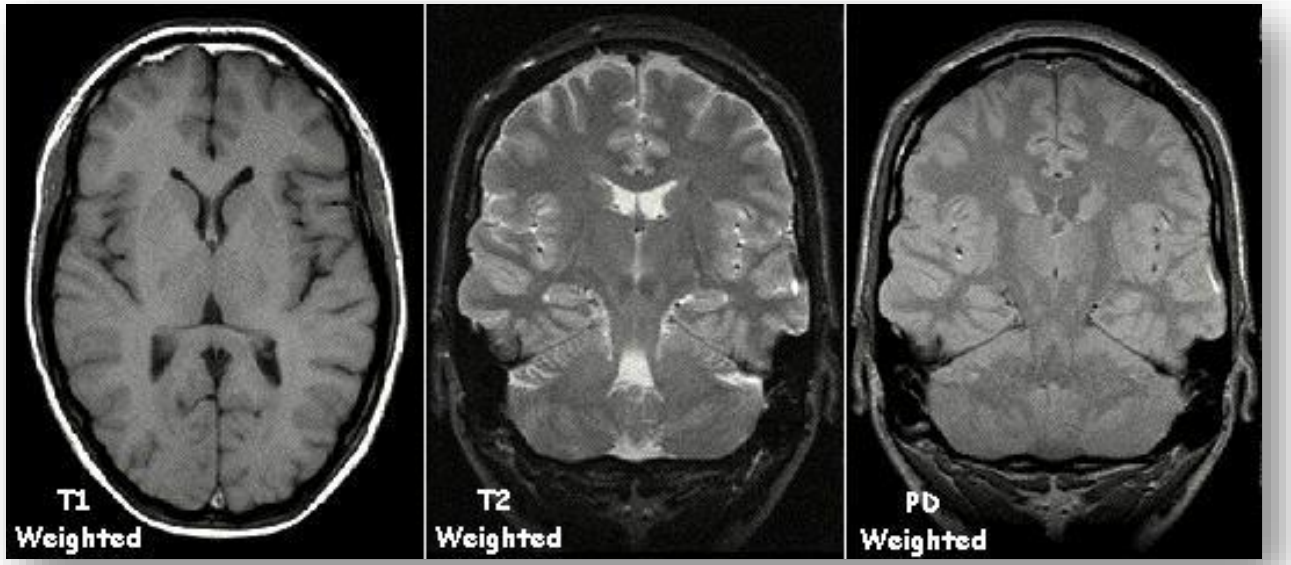
RIT Organization – 9 Colleges



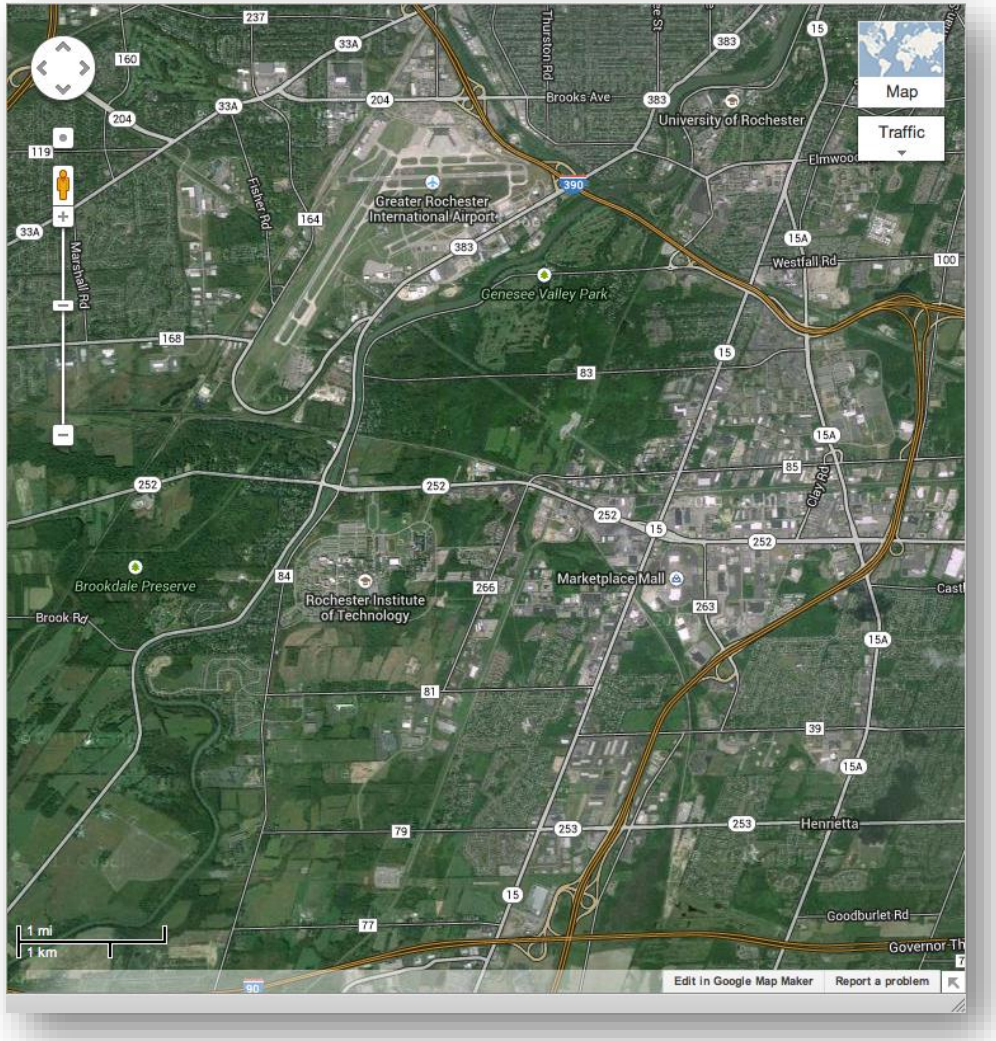
What is Imaging Science?



- What actually is an MRI?
- How does the machine create those 3D looking images?
- How can we process the images so doctors can more easily make diagnoses?

- How does the eye-brain system work?
- How do we visually interpret the world?
- How do we do that in Virtual, Augmented, and Mixed Reality (VR/AR/MR) environments?

What is Imaging Science?



Those satellite images on Google Maps are collected by a camera moving thousands of miles per hour…..

- How does it take a picture that's not blurry?
- How do we process that image to provide information for environmental science studies?
- Can I automatically locate and identify objects from imagery?

The Chester F. Carlson Center for Imaging Science (CIS)

- Formed in the 1980's as the imaging world moved into the digital realm
- 17 Core faculty with primary appointment in CIS
  - 25+ Program Affiliated Faculty across the RIT campus
- Degree Programs Offered:
  - BS / MS / Ph.D. in Imaging Science
  - MS / Ph.D. in Astronomical Sciences and Technology
- Total student population > 150
  - 115 graduate
  - 55 undergraduate

Imaging Science Research Program

- Over 20 full time research staff at all levels
- Approximately $5-7M in annual research expenditures
- Major Research Laboratories focused on:

1. Remote Sensing (9)
2. Human Visual System (3)
3. Multi-wavelength Astronomy (3)

- Other CIS Research Areas:
  - Computer/Machine Vision (1)
  - Ancient Document Restoration (1)
  - Optics & Photonics (3)
  - Biomedical Imaging (2)
  - Detectors (2)

Multi-rotor UAV with a multispectral camera used for precision agriculture studies

Digital Image and Remote Sensing (DIRS) Lab

- 30+ years of Remote Sensing Research
- Substantial research capacity:
  - 9 tenure-track and research faculty
  - 13 research and administrative staff
  - ~40 Graduate Students (MS + PhD)
- Current research program
  - ~ 35 funded projects
  - annual research revenue > $3.5M

DIRS Faculty

Chip Bachmann
Associate Professor
Weidman Chair

John Kerekes
Professor
Lab Director

Carl Salvaggio
Professor

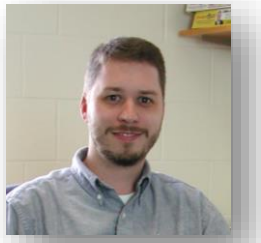
Jan van Aardt
Professor

Tony Vodacek
Professor
Miller Chair

Emmett Ientilucci
Assistant Professor

DIRS
Digital Imaging and
Remote Sensing Lab

Mike Gartley
Asst. Research Professor

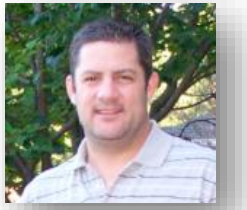


David Messinger
Professor
CIS Center Director

Bob Kremens
Research Professor

DIRS Staff

Matt Montanaro, PhD
Senior Scientist



Aaron Gerace, PhD
Senior Scientist

Scott Brown, PhD
Principal Scientist

Adam Goodenough, PhD
Senior Scientist

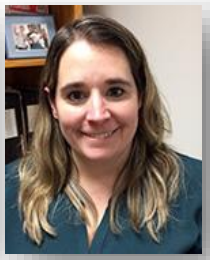
Rolo Raqueno, PhD
Research Engineer

Don McKeown
Distinguished
Researcher

Tania Kleynhans
Associate Scientist

Nina Raqueno
Assistant Scientist

Melanie Warren
Sr. Staff Assistant



Colleen McMahon
Sr. Staff Assistant

Tim Bauch
Lab Engineer

Jared Van Cor
Assistant Scientist

Sampling of Current DIRS Research Projects

Sponsor	Title
AFRL/Kitware	Global Surveillance Using Commercial Satellite Imaging
DOE	Integrated Tool for Fused Data Simulation of EO Remote Sensing Imagery and Nuclear Radiation Propagation Phenomenology
Harris	Spatial Spectral Image Modeling (SSIM)
LLNL	Modeling of Spectral Remote Sensing Systems
NASA	Support Of The SOLARIS Instrument Design And Build Using The Digital Imaging And Remote Sensing Image Generation (DIRSIG) Tool
ORNL	Image Registration, Lidar point cloud segmentation and labeling, UAV data collections
LANL	LWIR Spectral Variability Modeling
ONR	Trafficability and Mobility Analysis from Remote Sensing
Pictometry	Roof Condition Characterization from High Resolution Airborne Imagery
Property Drone Consortium	Drone-based Roof Inspection Research
USDA	Transforming White Mold Management in Snap Beans Through Remote Sensing
USGS	Calibration and Assessment of the Landsat Sensors
USGS	The Use of Landsat-8 for the Monitoring of Fresh and Coastal Water

Sampling of My Current Research Projects

1. Combined 3D EO Processing for reflectance retrieval
   - Ball Aerospace
2. Robust Hyperspectral Targeting and Reacquisition Software: BRDF Collections
   - AFRL / Spectral Sciences, Inc.
3. Image Science Support to ORNL
   - ORNL
4. Forward Modeling for Target Detection
   - Harris Corp
5. Global Surveillance Augmentation Using Commercial Satellite Imaging Systems
   - Kitware
6. Correction of stray light on LANDSAT 8 TIRS using GOES Data
   - USGS/LANDSAT
7. Earth Observing Statistical Performance Model with Applications to LWIR Spectral Variability and Detection
   - LANL

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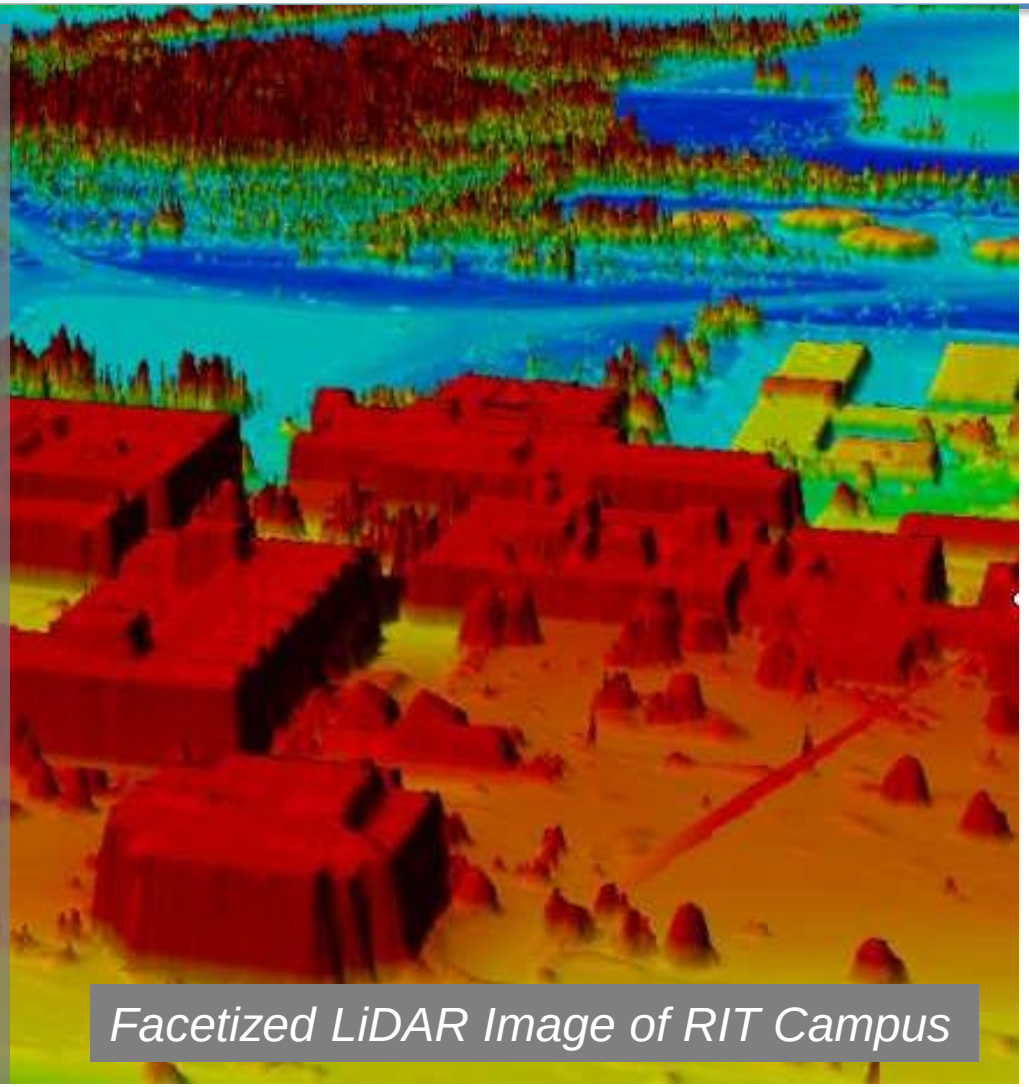
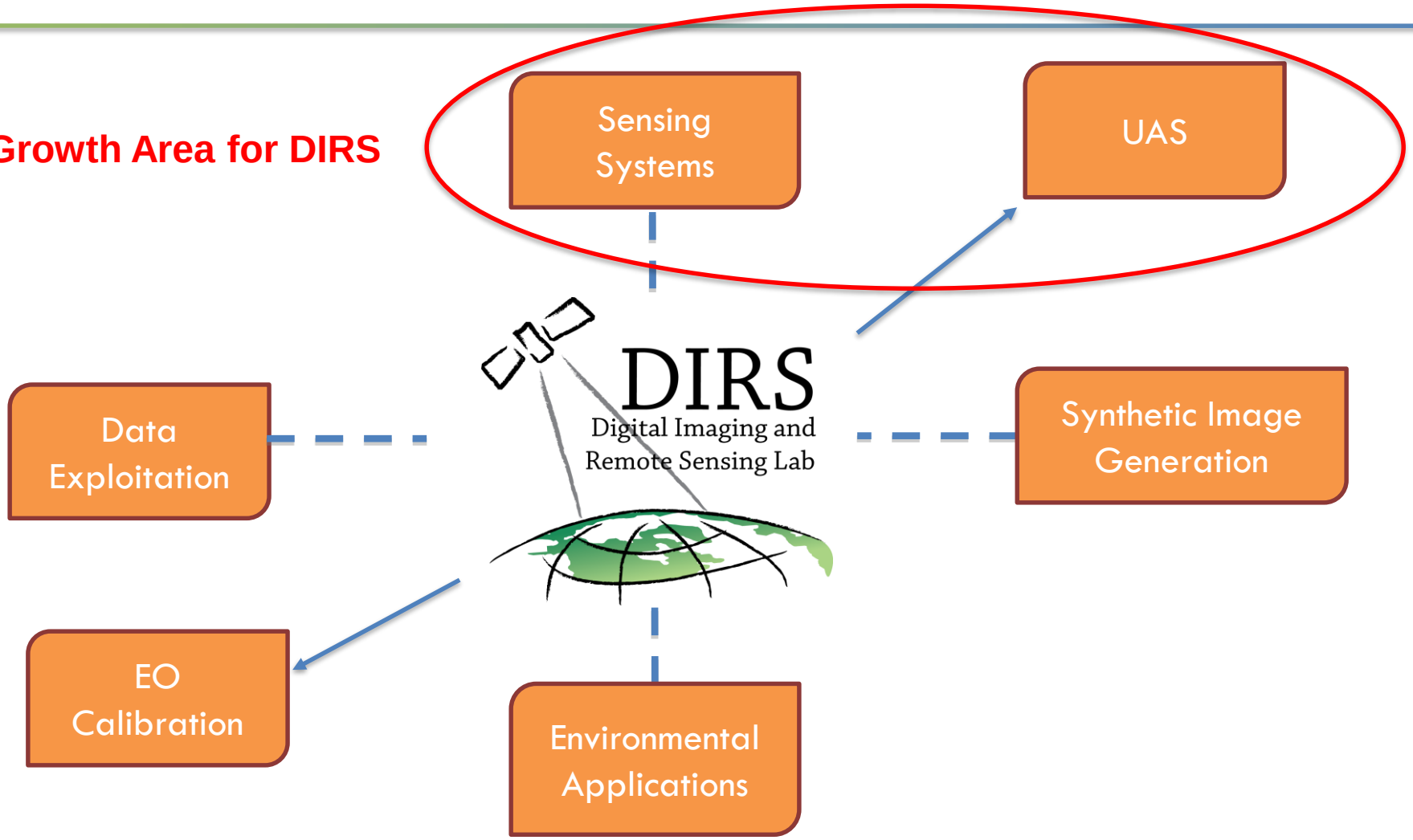


Facetized LiDAR Image of RIT Campus

DIRS Research Focus Areas

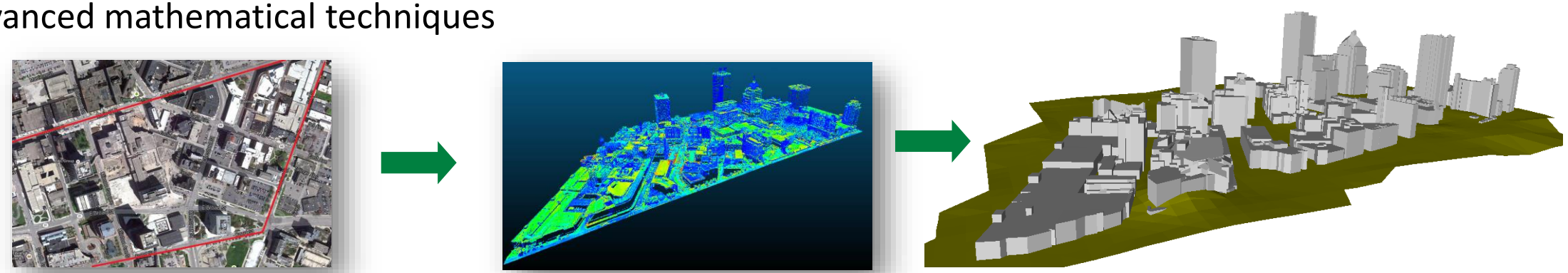
Big Data Growth Area for DIRS



Data Exploitation: Algorithms

- Development and testing of exploitation algorithms:
  - Spectrally driven with a physics-based philosophy
  - Multi- & hyperspectral applications
  - Applied to reflective, thermal, LIDAR, and multi-modal imagery
  - Applications such as **target** / anomaly detection, spectral unmixing, material classification, change detection, search, 3D model extraction
- Developing advanced capabilities
  - Exploitation using multi-modal data
  - Advanced mathematical techniques

3D model construction from passive airborne imagery



SIG: Digital Imaging and Remote Sensing Image Generation (DIRSIG)

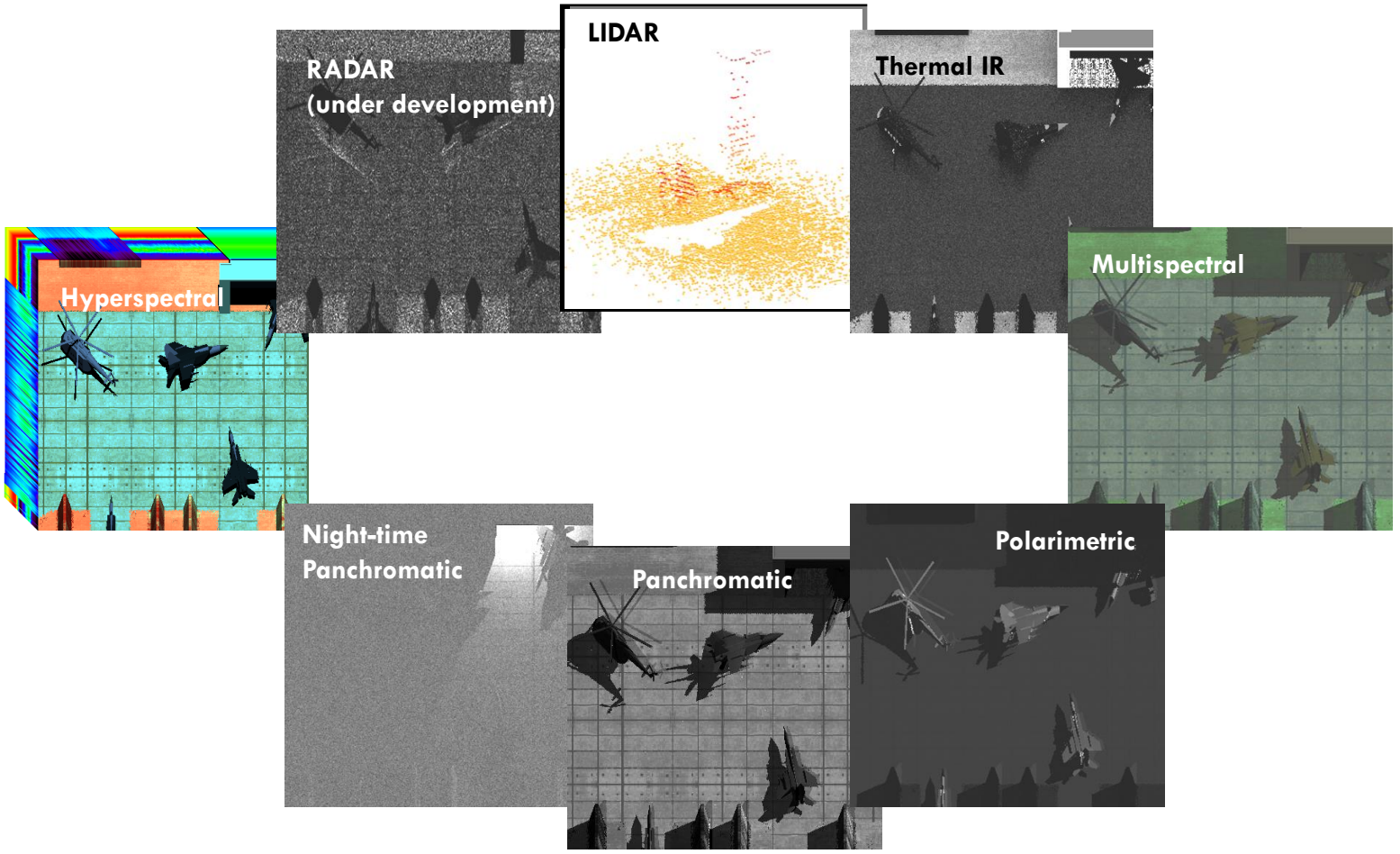
- Modeling and Simulation involves the precise radiometric representation of remote sensing scenes over a wide spectral regime
- RIT developed DIRSIG is leading tool for scene and image chain simulations
- Common uses include:
  - Sensor/system performance evaluation
  - Algorithm training and evaluation
  - Rapid parametric analysis
- Image Modalities
  - Visible through thermal infrared (0.4 - 20.0 microns)
  - Passive Sensing
    - Broad-band, multi-spectral (MS), hyper-spectral (HS) imaging.
    - Polarization (usually limited by material properties)
  - Active Laser sensing
    - Topographic LADAR and atmospheric/gas LIDAR.
    - Prototype Synthetic Aperture Radar imaging capability under development
- Instruments
  - Single pixel, 1D arrays and 2D arrays.
  - Filter, diffraction/refraction or interferogram-based photon collection.
- Platforms
  - Ground, air or space on static or moving platforms.
- Instrument/Platform Interfaces
  - Platform relative instrument scanning.
- Phenomenology
  - Passive thermodynamics, secondary light sources, dynamic scene content (moving geometry), volume radiometry (plumes, water, etc.), etc.

MegaScene Tile #1
- 5,000+ objects
- 500+ million facets
- 1.6 km^2 (0.6 mi^2)

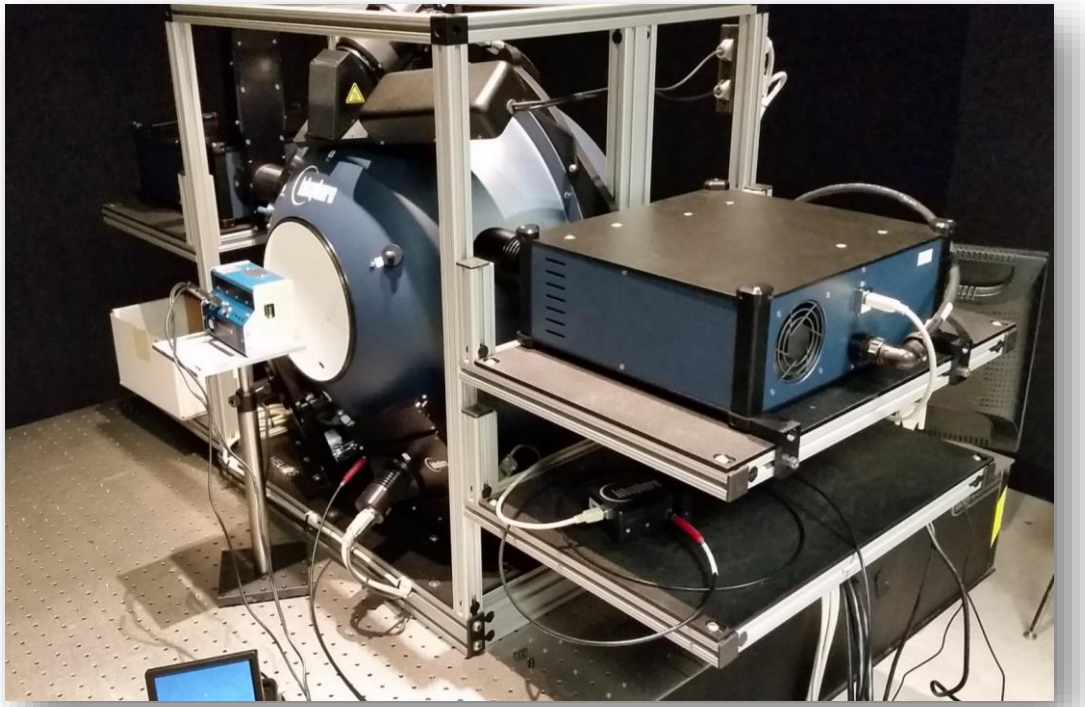
SIG: DIRSIG: Video Simulation

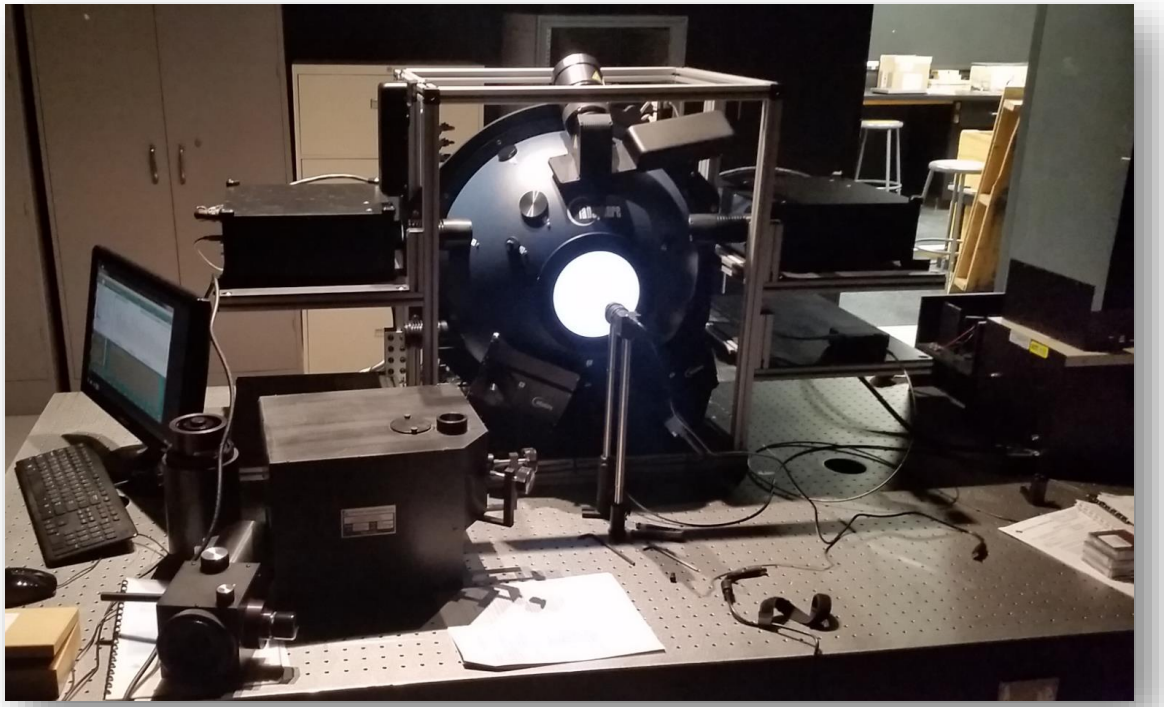
SIG: DIRSIG Multi-modal Scene Simulation Capability

- Modality Simulation Capability:
  - LiDAR
  - Thermal IR
  - Multispectral
  - Polarimetric
  - Panchromatic
  - Night-time Panchromatic
  - Hyperspecral
  - RADAR



Optical Calibration Facility at RIT





- NIST-tracable 20 in (51 cm) Integrating sphere
- OL 750 Monochromator
- OE Collimator

- Radiometrically and spectrally calibrate our in-house instruments
- Calibrate customer systems

Sensing Systems: Material Property Characterization

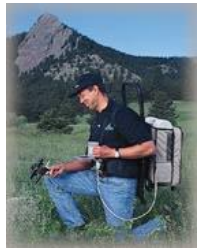
Significant capabilities to characterize material optical properties over a wide spectral regime

Field

Measurement

0.4 to 20µm coverage

- ASD Field Spec Pro
- SVC HR-1024i
- SOC 400T
- D&P Model 10?

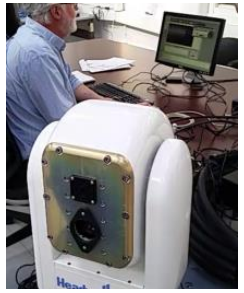


Imaging

Spectrometer

0.4 to 1.0 µm coverage

- Headwall MicroHE (VNIR)
- *Headwall (SWIR) Late 2017*



Laboratory

Measurement

0.4 to 20µm coverage

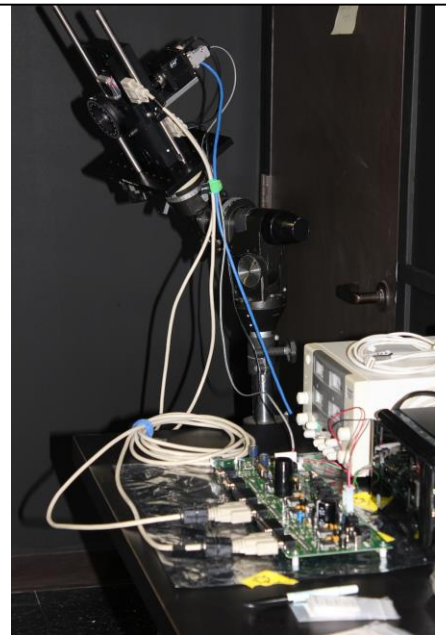
- Varian Cary (Vis/NIR)
- SOC 100 (IR)

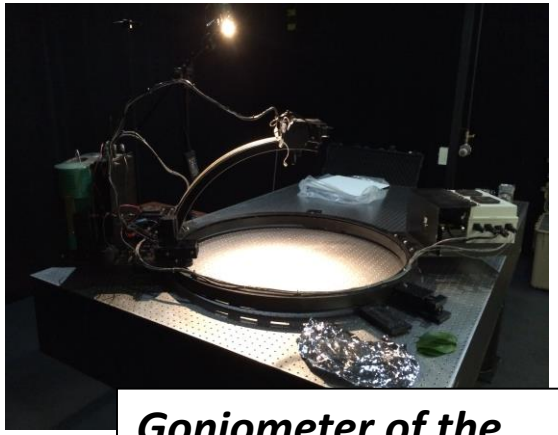
Sensing Systems: Sensor System Development

RIT builds and operates several airborne sensing systems covering the full EO-IR spectrum

Portable ground-based LIDAR
- semi-circular scan combined with rotating stage
- hemispherical point cloud
- range ~ 30m
- primary use for forest canopy studies

MAPPS: Multispectral Aerial Passive Polarimeter System
- 8 spectral bands
- 4 polarization states
- two filter wheel design





Goniometer of the Rochester Institute of Technology (GRIT)
- full range light source
- ASD spectroradiometer
- 360° hemisphere scan

UAS: An Historic Convergence of Technologies

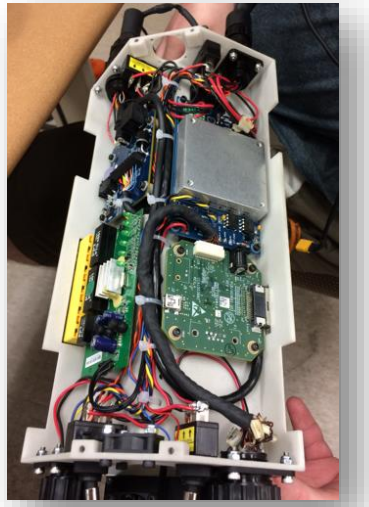
UAV VEHICLES

High performance
Precise navigation
Low cost

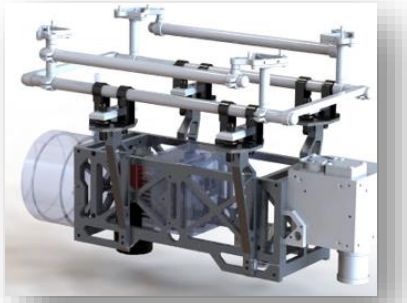
Meaningful, high quality remote sensing data at spatial and temporal scales unimaginable a decade ago….AT ACCEPTABLE COST

SENSORS

High performance
All modalities
Compact
Low power
Low weight
Low cost



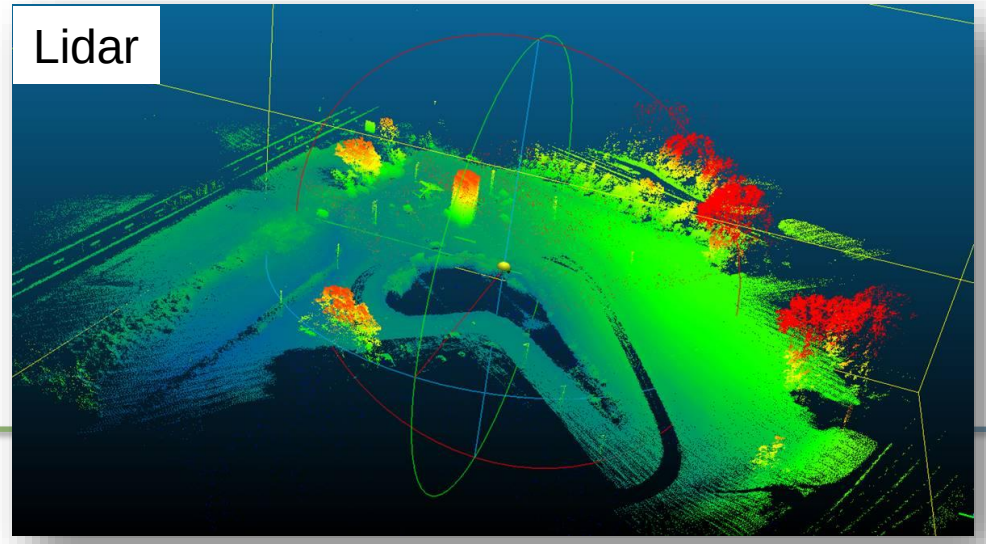
- Key Application Focus Areas
  - Multi-modal phenomenology
  - Crop disease monitoring
  - Forest Inventory
  - Infrastructure monitoring/inspection



UAS Platforms that capture LiDAR, RGB, LWIR, and HSI Simultaneously.

UAS: Example Simultaneous Data Collection

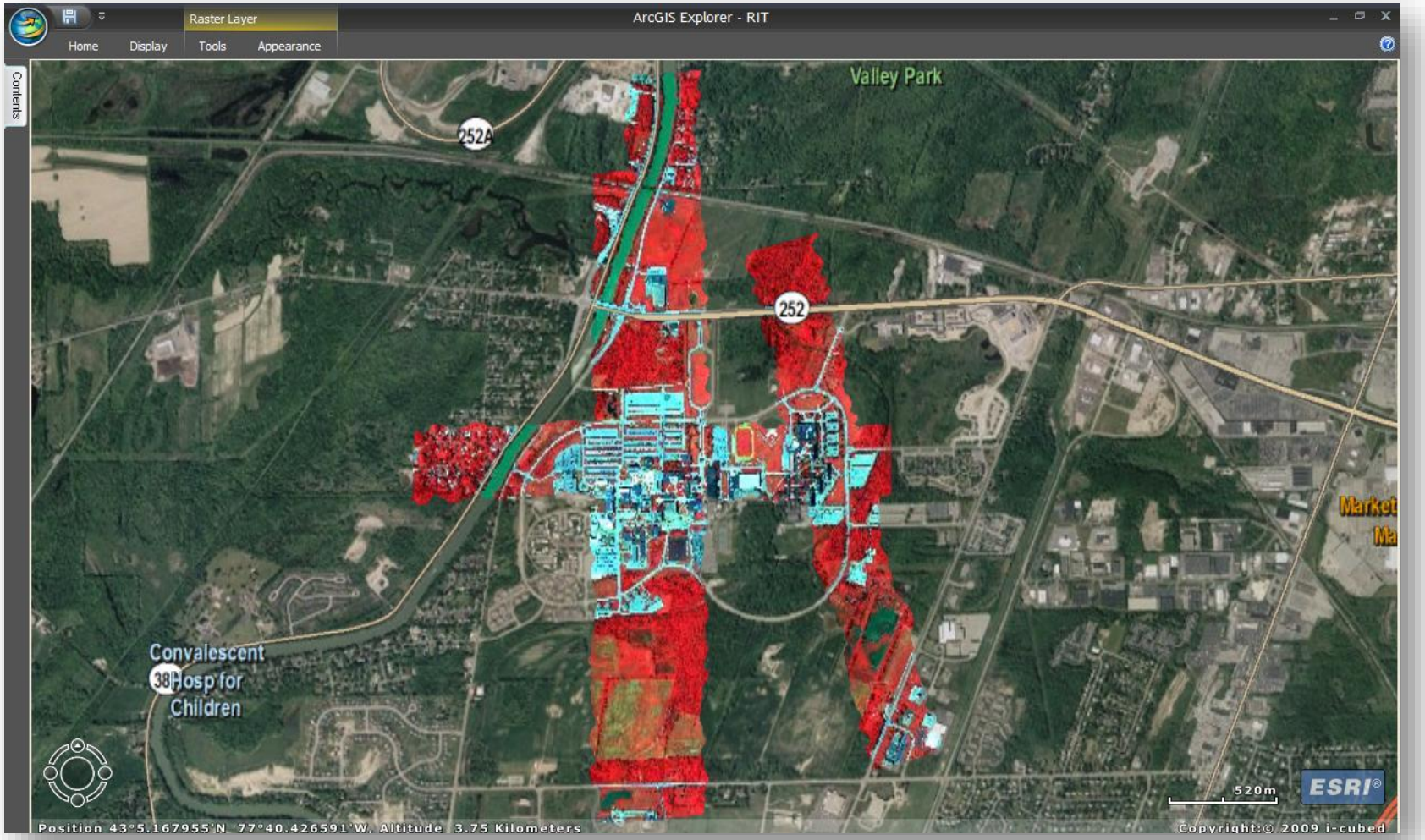
All Imagery Over Same Plot of Land



What “Big Data” means to DIRS

- In the last 7 years, the DIRS Lab has been collecting data at an every increasing rate.
  - Ground measurements
  - Satellite sensors (RGB, Multi- Hyperspectral)
  - Airborne sensor (RGB, Mulit- Hyperspectral, LiDAR, Polarization, Thermal)
  - UAV (RGB, Mulit- Hyperspectral, LiDAR, Polarization, Thermal)
    - 3-5 TB per summer (50 GB per flight)
- This data is used for analysis in:
  - Water quality studies
  - Crop health and precession agriculture
  - Classification, Change Detection, video analysis tracking
  - Pixel unmixing, Target detection (& temporal studies)
  - Lidar cloud segmentation, etc. etc.

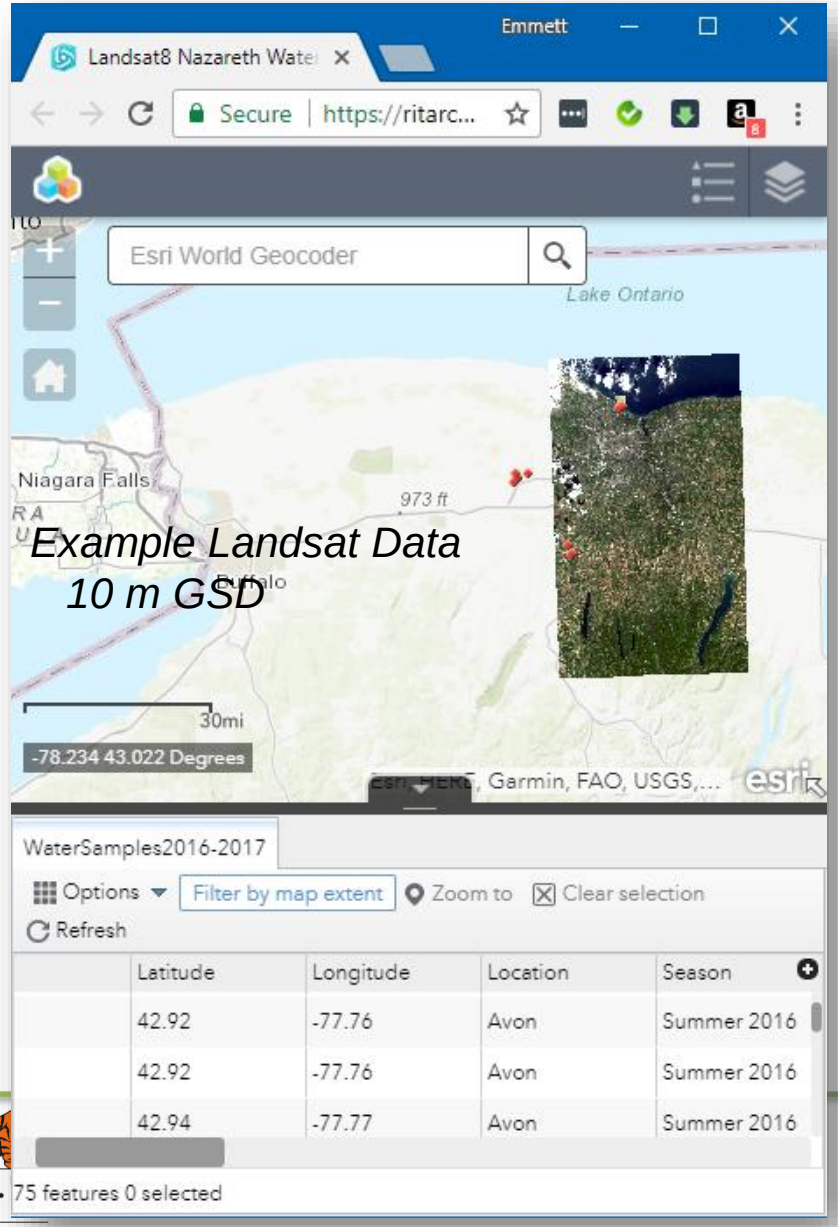
Management of (So Much) Data



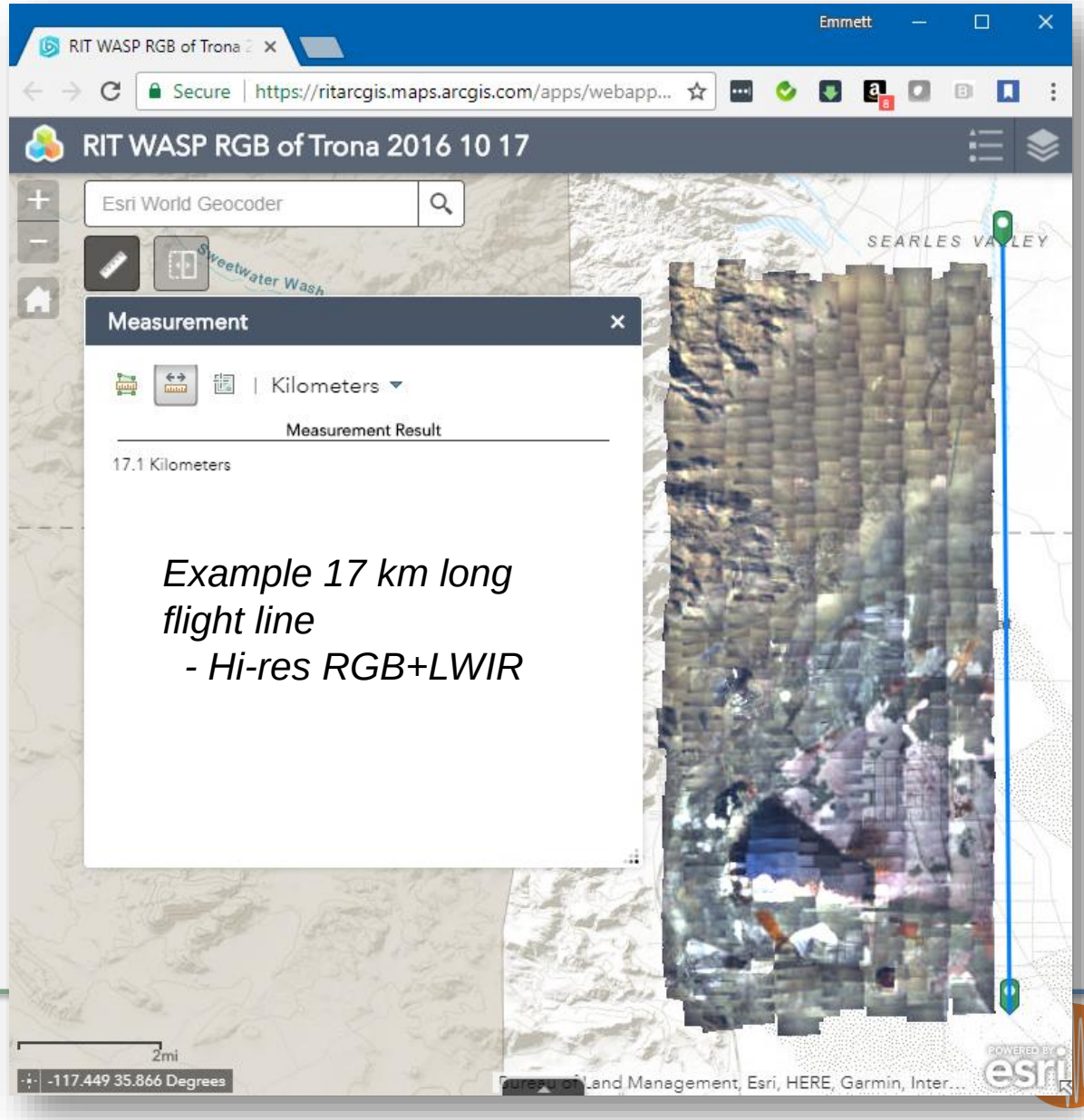
We have so much data, we have had to re-think how we store, visualize, and access this data.

We take advantage of ESRI ArcView with our Staff GIS Expert

Management of (So Much) Data: Examples

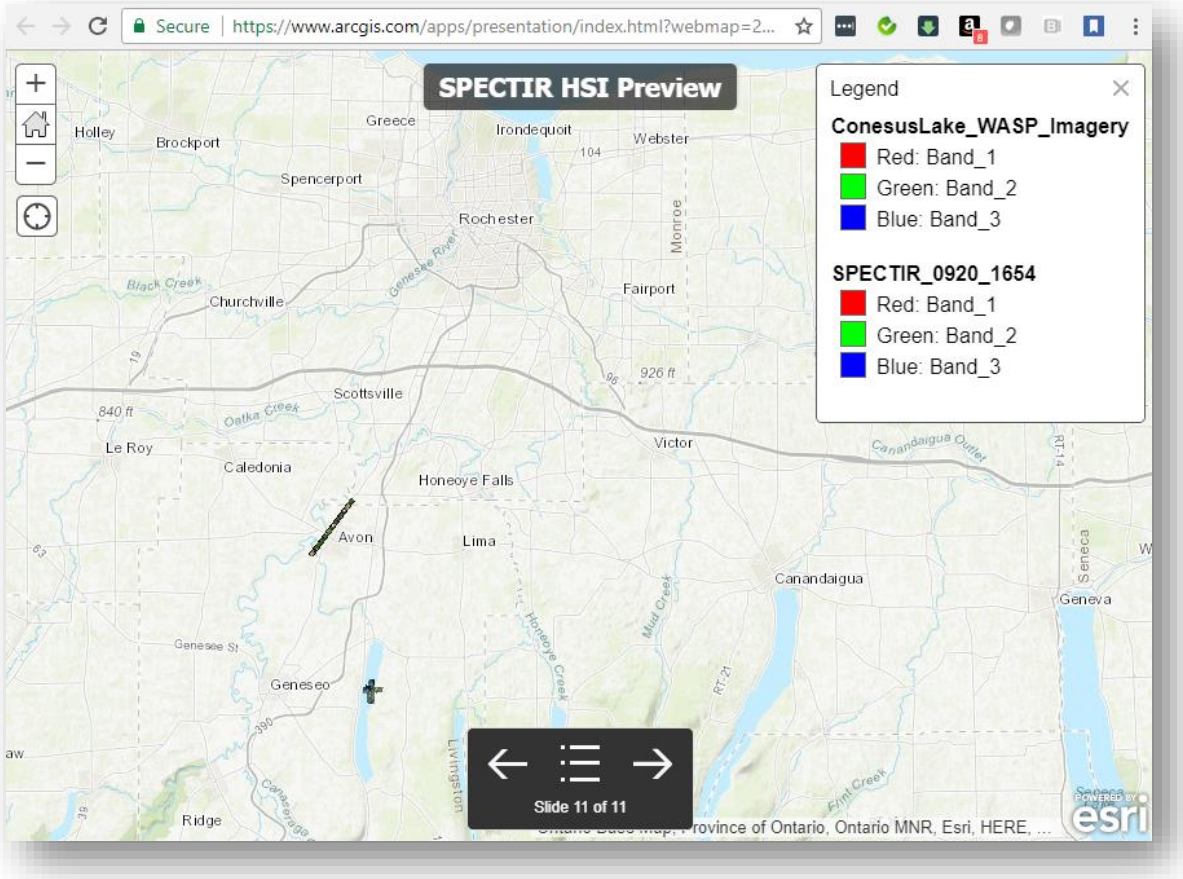


Example Landsat Data
10 m GSD



Example 17 km long flight line
- Hi-res RGB+LWIR

Management of (So Much) Data: Examples



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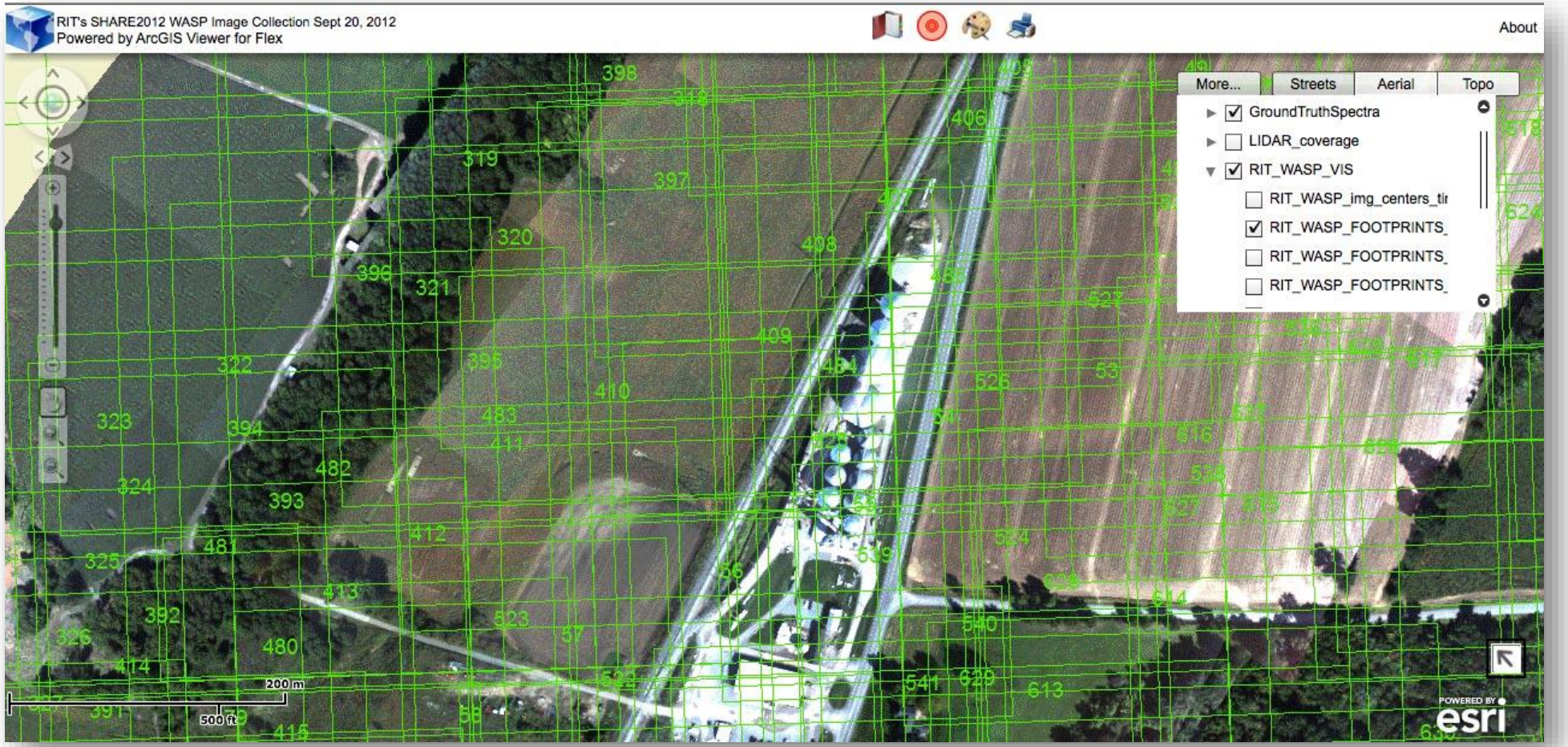

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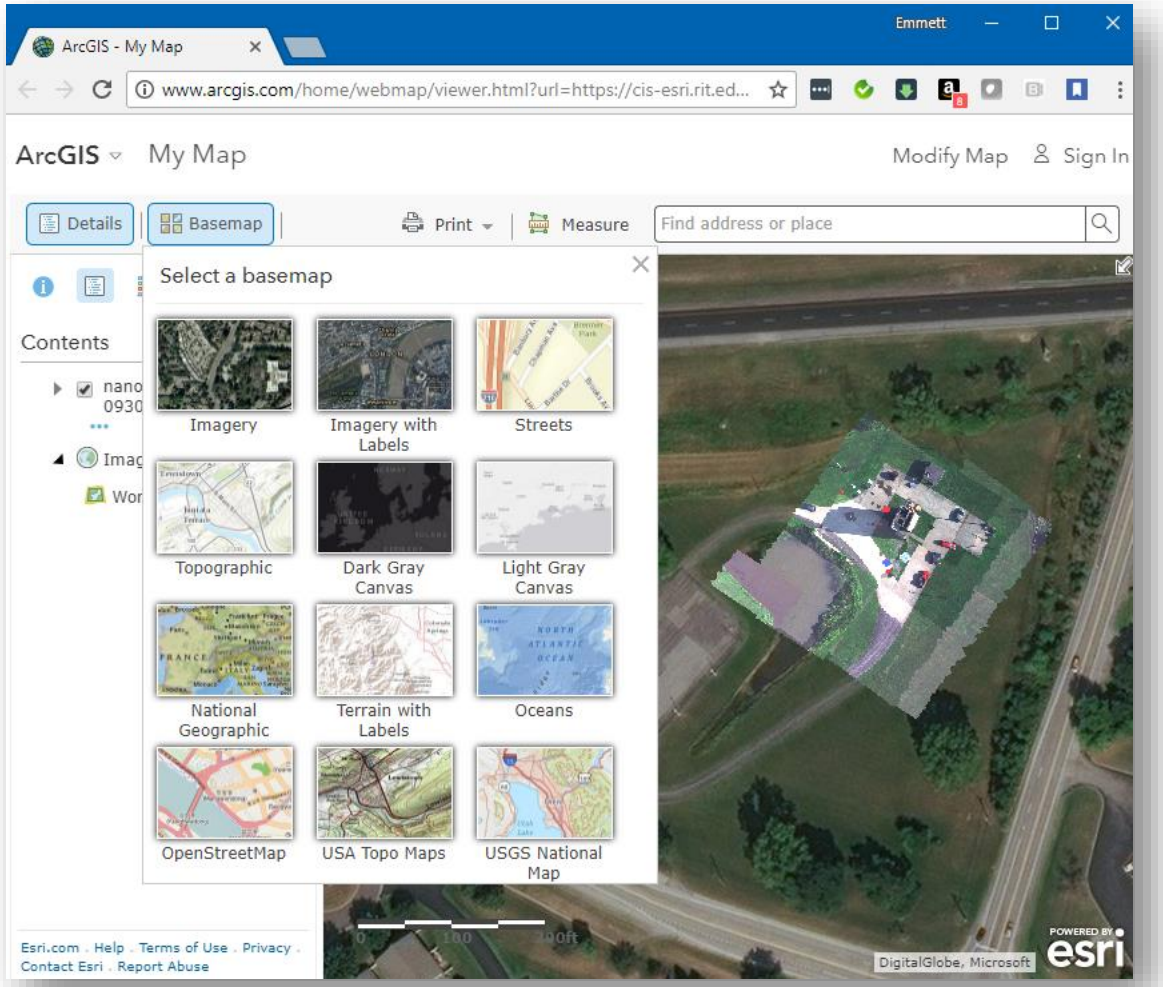

- Recent UAS collect Example
- Combine w/ layers such as:
  - Imagery (DIRS or Others)
  - Street map
  - Topographic
  - etc…
- We can then also ingest results and products from our own algorithmic studies

DIRS.CIS.RIT.EDU/RESOURCES

Data Available on Website
- FREE -

- WASP data (Geo-TIFF)
- LiDAR Data (LAS)
- SpecTIR Data (ENVI)
- All ground truth (Various formats)

THE WESTERN NEW YORK GEOSCIENCE AND REMOTE SENSING SOCIETY (WNY GRSS)

Western New York Chapter History

- Officially formed by Dr. John Kerekes of RIT on May 27, 2007
- WNY Chapter spans 5 IEEE Sections of Region 1, Area D:
  - Rochester, NY (Rochester serves as the parent Section)
  - Binghamton, NY
  - Buffalo, NY
  - Ithaca, NY
  - Syracuse, NY

Current Chapter Officers and Membership

- Chapter Chair: Emmett Ientilucci, RIT
- Chapter Vice-Chair: Sildomar Monteiro, RIT
- Chapter Secretary: John Kerekes, RIT
- Buffalo Section Coordinator: Bea Csatho, University at Buffalo
- Ithaca Section Coordinator: Bill Philpot, Cornell University
- Syracuse Section Coordinator: Jay Kyoon Lee, Syracuse University
- Binghamton Section Coordinator: Open

- Membership and Promotion
  - 22 members current
  - One person attends the Rochester IEEE Section monthly meeting
    - An additional venue for advertising our activities (2 pages in RES)
    - Eases interfacing with the Section Treasurer to access Chapter funds

Recent Article in Dec 2017 Issue of GRS Magazine

CHAPTERS

EMMETT IENTILUCCI

GRSS Western New York Chapter Status and Activities 2016–2017

The Western New York (WNR) Chapter of the IEEE Geoscience and Remote Sensing Society (GRSS) has hosted a number of important activities since 2016. Following are a brief history of our Chapter and descriptions of some of our more recent functions.

GRSS WNY CHAPTER HISTORY

The GRSS WNY Chapter was officially inaugurated on

The Chapter chair is elected by the membership, while Section coordinator positions are appointed by the chair. Due to the large geographic distance covered by the Chapter, we have found the Section coordinator positions to be helpful in staying in touch with local members and arranging meeting logistics.

2016–2017 MEMBERSHIP

GRSS Sponsored Seminars in 2016-17

December 6, 2017
Thermal Infrared Hyperspectral Imaging: Instrumentation and Applications
Dr. Martin Chamberland, VP of Technology, Telops, Inx., Quebec, Canada

October 20, 2017
The 2017 STRATUS Workshop
Dr. Emmett Ientilucci, General Chair, RIT

October 18, 2017
Candidate Imager Architectures for Sustainable Land Imaging
Dr. Jeffery Puschell, Principal Engineering Fellow, Raytheon Space and Airborne Systems, El Segundo, CA

March 1, 2017
Sunnier Than a Sunny Day: Recent Advances in Hyperspectral Image Simulation for Partly Cloudy Scenes
Dr. Rob Sundberg, President of Spectral Sciences, Inc. Burlington, Massachusetts

October 28, 2016
The 2016 STRATUS Workshop
Dr. Emmett Ientilucci, General Chair, RIT

October 31, 2016
Imaging Spectroscopy Technologies and Applications
Dr. Zakos Mouroulis, Sr. Research Scientist, JPL

March 16, 2016
An Overview of Non-linear Mixing Models for Hyperspectral Imagery
Dr. Joshua Broadwater, Principal Scientist Johns Hopkins Applied Physics Laboratory

2017 IEEE GRSS STRATUS Workshop

- **S**ystems and **T**echnologies for **R**emote Sensing **A**pplications **T**hrough **U**nmanned Aerial **S**ystems

- Aim is to facilitate interaction between academic researchers, industry researchers and students working in Remote Sensing utilizing UAS

- 82 people registered
  - 15 oral Presentations
  - 2 Keynote Speakers
  - Student Awards: Best Paper/Poster/Presentation ($200 each)

STRATUS
2016 IEEE GRSS STRATUS Workshop
Systems and Technologies for Remote Sensing Applications
Through Unmanned Aerial Systems
28 October 2016

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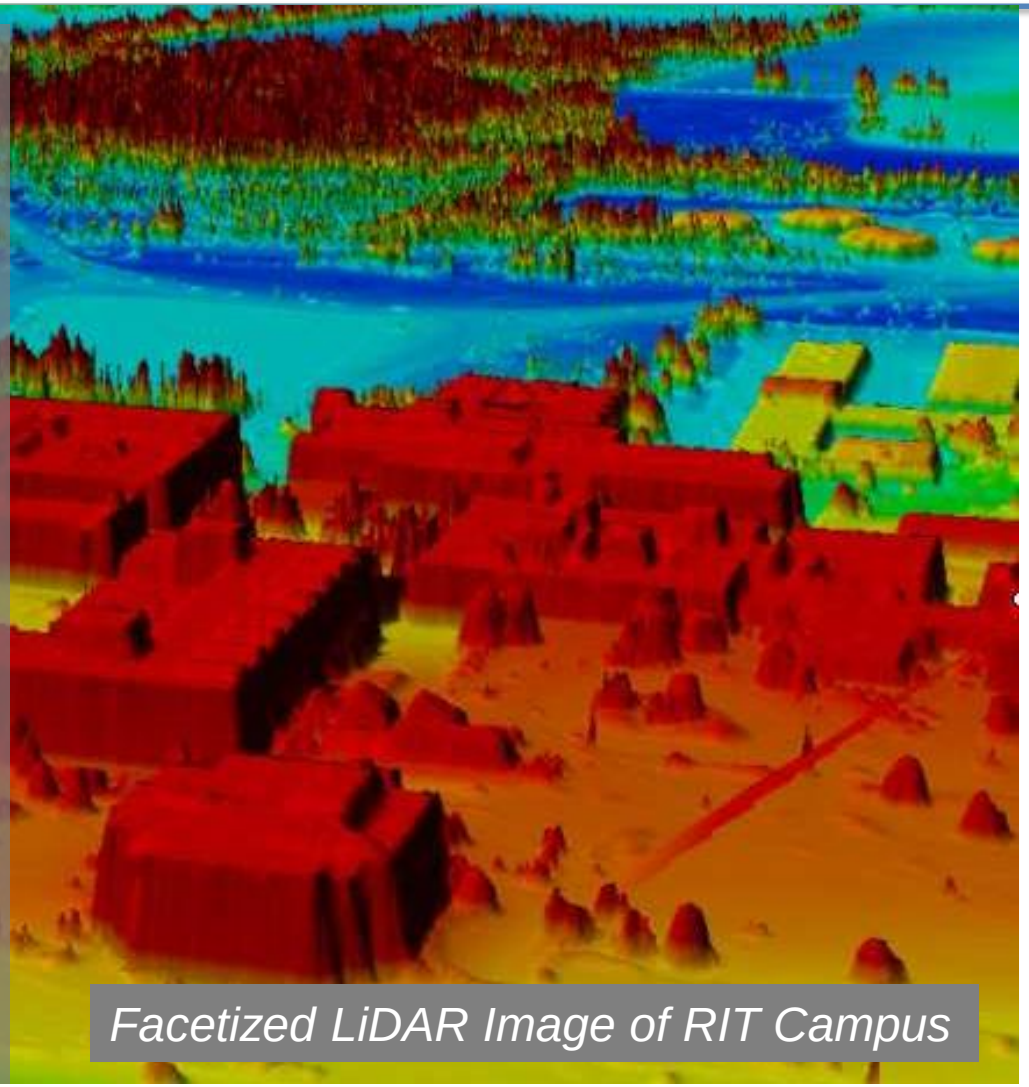
IEEE

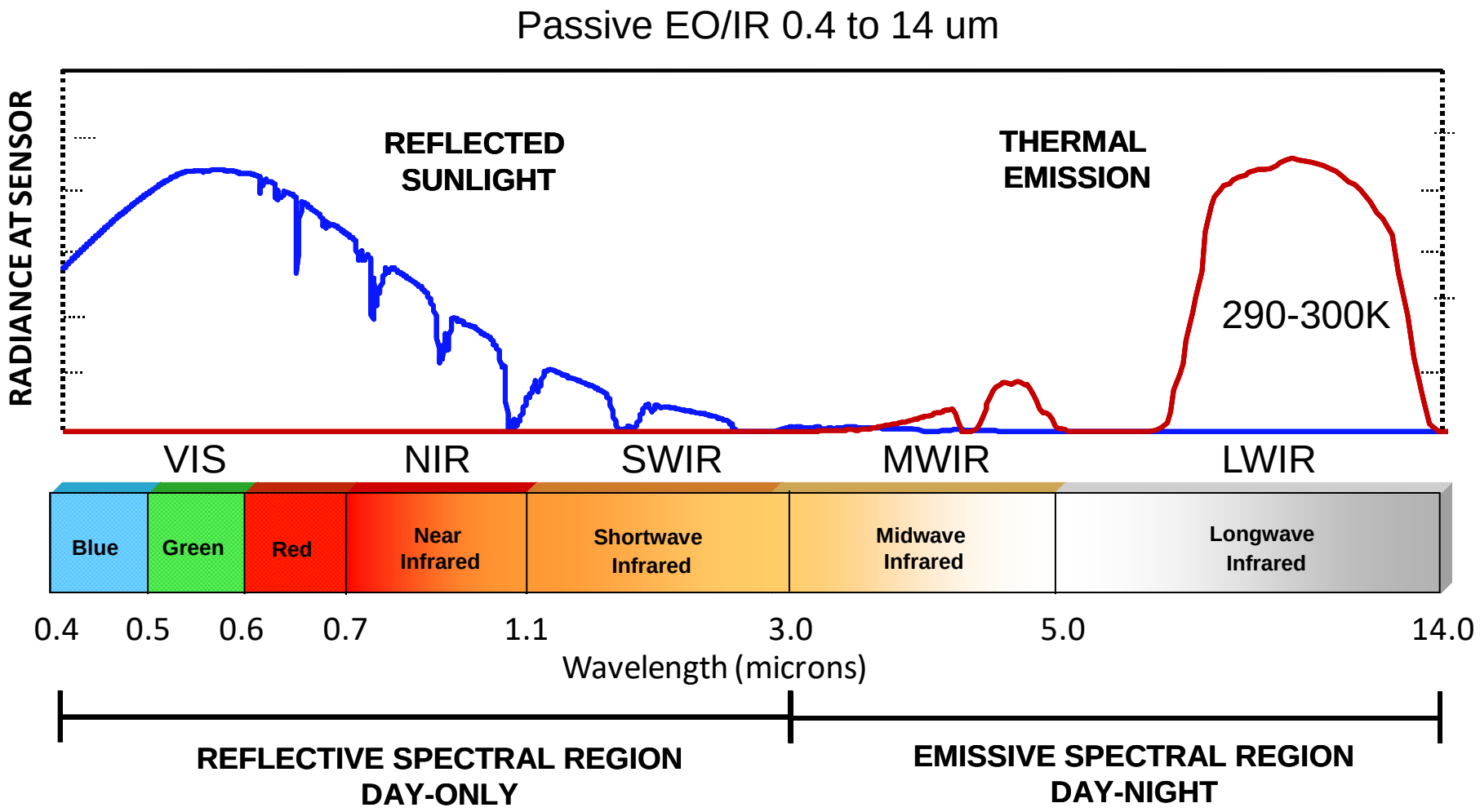
Todays Talk

- PART I
  - Background on:
    - Rochester, RIT, CIS, DIRS
- PART II
  - DIRS Research Focus Areas
  - Growth and Management of Data
  - WNY GRSS
- PART III
  - Hyperspectral Imaging
  - Target Detection w/ HSI and LiDAR
  - Where do we go from hear?



Facetized LiDAR Image of RIT Campus

Passive EO/IR Sources of ELM Radiation



HSI at night is not practical. SNR is very low unless looking fires, for example

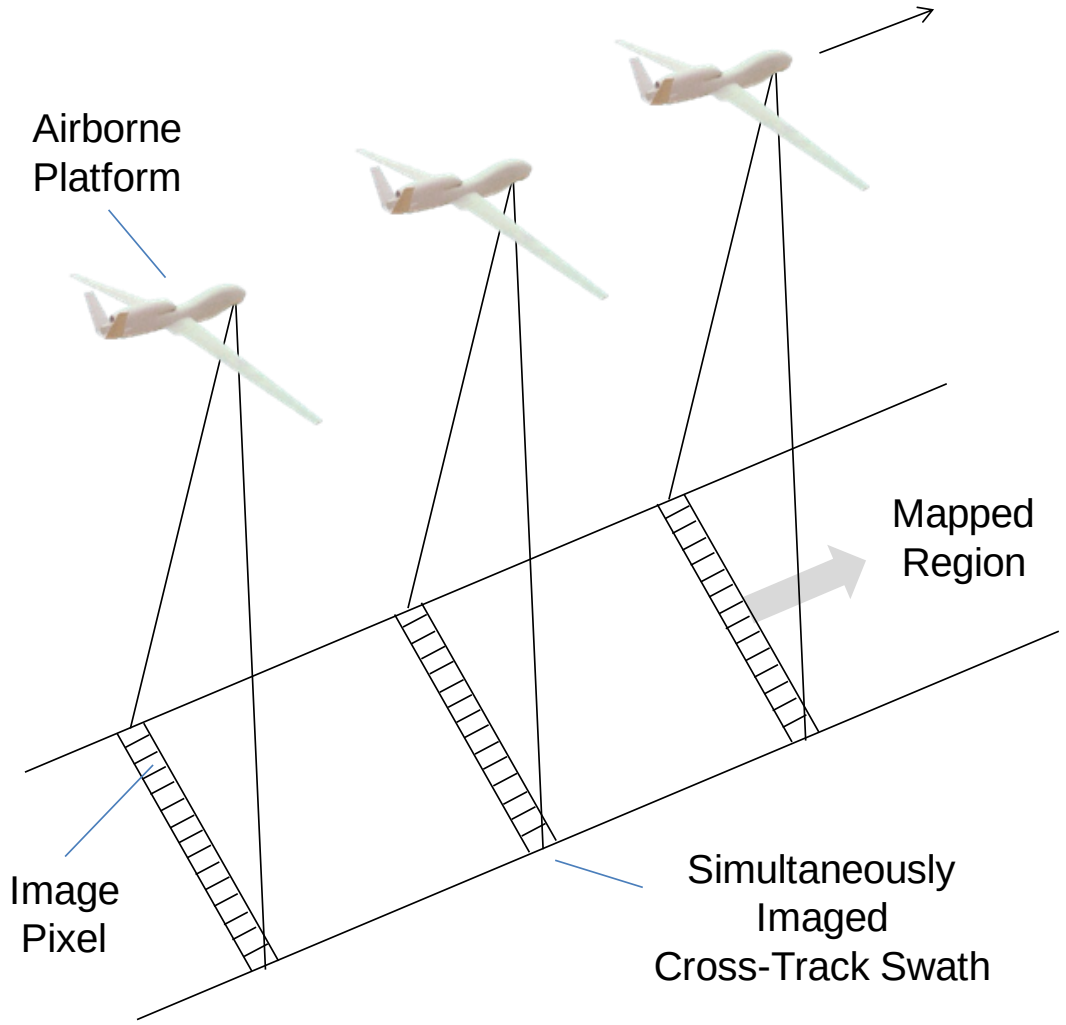
Hyperspectral Remote Sensing

- Hyperspectral remote sensing combines two sensing modalities
  - 1. Imaging
  - 2. Spectrometry
    - Measures the variation in power with the wavelength of light
    - Captures information related to the chemical composition of the material
    - Instrument is called a (imaging) Spectrometer

- Enabled by recent advances in the manufacturing of large, 2D optical detector arrays, **hyperspectral imaging** sensors are able to simultaneously capture both the spatial and spectral content of a scene

- The data collected is often called a **hyper-cube**

1D Linear: Pushbroom Scanning



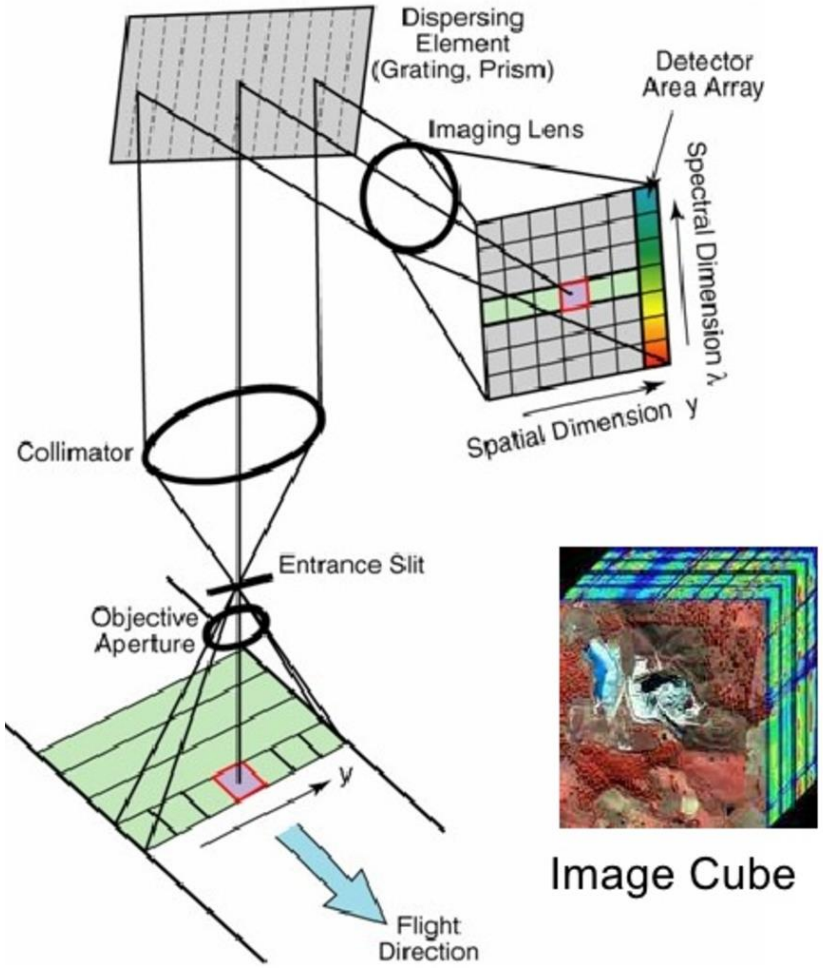
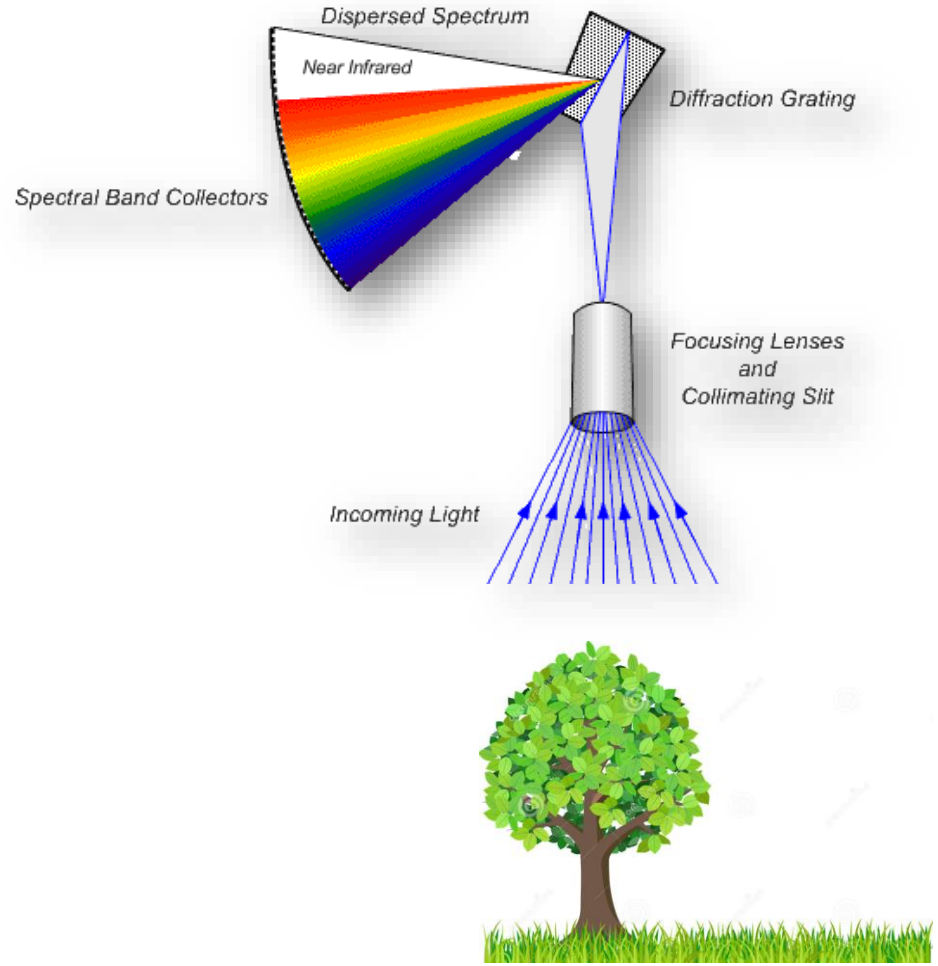
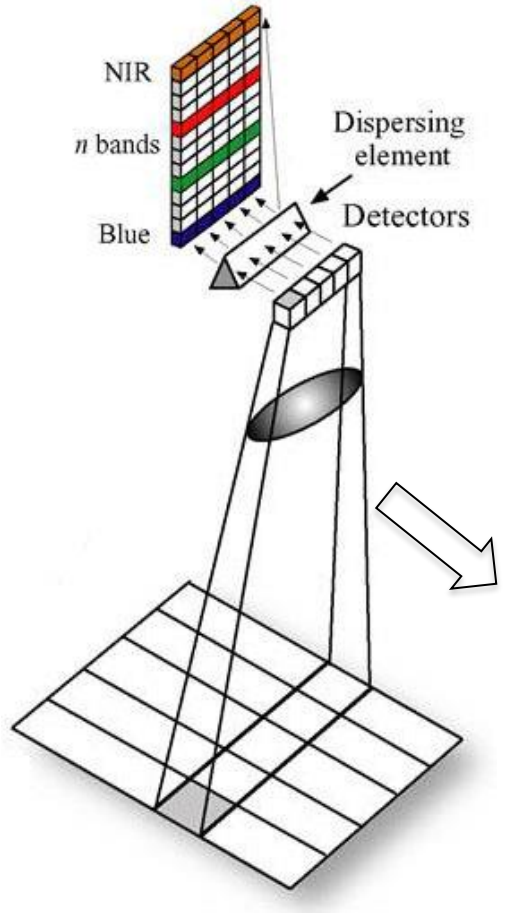


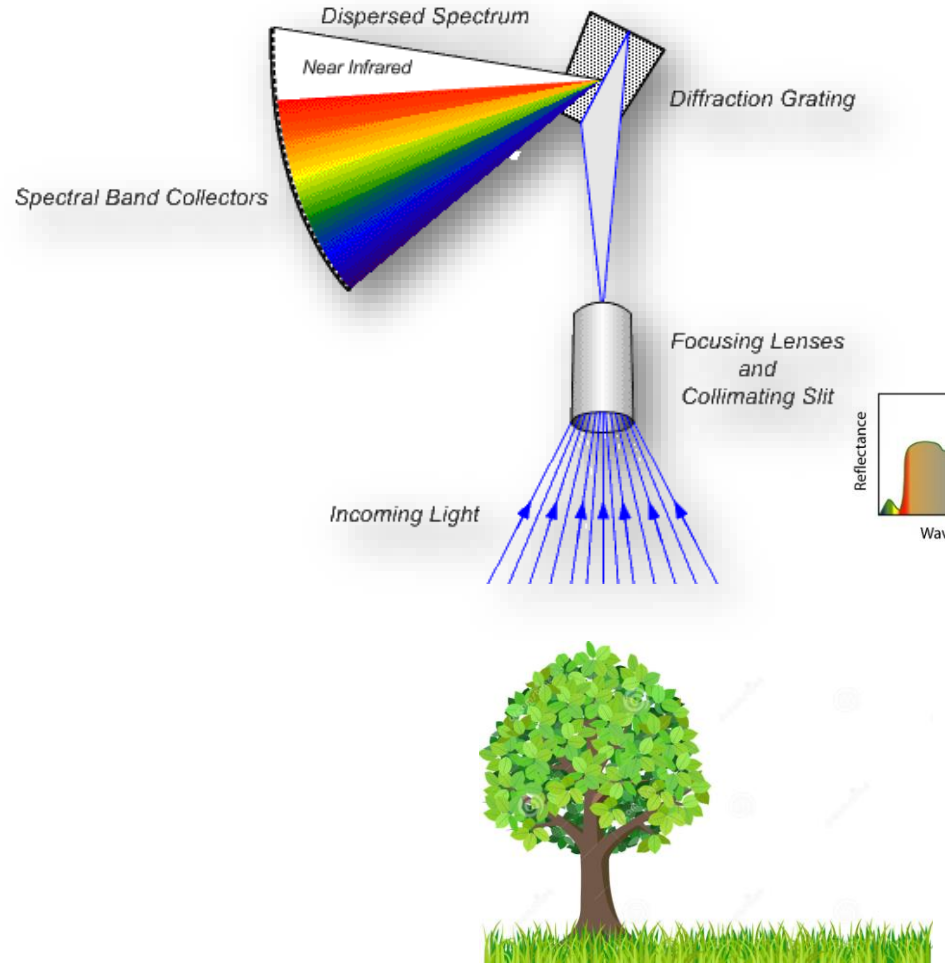
Image Cube

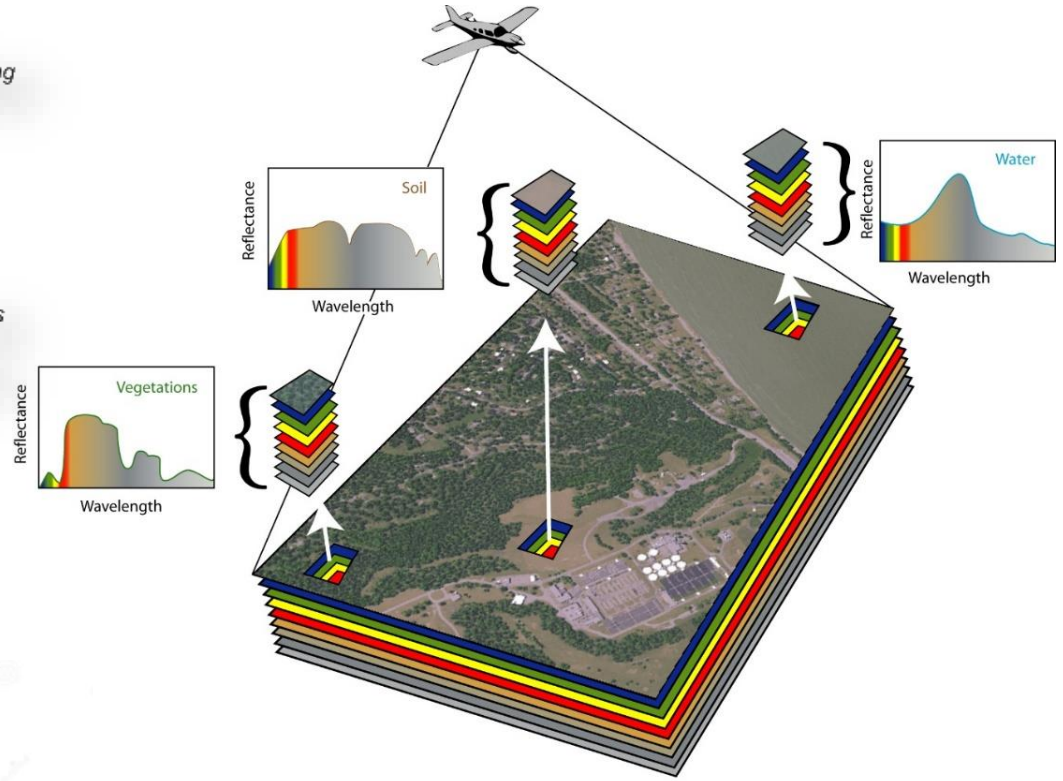
Hyperspectral Imaging





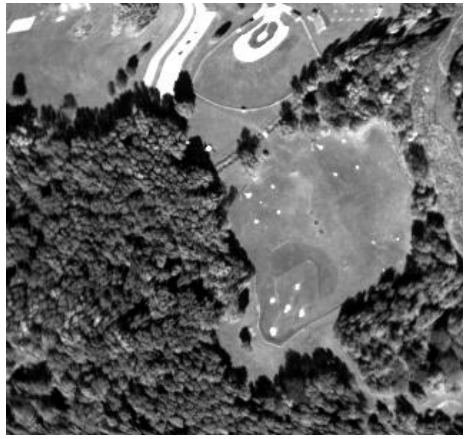
Hyperspectral Imaging





n-Dimensional Vectors, not 3D [RGB]

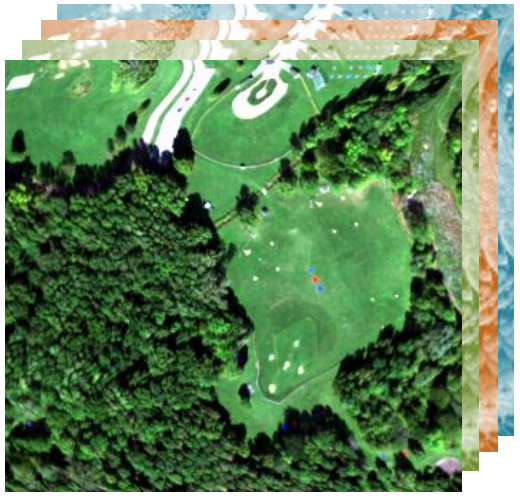
Hyperspectral Imaging



Scalar

Pixel = [7]

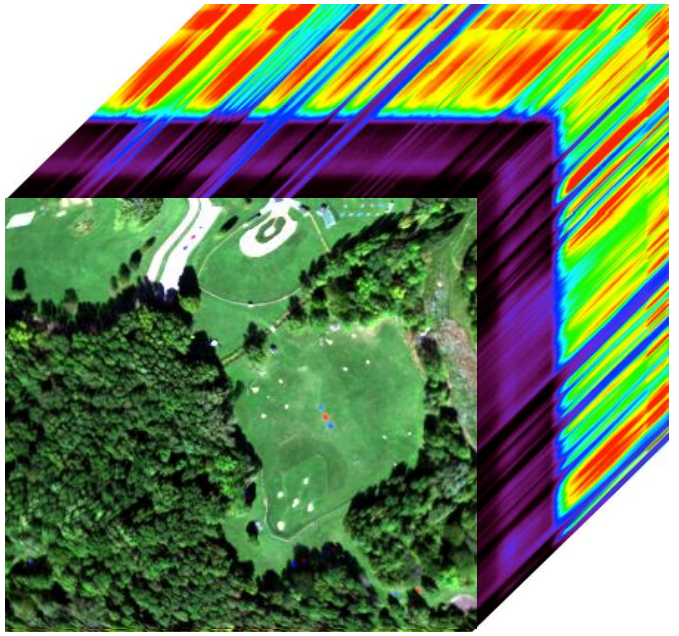
digital count



3-vector

Pixel = [12,136,71]

blue green red



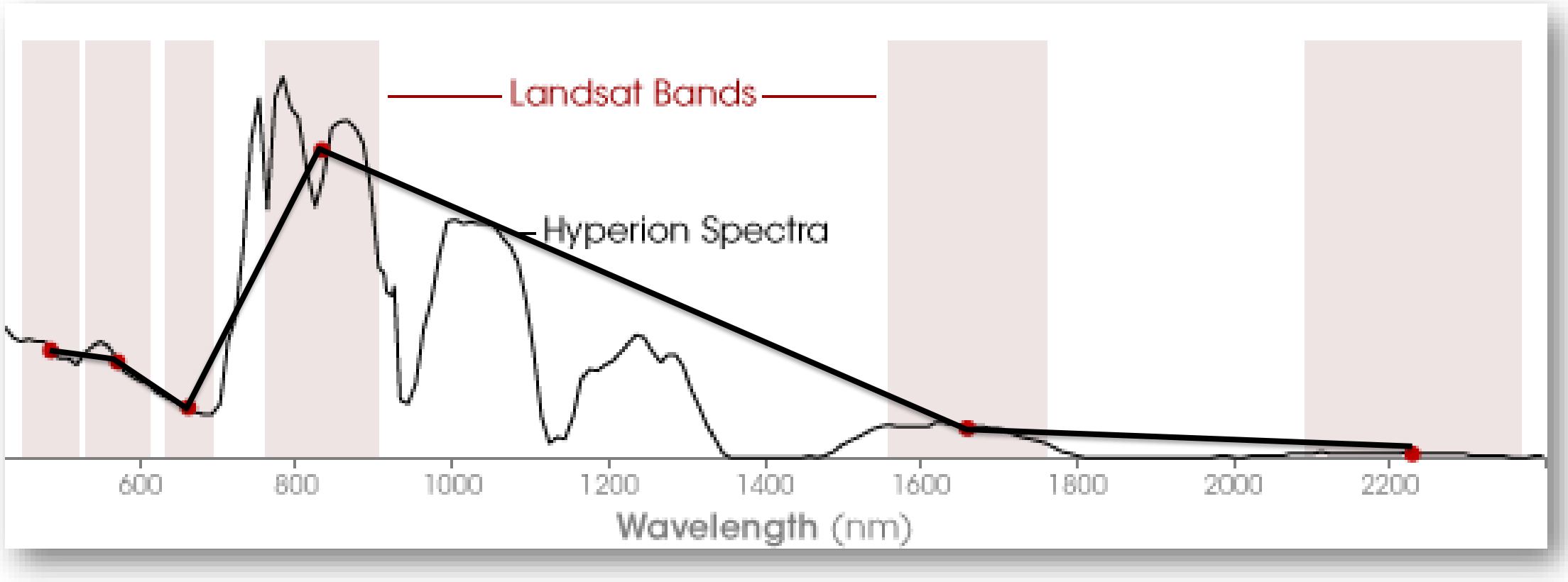
***n*-vector**

Pixel = [0.13,0.65,0.71,….,0.23]

radiance / reflectance / emissivity

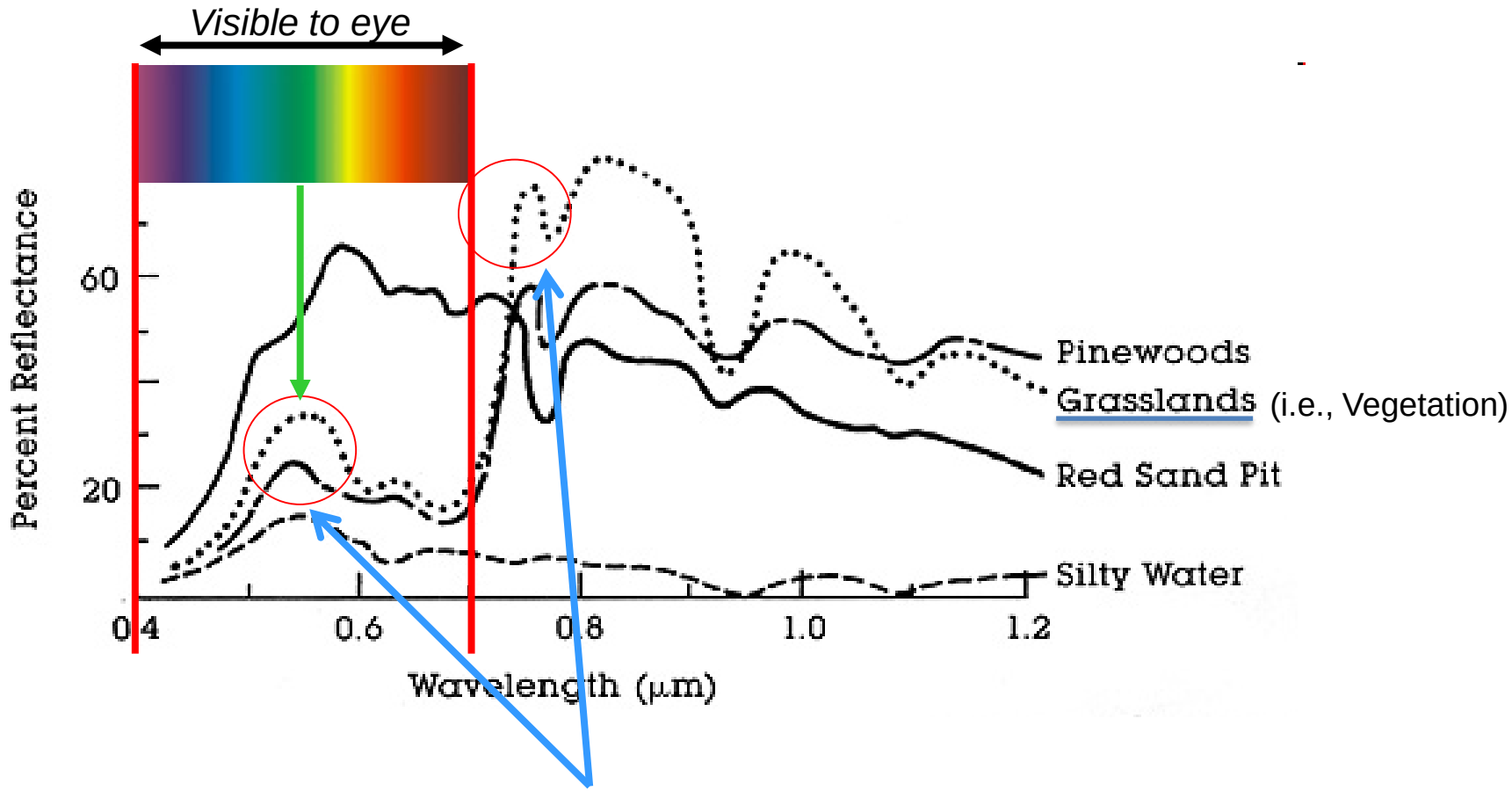
Note: each image is a set of n-dimensional vectors/pixels/points in $\mathbb{R}^n$ where *n* is the number of spectral wavelengths or “bands”

Multispectral vs. Hyperspectral



Benefits of Higher Spectral Resolution

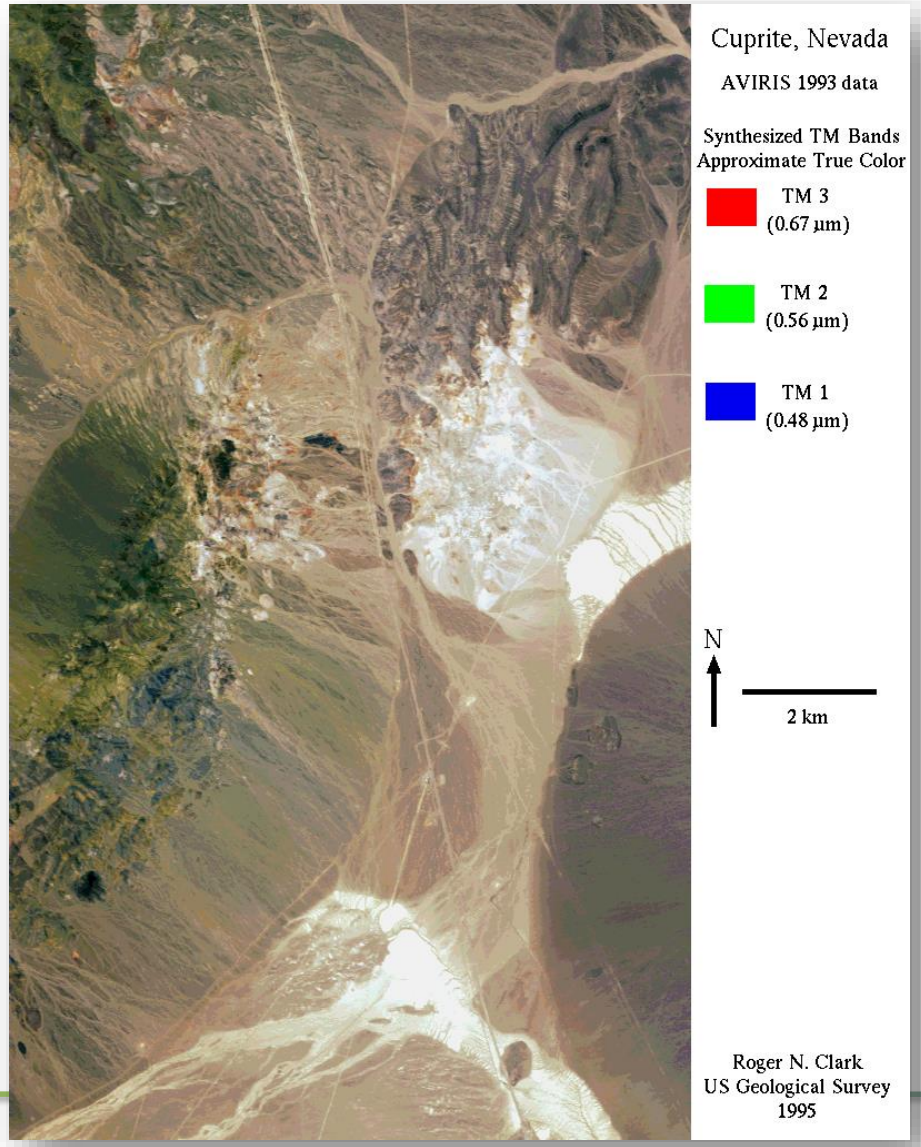
- High spectral resolution enables the detection of spectral features of interest in natural or man-man objects

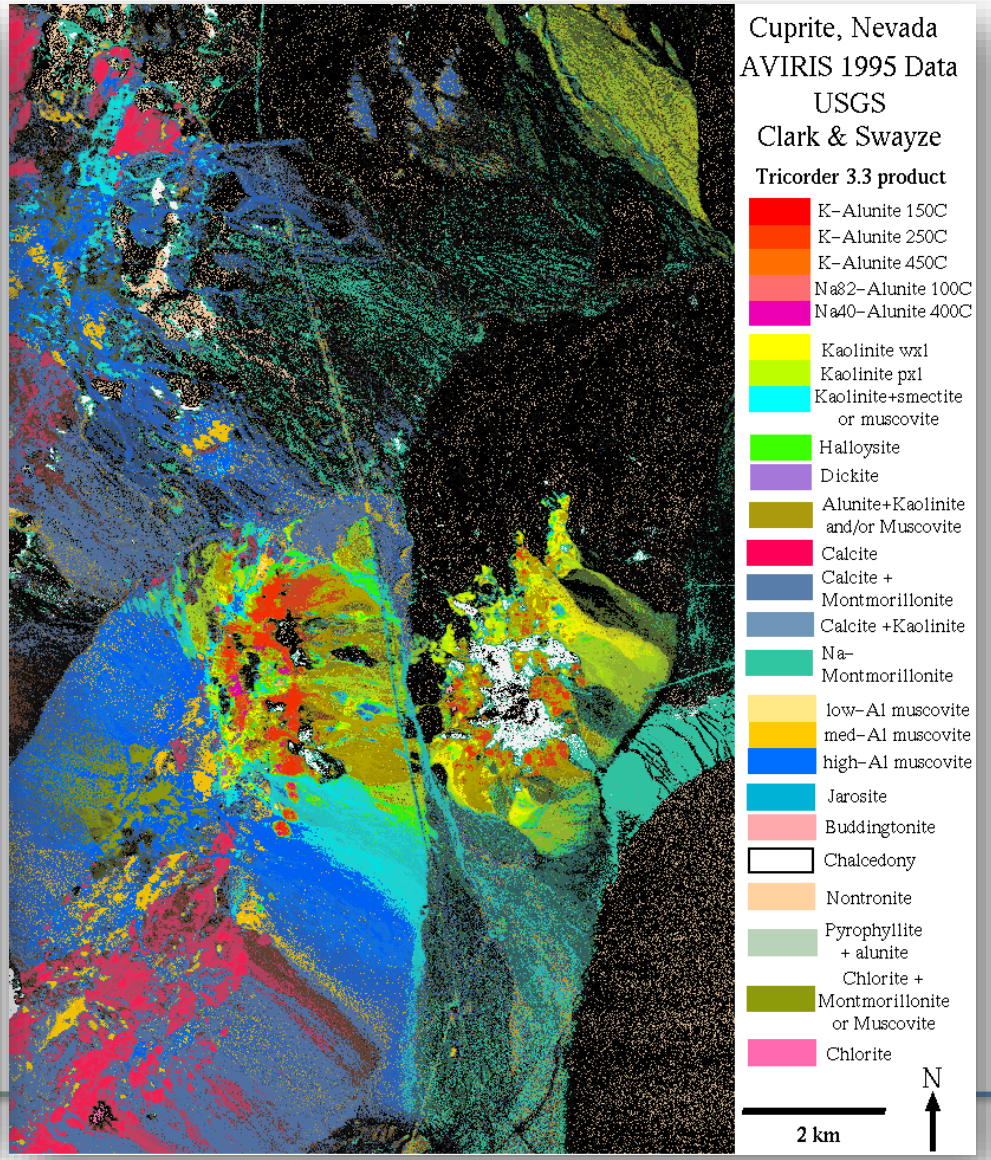


Plants are relatively bright in the “green” and far “red” part of the spectrum

Example: Mineral Mapping Results

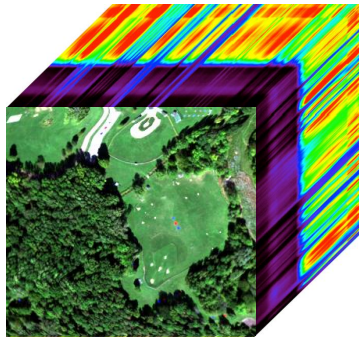
JPL AVIRIS





TARGET DETECTION WITH HYPERSPECTRAL AND LIDAR DATA

HSI Typical Processing Chain (for Detection)



Collected Raw Data

- Radiometric Cal
- Spectral Cal
- Dark Noise Removal
- Bad Element Map
- Saturated Pixel Map

- Geometric Processing (*i.e.*, Geo- or Ortho-rectify)

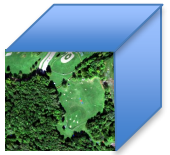
(might add spectral info)

Atmospheric Compensation using in-scene or Physical Models

(or)

Processing of Reflectance Signature to Radiance

Reflectance / Radiance data used as input to **Detection Algorithm**



Spectral Radiance

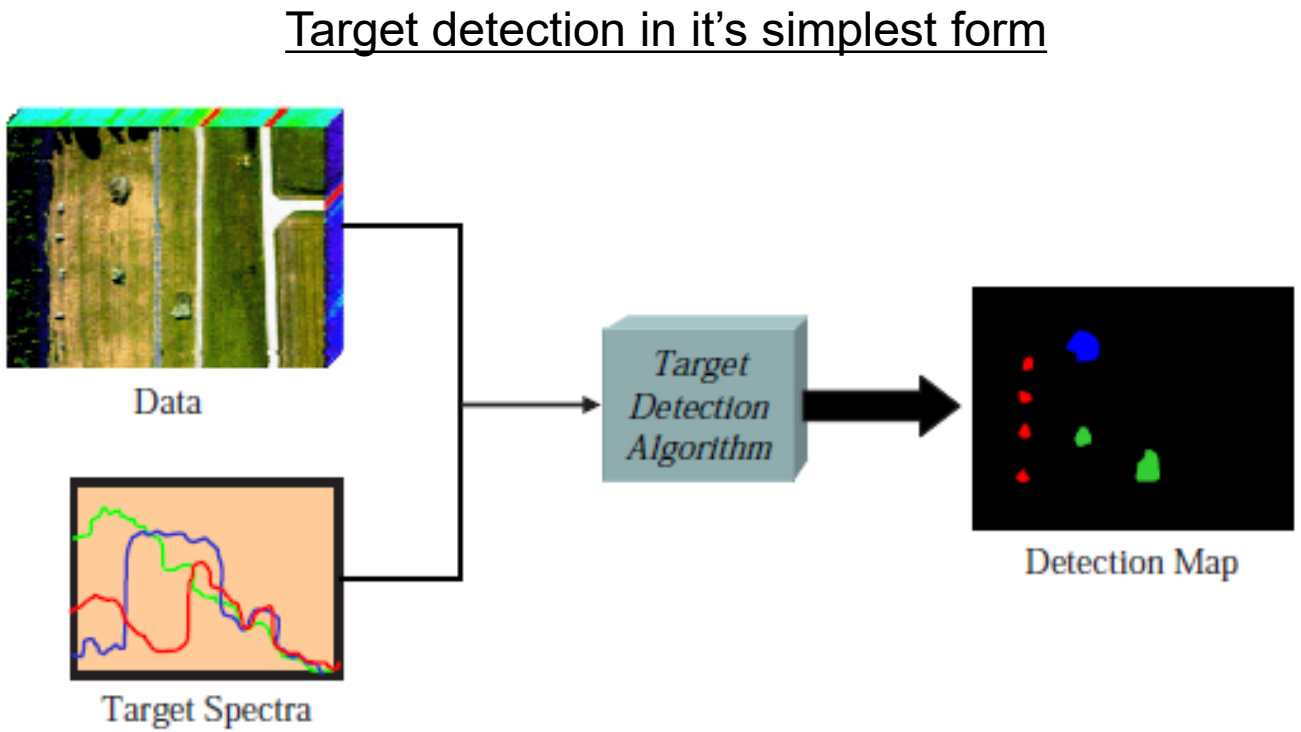
Halon Spectrolon

-ASD
-SVC
BRDF ?

Measurements of reference target signature

- *End to end uncertainty analysis*

The Basic Detection Problem



- I still have to contemplate the following:
  - What detection algorithm do we use? Geometric / Stochastic?
  - In radiance or reflectance space
  - Pre-process the data? Dimensionality reduction?
  - How to characterize the background
  - How do I decide on a threshold as to "what is target" from the detector output?

Signal Detection Theory

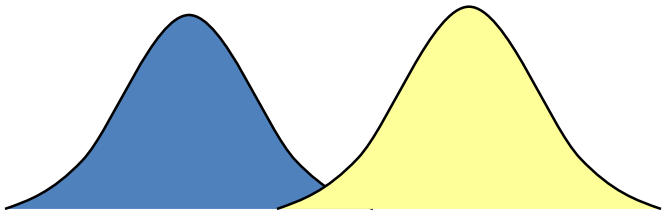
- The objective of hyperspectral target detection is to find objects of interested within a hyperspectral image by using the particular spectral features associated with an object's surface-material content.

- In HS target detection, objects of interest are scarcely populated in the scene, un-like a classification problem. We must "decide" if:
  - The spectrum **x** corresponds to the object (i.e., target)
  - Or…it corresponds to something other than the target (background)
    - This is a "binary hypothesis" testing problem.

- Thus, we use Statistical Signal Detection Theory to categorize decision making about whether or not a particular event occurs.

Statistical Hypotheses Testing

- Say we have some general Probability Density Model " f ", that describes the distribution of some observed pixel/vector **x**
  - Might be Gaussian, might be something else



- Then we can formulate the statistical target detection problem as a hypothesis test between:

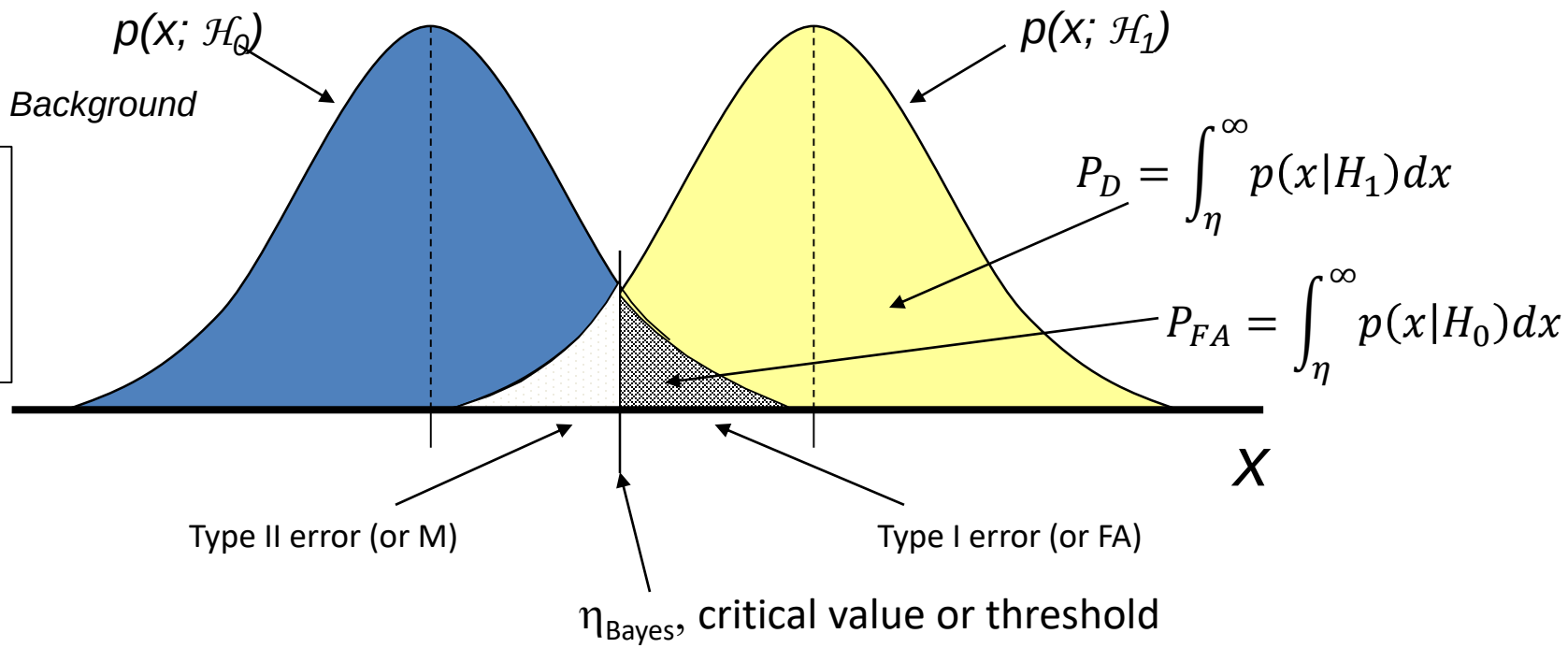
Null: $H_0 : \mathbf{x} \sim f(\mathbf{x}|H_0)$ (Target absent) i.e., Background

Alternative: $H_1 : \mathbf{x} \sim f(\mathbf{x}|H_1)$ (Target present)

This says, "Cond. Prob. of deciding **x** given that H_j is true"

Bayes Decision Rule - Univariate

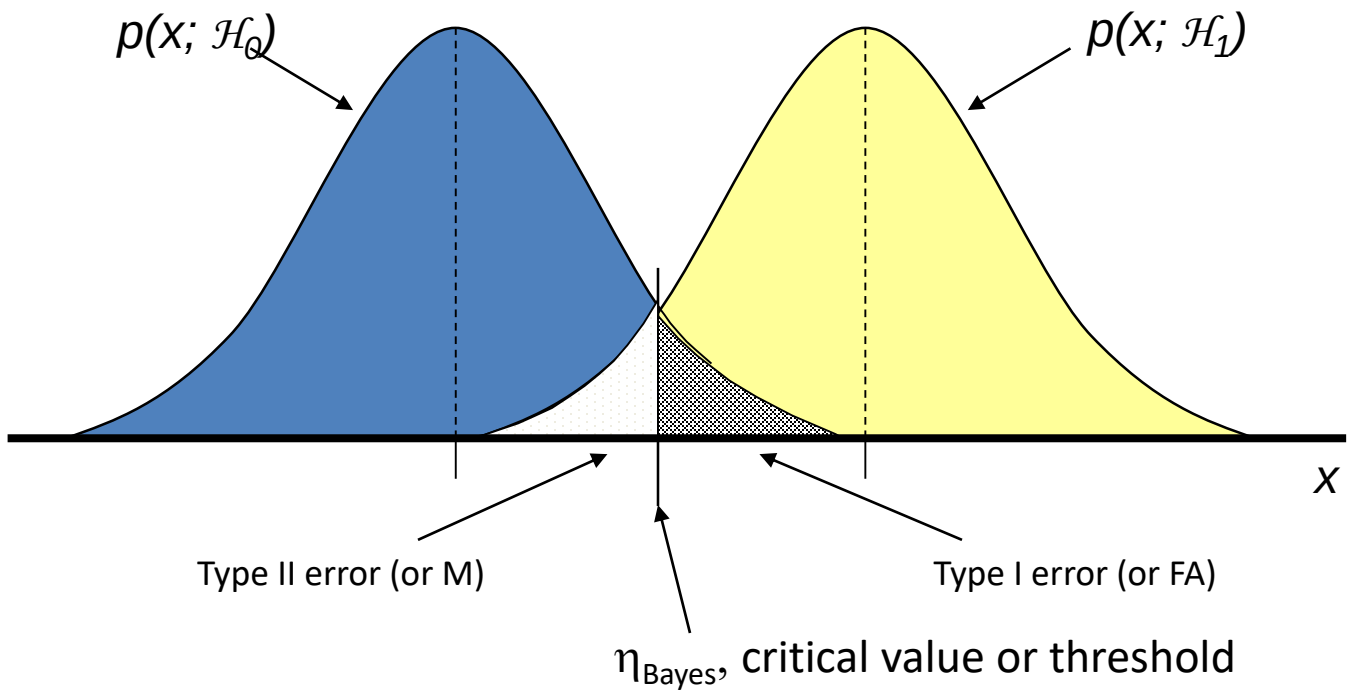
It would be ideal if the distributions were fully separated, but they typically are not



- Where is the best spot to draw the threshold ??

- The Bayes criterion seeks to minimize the average probability of error.
  - i.e., we choose a threshold η_{Bayes} that leads to **minimize both FA and M**.

Bayes Decision Rule



- According to Bayesian hypothesis testing for a 2-class detection problem (in which there is no *prior* probability information) a sufficient test statistic L(x) for target detection is the Likelihood Ratio (LR):

$$L(x) = \frac{p(x|H_1)}{p(x|H_0)}$$

These are the "Likelihood" terms from Bayes Theorem. And comes about by ratioing the probabilities of the distributions)

LR and LR Test

$$L(x) = \frac{p(x|H_1)}{p(x|H_0)} \quad \text{LR}$$

- $p(x|H_1)$ is the PDF (i.e., likelihood function) for the image vector **x** under the alternative
- $p(x|H_0)$ is the PDF (i.e., likelihood function) for the image vector **x** under the null

- We can implement a decision rule or "test" as:

$$L(x) = \frac{p(x|H_1)}{p(x|H_0)} \lessgtr \eta_{Bayes} \quad \text{LRT}$$

- Which says, we choose H_1 if $L(x) > \eta_{Bayes}$ and hypothesis H_0 if $L(x) < \eta_{Bayes}$.
  (Target) *(Not Target)*

- It is nice to pick a threshold such that one maximized the number of correct detections while minimizing the number FA's and M's.

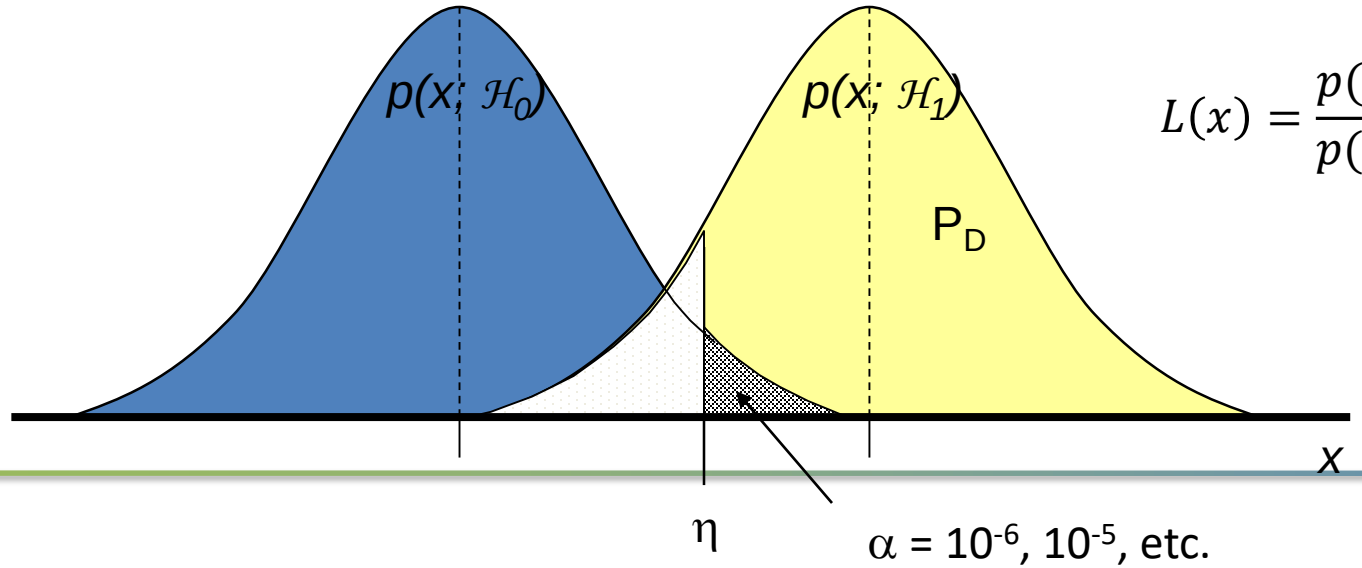
- However, in detection applications, where the probability of occurrence of a target is very small, we have to alter the criterion.
  - What value of P_{FA} can you afford….and maximize P_D?

Neyman-Pearson (NP) Criterion

- Ideally, we want P_{FA} as small as possible and P_D as large as possible
  - These are conflicting requirements !!
  - We increase P_D….you increase P_{FA} !!

- The NP Criterion attempts to maximize the probability of detection (P_D) given a fixed value α for the probability of false alarms (P_{FA}).

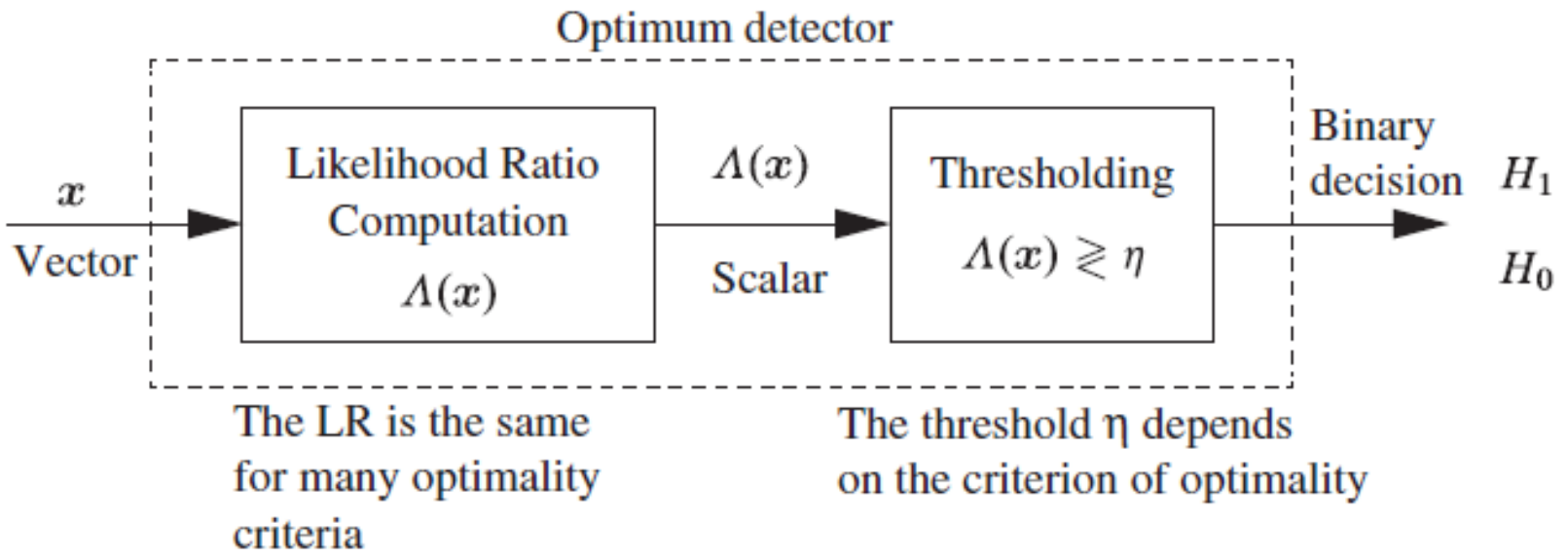
Max P_D subject to $P_{FA} \leq \alpha$ $\alpha = 10^{-6}, 10^{-5}$



$$L(x) = \frac{p(x|H_1)}{p(x|H_0)} \lessgtr \eta$$ LRT

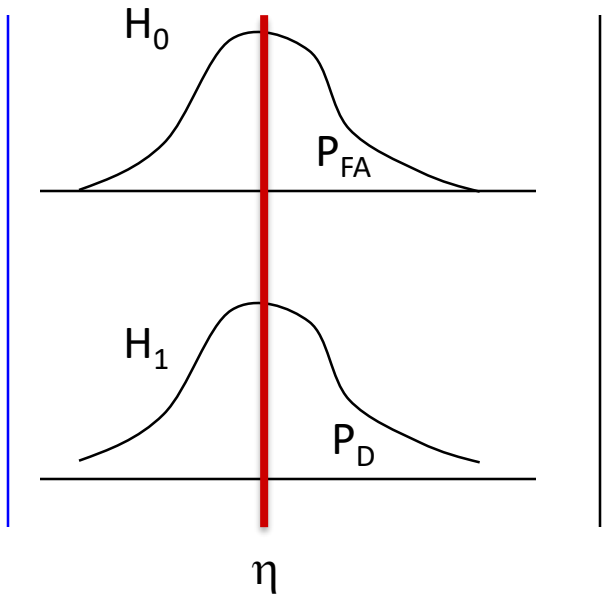
Detector Structure

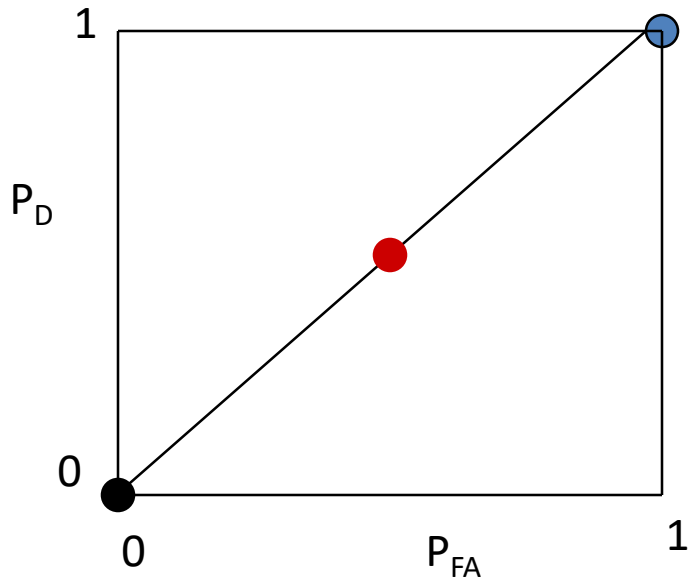
Thus, an optimal detector computes the likelihood ratio for each observation vector and then makes a decision by comparing this value to a fixed threshold



ROC Curve

- For the Neyman-Pearson test, we see there is a trade-off between P_D and P_{FA}.
- To study this trade-off, we use a parametric plot of P_D versus P_{FA} as the threshold η varies
- The resulting curve is know as a Receiver Operating Characteristic (ROC) curve.





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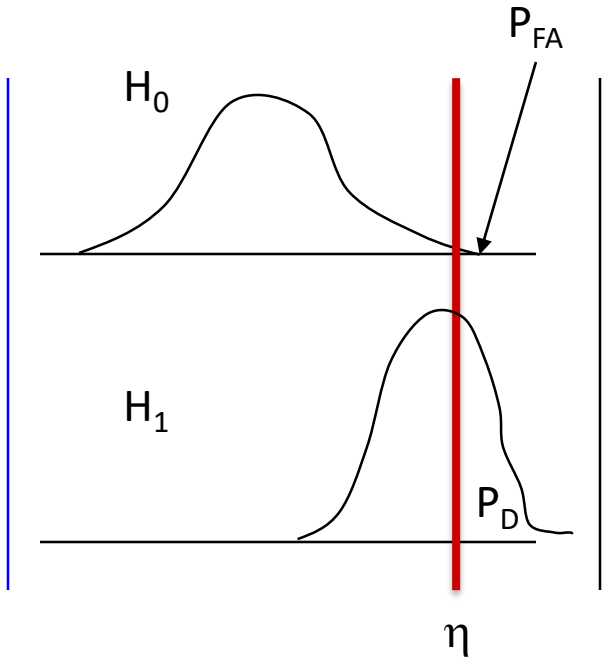

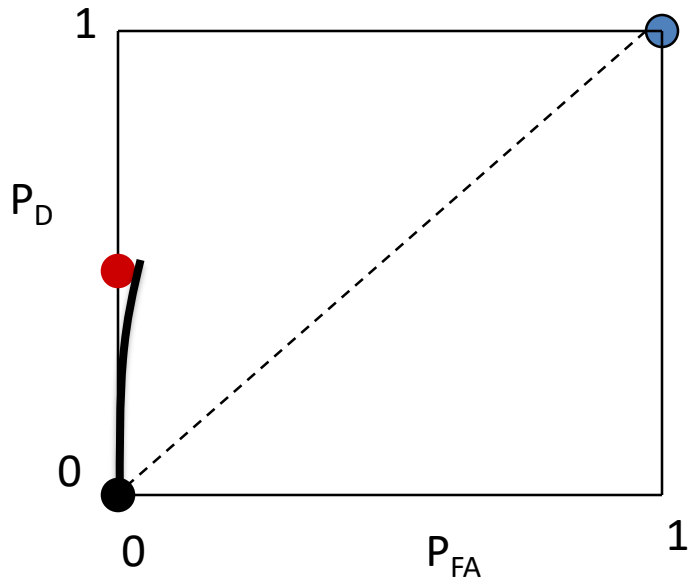

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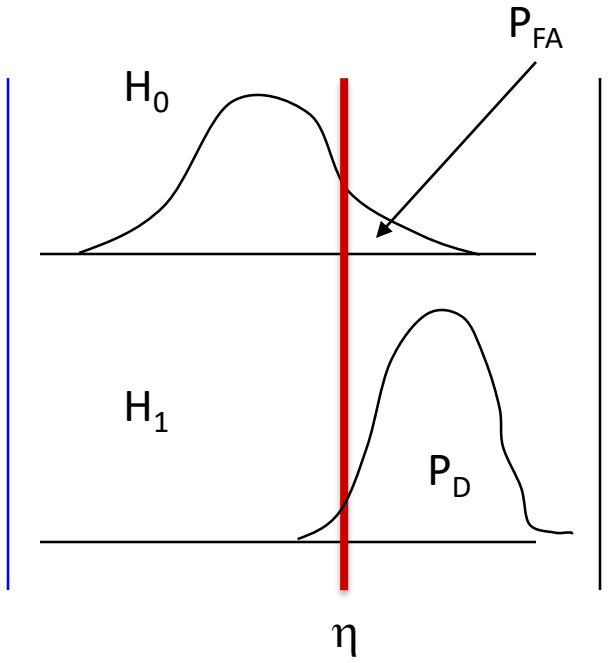

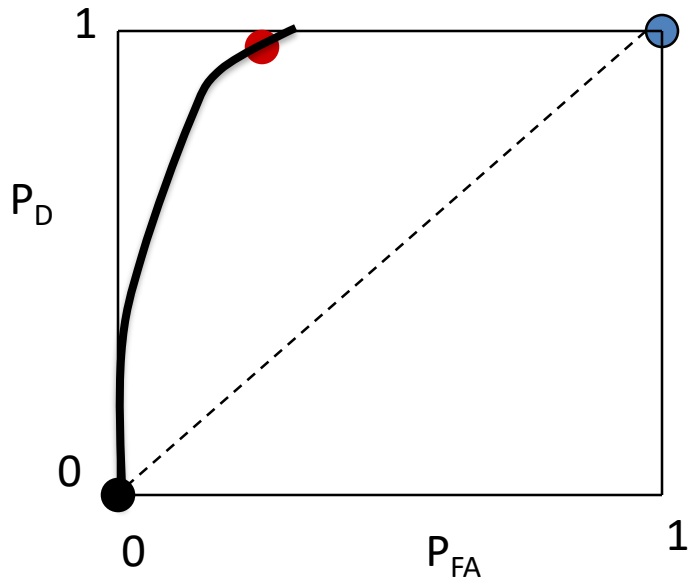

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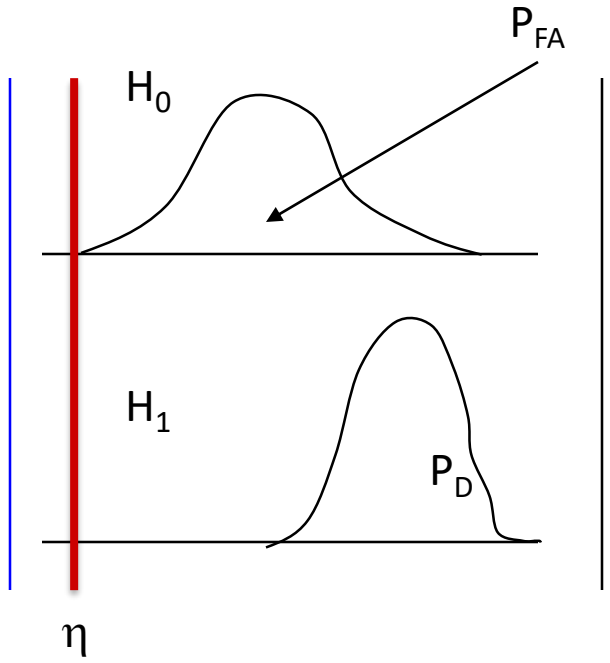
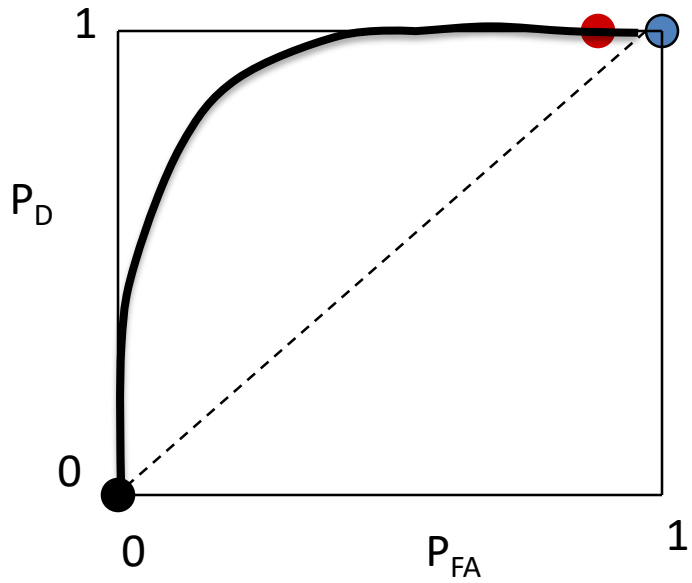
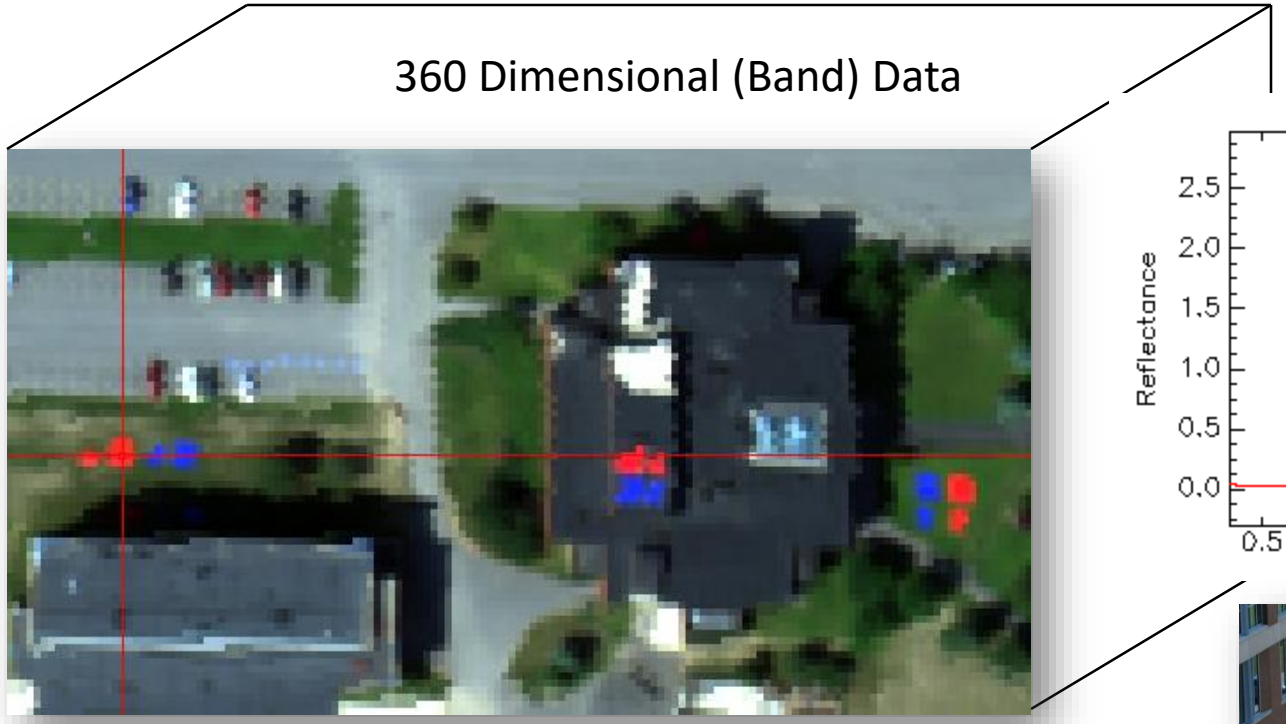
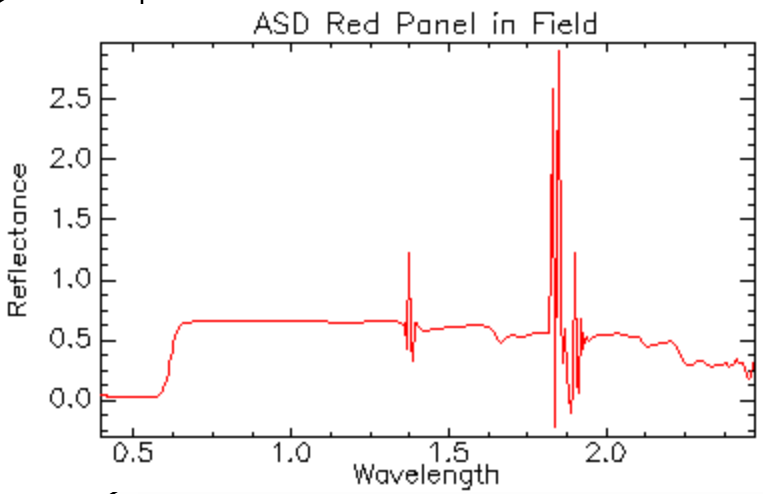
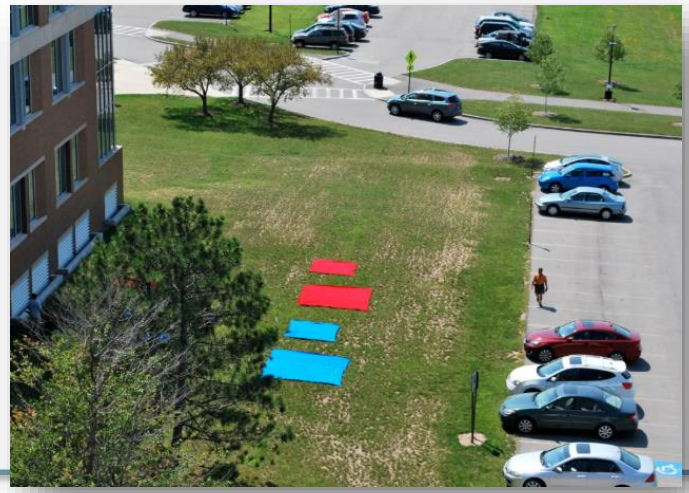




Simple Hyperspectral Detection





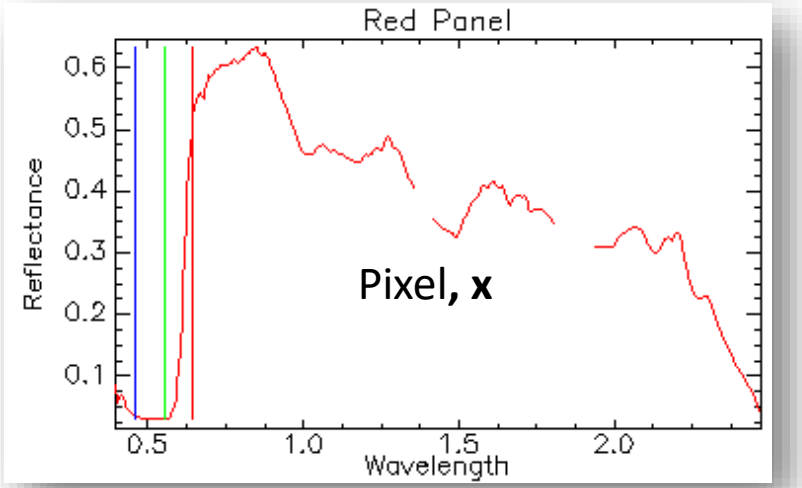


- Each pixel is a 360 dimensional vector, $\mathbf{x}_i$

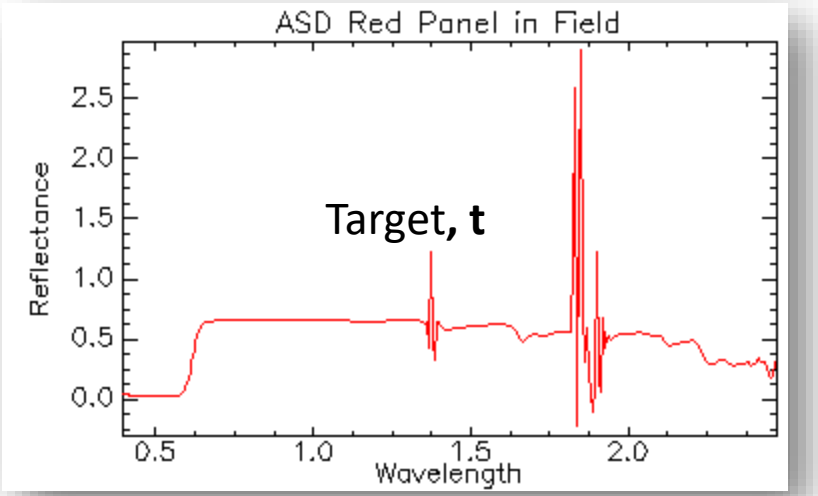
- Given such an HS image, and a measure of what a "target" looks like (from the field, lab, spectral lib, etc.)
  - How can I "find" this target in the image?

Simple Detection

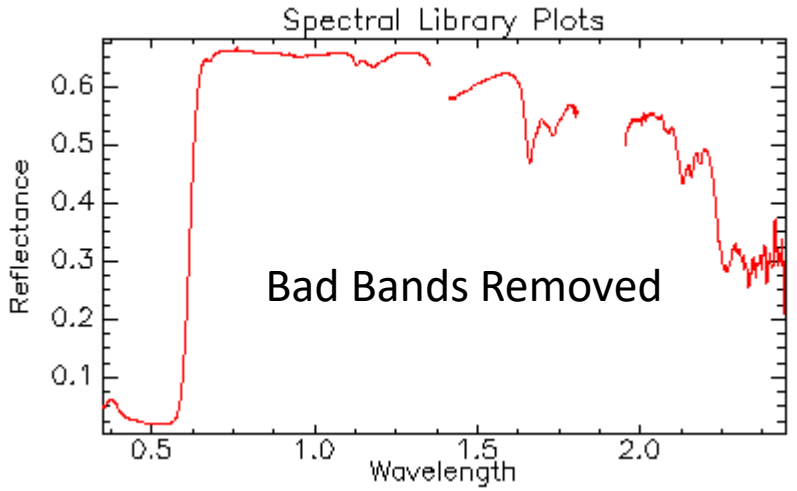
Image Pixel



Field Measurement



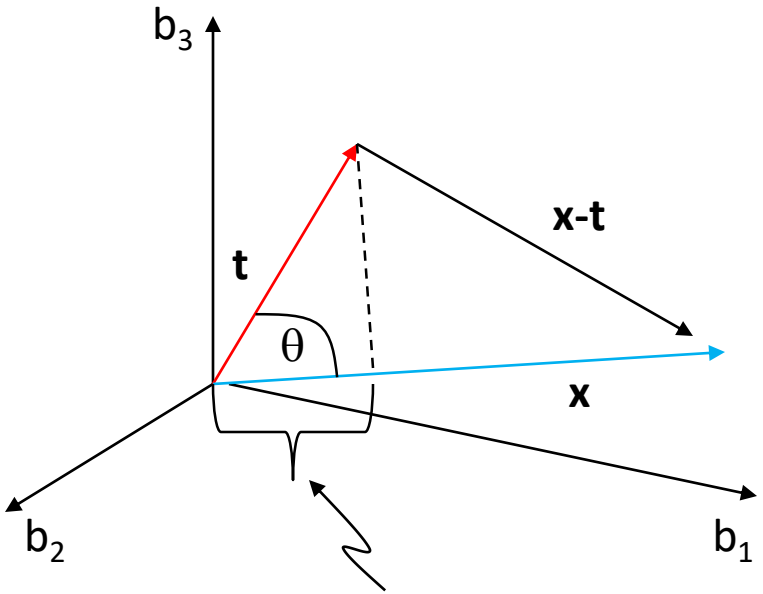
- What if I simply computed the dot product between **t** and **x**, for every pixel in the image?
  - See which is “least” orthogonal?



Simple Detection

- The dot product can be given a geometric interpretation in terms of the angle θ between **x** and **t**

$$\boldsymbol{x}^T \cdot \boldsymbol{t} = |\boldsymbol{x}|\,|\boldsymbol{t}| \cos\theta$$



$$\frac{\boldsymbol{x}^T \cdot \boldsymbol{t}}{|\boldsymbol{x}|} = |\boldsymbol{t}| \cos\theta$$

Where:

$$|\boldsymbol{x}| = \sqrt{\boldsymbol{x}^T \boldsymbol{x}}$$

$$|\boldsymbol{t}| = \sqrt{\boldsymbol{t}^T \boldsymbol{t}}$$

- What if we just use the angle as a metric ?

Spectral Angle Mapper

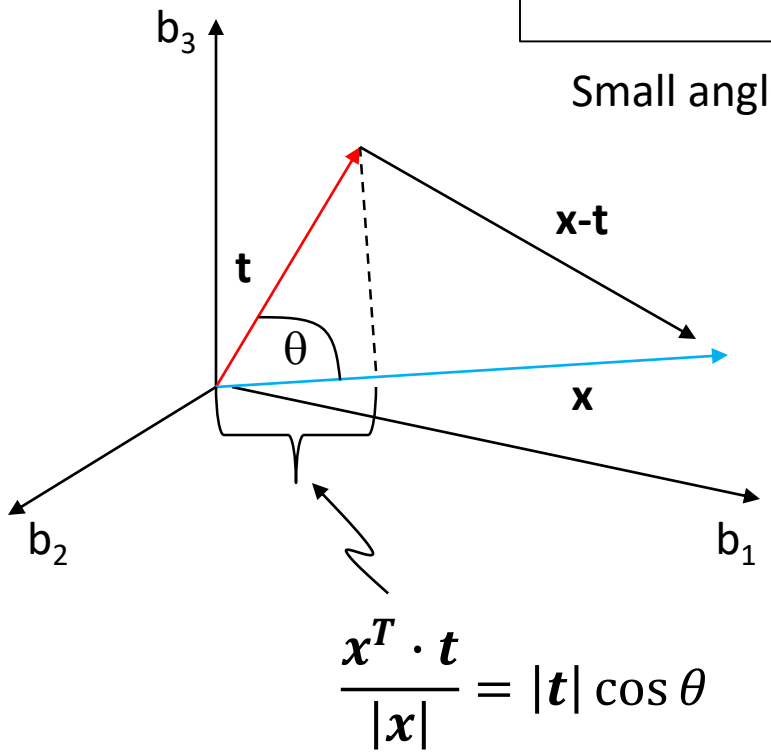
- Look for those vector combinations that produce “small” angles (i.e., **x** looks like **t**.

$$\theta = cos^{-1}\left[\frac{\boldsymbol{x}^T \cdot \boldsymbol{t}}{|\boldsymbol{x}|\,|\boldsymbol{t}|}\right]$$

Small angles = good

$$\theta = -cos^{-1}\left[\frac{\boldsymbol{x}^T \cdot \boldsymbol{t}}{|\boldsymbol{x}|\,|\boldsymbol{t}|}\right]$$

Big angles = good



$$\frac{\boldsymbol{x}^T \cdot \boldsymbol{t}}{|\boldsymbol{x}|} = |\boldsymbol{t}| \cos\theta$$

Where:

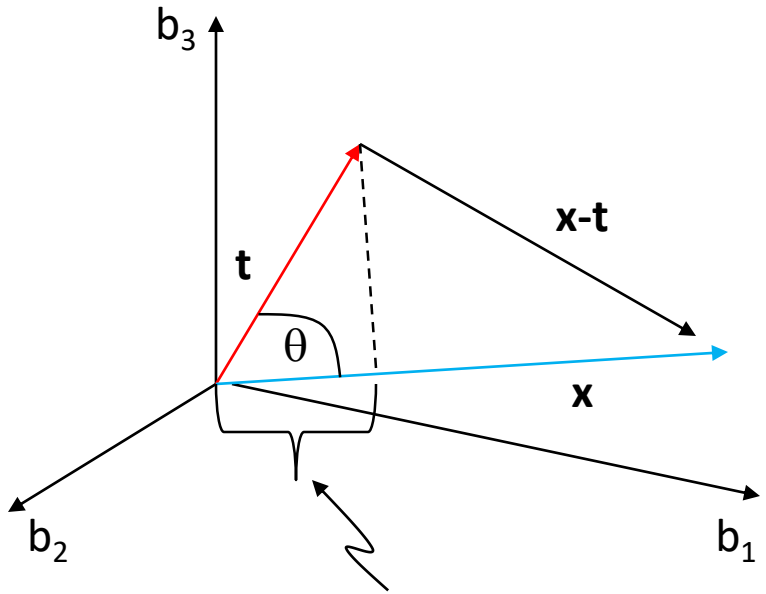
$$|\boldsymbol{x}| = \sqrt{\boldsymbol{x}^T \boldsymbol{x}}$$

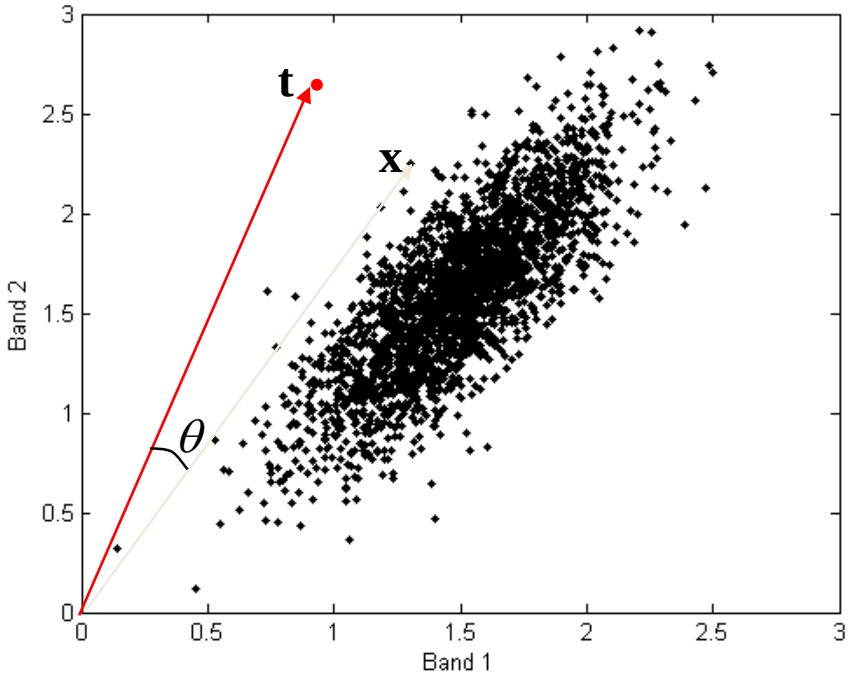
$$|\boldsymbol{t}| = \sqrt{\boldsymbol{t}^T \boldsymbol{t}}$$

- This actually has a name:
- The Spectral Angle Mapper (SAM)
  - We’ll show results in a minute….

Spectral Angle Mapper

- Spectral Angle Mapper (SAM)



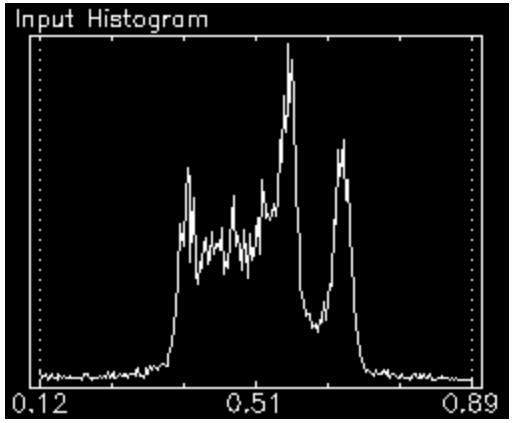


$$\frac{\boldsymbol{x}^T \cdot \boldsymbol{t}}{|\boldsymbol{x}|} = |\boldsymbol{t}| \cos\theta$$

Simple Detection: SAM Result

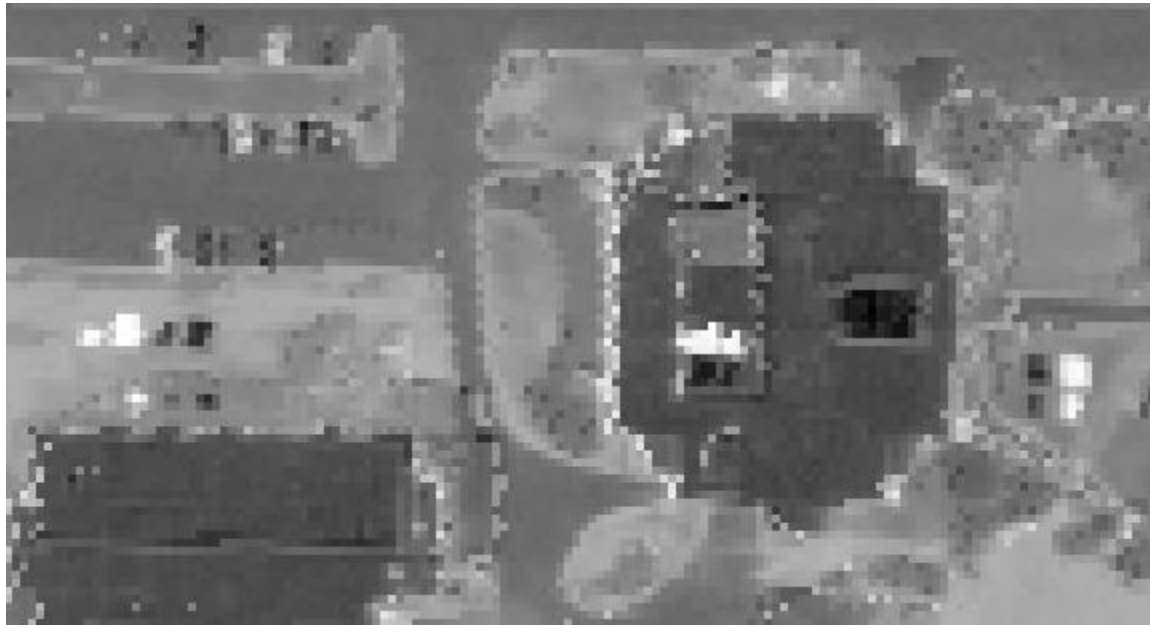
Map of Angles in Radians

Histogram

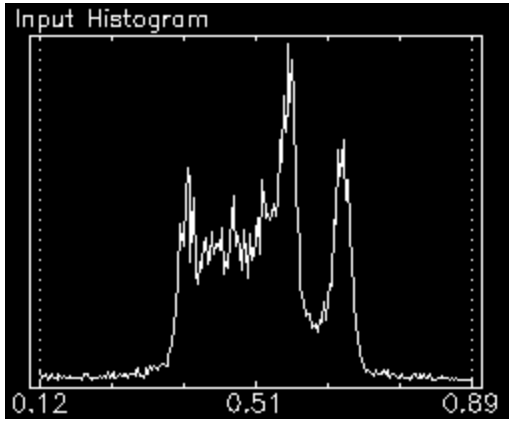


Simple Detection: SAM Result

Map of Angles in Radians (Reverse Colors)



Histogram



This result is “OK” but there are may pixels (gray values) that are close in brightness to the target.
- We can do better…

Class of Detection Algorithms

- **Full-Pixel Algorithms**
  - Background and Target Statics Known
    - QD
    - MF
  - Background Statistics Known, Target Mean Unknown
    - AD (Anomaly Detector)
  - Target Mean Known (Geometric Method)
    - SAM
- **Sub-Pixel Algorithms**
  - Structured (or Geometric) Background Models
    - GLR
    - MSD, ASD
    - OSP
    - MFWN
  - Unstructured (or Stochastic) Background Models
    - GLR
    - Kelly
    - ACE
    - AMF
    - CEM

Background and Target Statistics Known

Lets assume the model and hypothesis:

$$\mathcal{H}_0: \quad \mathbf{x} \in \mathcal{N}(\boldsymbol{\mu}_b, \boldsymbol{\Sigma}_b)$$
$$\mathcal{H}_1: \quad \mathbf{x} \in \mathcal{N}(\boldsymbol{\mu}_t, \boldsymbol{\Sigma}_t)$$

where in the stochastic representation the assumption is that $\mathbf{x}$ comes from either the multivariate distribution $\mathcal{N}(\boldsymbol{\mu}_t, \boldsymbol{\Sigma}_t)$ or $\mathcal{N}(\boldsymbol{\mu}_b, \boldsymbol{\Sigma}_b)$.

We can assemble this into a LR, which we have yet to do.

$$\mathcal{L}(\mathbf{x}) = \frac{p(\mathbf{x}; \mathcal{H}_1)}{p(\mathbf{x}; \mathcal{H}_0)} = \frac{(2\pi)^{-p/2}|\boldsymbol{\Sigma}_t|^{-1/2} \exp\left[-0.5(\mathbf{x}-\boldsymbol{\mu}_t)^T \boldsymbol{\Sigma}_t^{-1}(\mathbf{x}-\boldsymbol{\mu}_t)\right]}{(2\pi)^{-p/2}|\boldsymbol{\Sigma}_b|^{-1/2} \exp\left[-0.5(\mathbf{x}-\boldsymbol{\mu}_b)^T \boldsymbol{\Sigma}_b^{-1}(\mathbf{x}-\boldsymbol{\mu}_b)\right]}$$

Mahalanobis Distance

Which reduces to

$$\mathcal{L}(\mathbf{x}) = \frac{|\boldsymbol{\Sigma}_b|^{1/2}}{|\boldsymbol{\Sigma}_t|^{1/2}} \exp\left[0.5(\mathbf{x}-\boldsymbol{\mu}_b)^T\boldsymbol{\Sigma}_b^{-1}(\mathbf{x}-\boldsymbol{\mu}_b) - 0.5(\mathbf{x}-\boldsymbol{\mu}_t)^T\boldsymbol{\Sigma}_t^{-1}(\mathbf{x}-\boldsymbol{\mu}_t)\right]$$

The quadratic term $(\mathbf{x}-\boldsymbol{\mu}_y)^T\boldsymbol{\Sigma}_y^{-1}(\mathbf{x}-\boldsymbol{\mu}_y)$, for y equal to t or b, is a statistical distance measure and is referred to as the square of the *Mahalanobis distance*. If the target and background covariances are whitened, (*i.e.*, $\boldsymbol{\Sigma} = \sigma^2\mathbf{I}$) then the distance measure becomes a simple Euclidean one. Taking the natural logarithm (a monotonically increasing transformation) of both sides does not change the relation.

Therefore, we have the detection statistic, y

$$y = \ln\mathcal{L}(\mathbf{x}) = \ln\left(\frac{|\boldsymbol{\Sigma}_b|}{|\boldsymbol{\Sigma}_t|}\right)^{1/2} + 0.5(\mathbf{x}-\boldsymbol{\mu}_b)^T\boldsymbol{\Sigma}_b^{-1}(\mathbf{x}-\boldsymbol{\mu}_b) - 0.5(\mathbf{x}-\boldsymbol{\mu}_t)^T\boldsymbol{\Sigma}_t^{-1}(\mathbf{x}-\boldsymbol{\mu}_t)$$

Quadratic Detector (QD)

the natural logarithm of the ratio of the covariance determinants will be constant for each pixel under test. This constant does not effect our discriminant and is usually ignored. In doing so, we have

$$y = T_{QD}(\mathbf{x}) = 0.5(\mathbf{x}-\boldsymbol{\mu}_b)^T\boldsymbol{\Sigma}_b^{-1}(\mathbf{x}-\boldsymbol{\mu}_b) - 0.5(\mathbf{x}-\boldsymbol{\mu}_t)^T\boldsymbol{\Sigma}_t^{-1}(\mathbf{x}-\boldsymbol{\mu}_t) \underset{H_0}{\overset{H_1}{\gtrless}} \eta$$

This is called a *quadratic detector*. It simply compares the distances of the observed spectrum $\mathbf{x}$ from the centers of the two target and background classes.

In Signal Detection Theory, this is the most General Gaussian Detection Problem:

- $\Sigma_b \neq \Sigma_t$
- $\mu_b \neq \mu_t$

Matched Filter (MF)

The case of **Equal Covariance** Matrices (which is most often assumed)
- $\Sigma_b = \Sigma_t$
- $\mu_b \neq \mu_t$

In the event that the target and background classes have the same (or pooled) covariance, $\boldsymbol{\Sigma}_t = \boldsymbol{\Sigma}_b = \boldsymbol{\Sigma}$, the QD becomes linear in form and reduces to

$$y = T_{MF}(\mathbf{x}) = (\boldsymbol{\mu}_t - \boldsymbol{\mu}_b)^T \boldsymbol{\Sigma}^{-1} \mathbf{x}.$$

$\geq \eta \Rightarrow$ target
$< \eta \Rightarrow$ no target

This detector is known as the *matched filter*

Often the matched filter (MF) is written in terms of the operator, **h**.

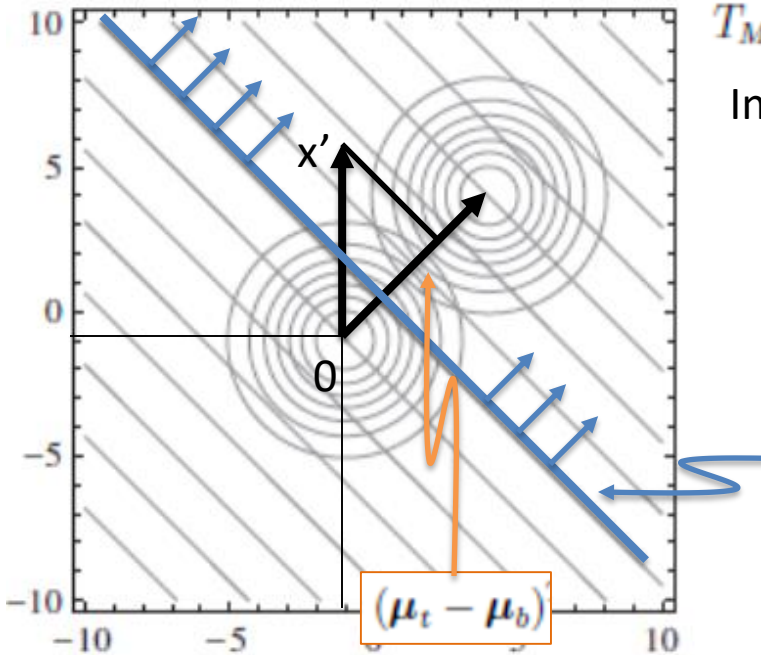
$$y = \boldsymbol{h}^T \boldsymbol{x}$$

$$\boldsymbol{h} = \boldsymbol{\Sigma}^{-1}(\boldsymbol{\mu}_t - \boldsymbol{\mu}_b)$$

Special Case of MF: *Spherical Covariance*

The case of **Equal Covariance** Matrices (and mean-centered)

- $\Sigma_b = \Sigma_t = \sigma^2\mathbf{I}$
  - (Diagonal (i.e., de-correlated) and the variance IS the same on the diagonal for every band. Hence the data IS round)
- $\mu_b \neq \mu_t$



$$T_{MF}(\mathbf{x}) = (\boldsymbol{\mu}_t - \boldsymbol{\mu}_b)^T \boldsymbol{\Sigma}^{-1}\mathbf{x}.$$

In de-meaned space, $\mu_b = 0$

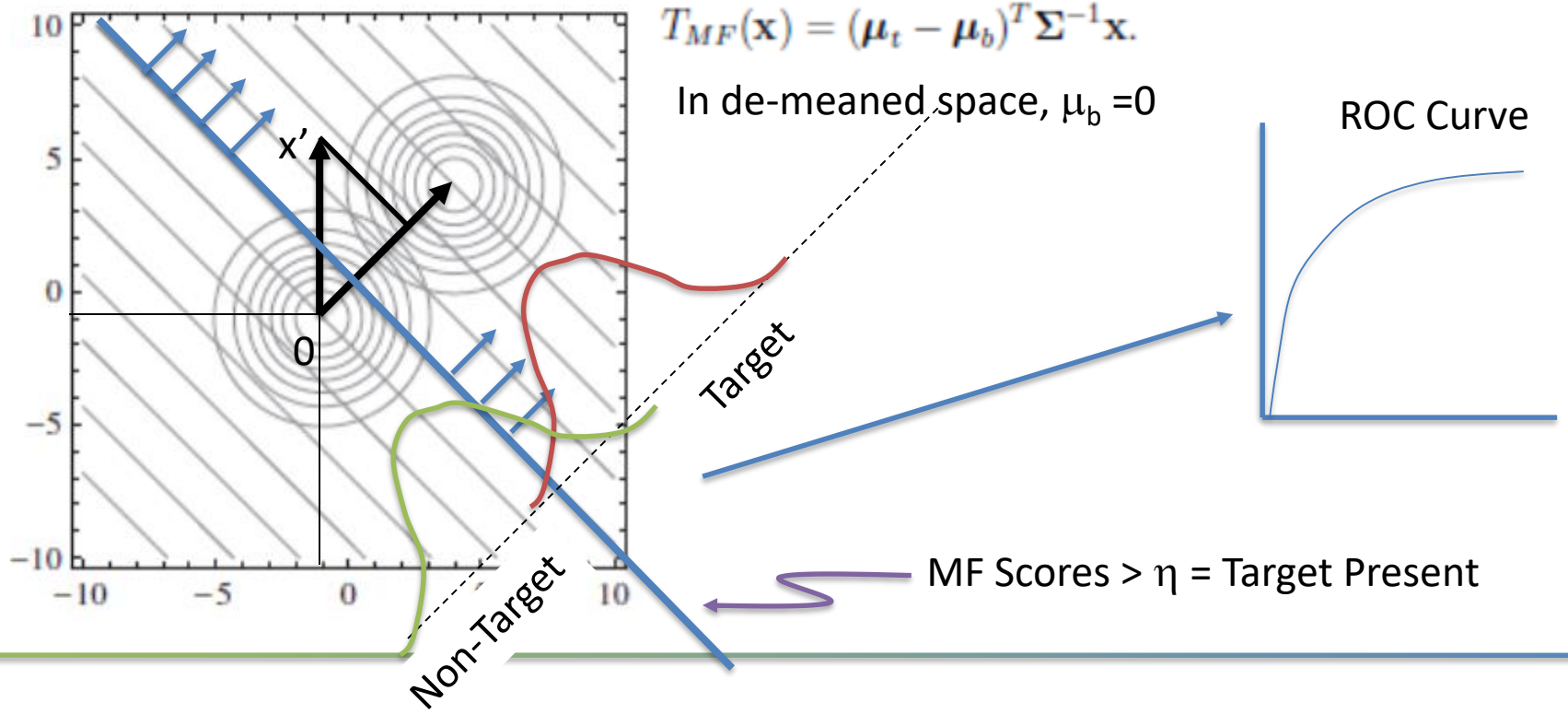
MF Scores > η = Target Present

Equal "Spherical" Covariance's (We'll assume mean-centered)

Special Case of MF: *Spherical Covariance*

The case of **Equal Covariance** Matrices (and mean-centered)

- $\Sigma_b = \Sigma_t = \sigma^2\mathbf{I}$
  - (Diagonal (i.e., de-correlated) and the variance IS the same on the diagonal for every band. Hence the data IS round)
- $\mu_b \neq \mu_t$

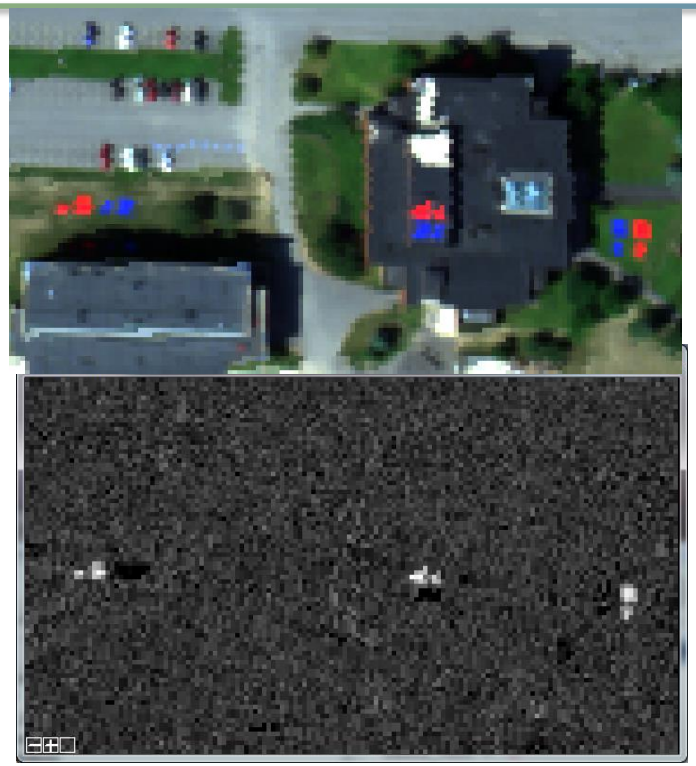


MF Results

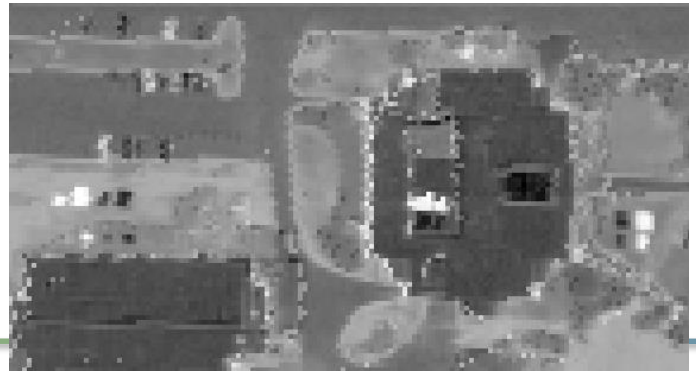
Looks like MF (and having an understanding of the background) suppresses background much more than SAM

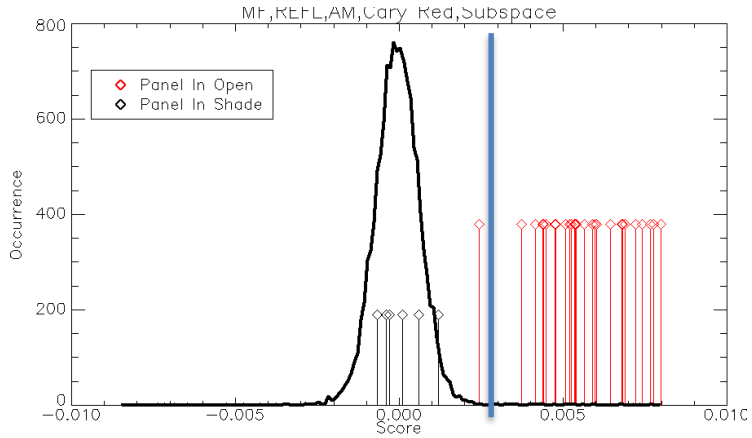
But what about those shadowed pixels ??

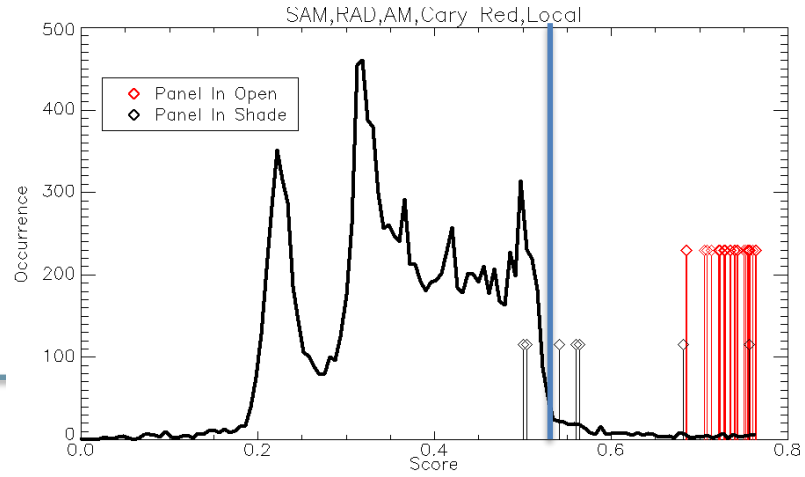
MF



SAM





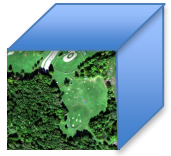


Understanding the Physics of the Light Interactions

- Another approach tries to help these detectors perform more optimally by understanding the physics of the problem.

- i.e., understand, per-pixel, how light is interacting with the materials.

But first...What Could Possibly Go Wrong?



Collected Raw Data

- Radiometric Cal
- Spectral Cal
- Dark Noise Removal
- Bad Element Map
- Saturated Pixel Map

- Geometric Processing (*i.e.*, Geo- or Ortho-rectify)

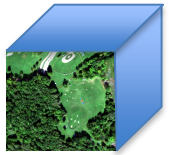
(might add spectral info)

Atmospheric Compensation using in-scene or Physical Models

(or)

Processing of Reflectance Signature to Radiance

Reflectance / Radiance data used as input to **Detection Algorithm**



-ASD
-SVC
BRDF ?

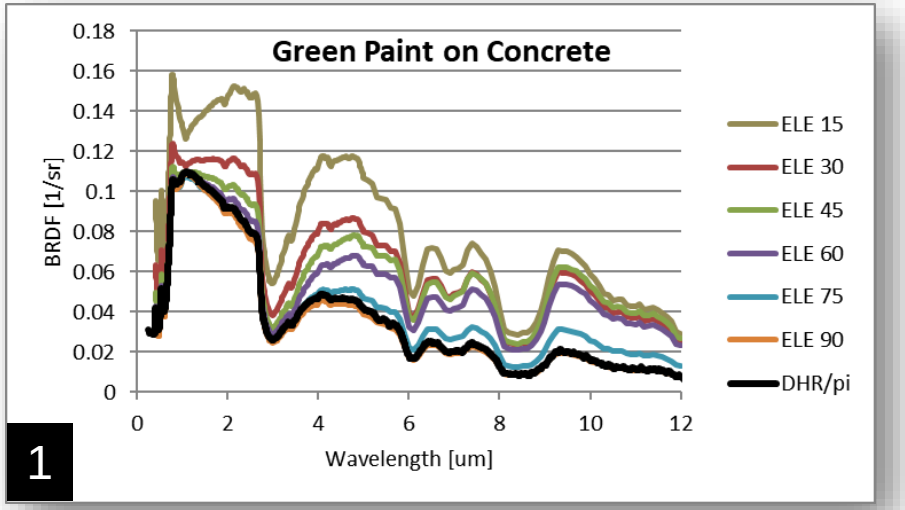
Spectral Radiance

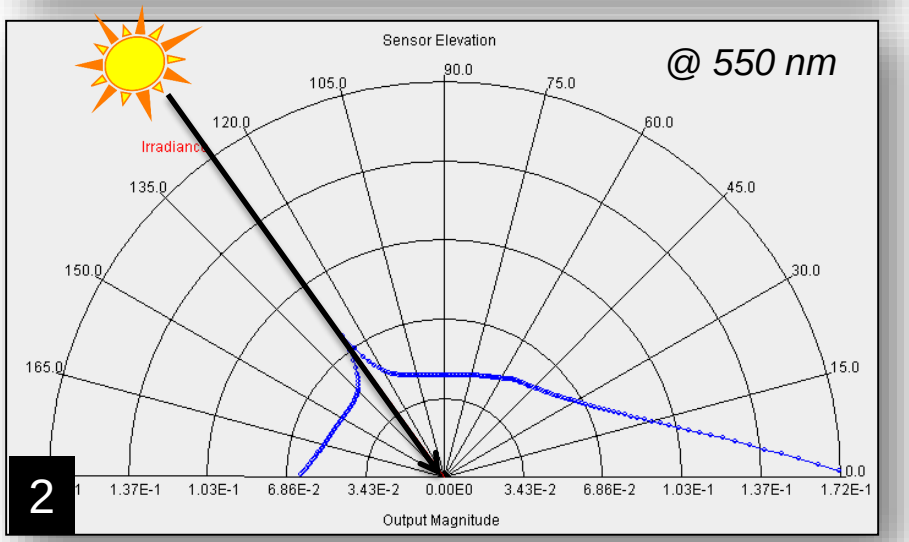
Halon Spectrolon

Measurements of reference target signature

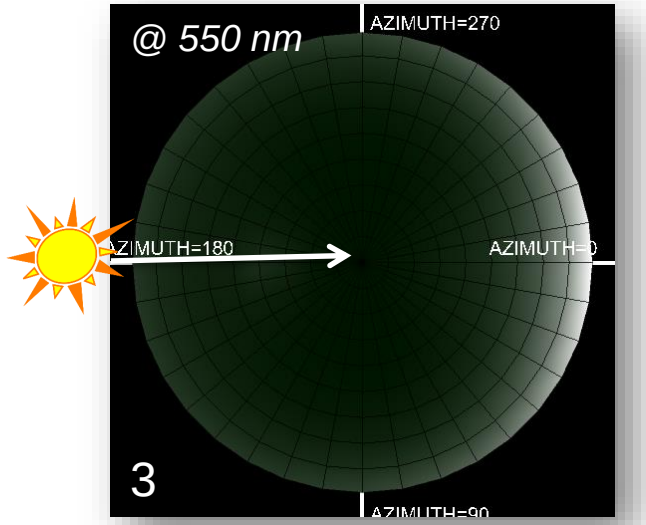
- *End to end uncertainty analysis*

Target Detection and BRDF



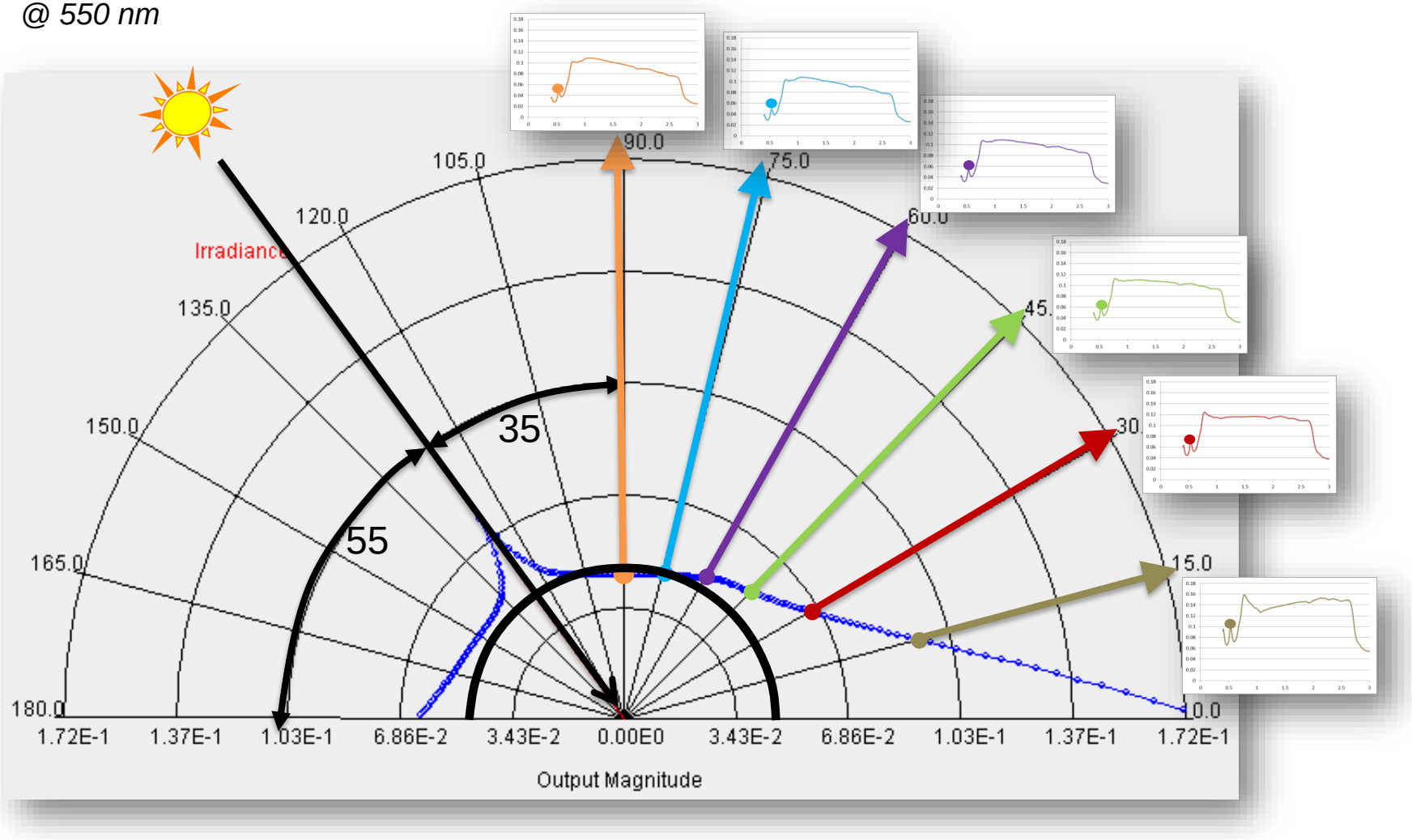


1. BRDF as a function of wavelength
2. BRDF angular magnitude at 550nm
3. 2D Projection of BRDF magnitude



Target Detection and BRDF

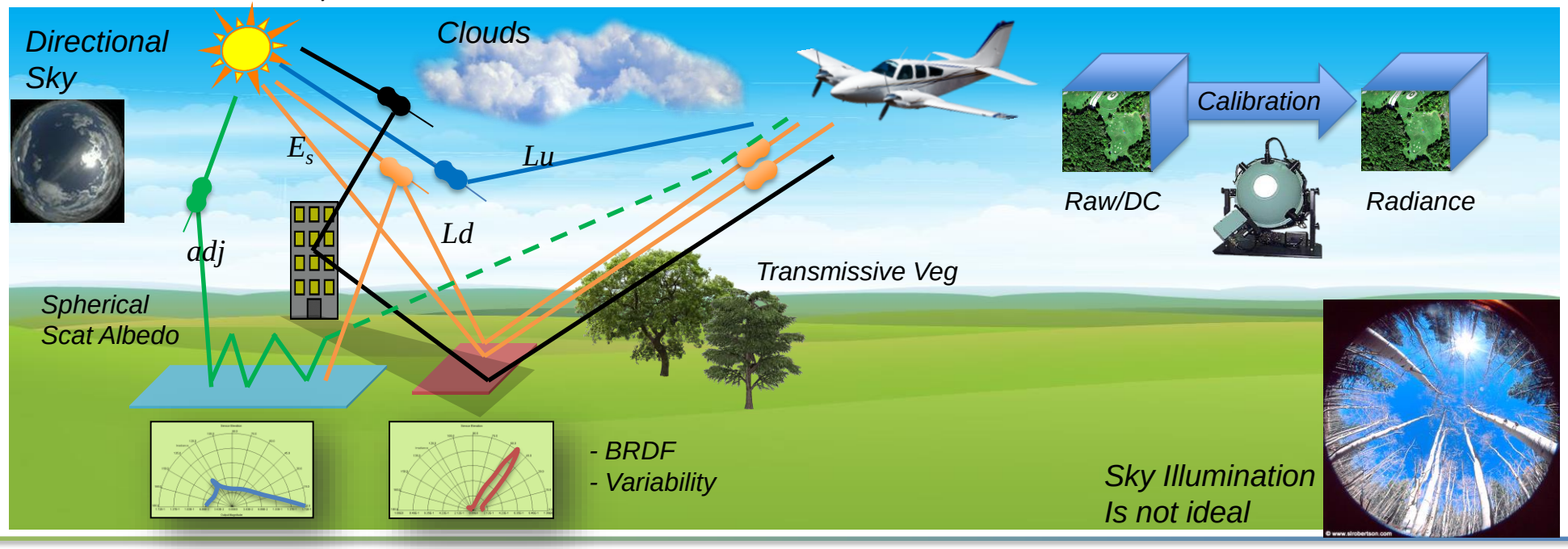
@ 550 nm



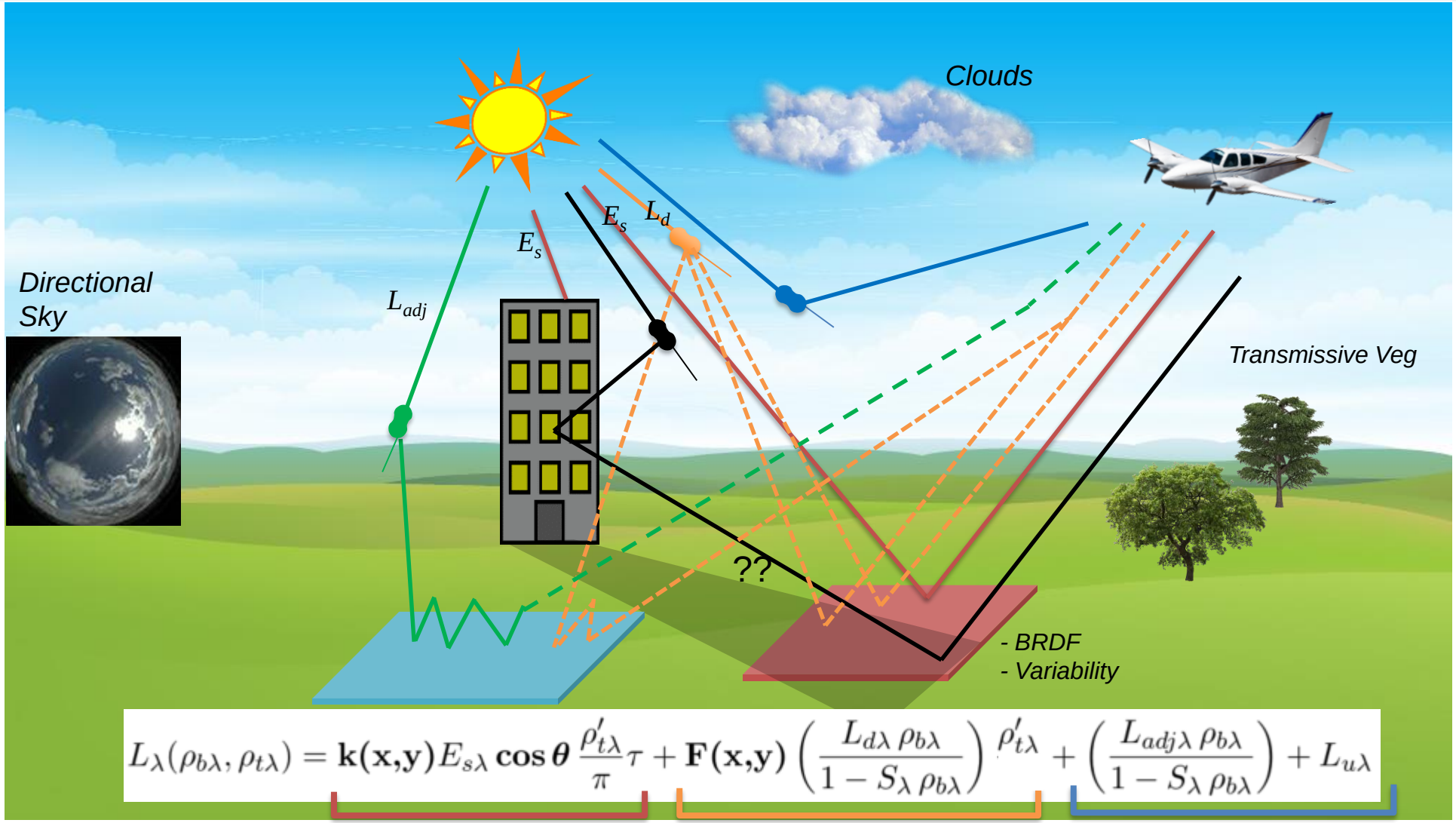
Ideal World (VIS-NIR Region)

1. Given perfectly calibrated aerial radiance data and
2. an ideal forward model that captures all interactions from Sun-Target-Sensor (including direct and indirect illumination), GSD dependency aside:

- We *should* be able to perfectly predict:
  - The ground reflectance or at-aperture radiance (regardless of location, other than being obscured)



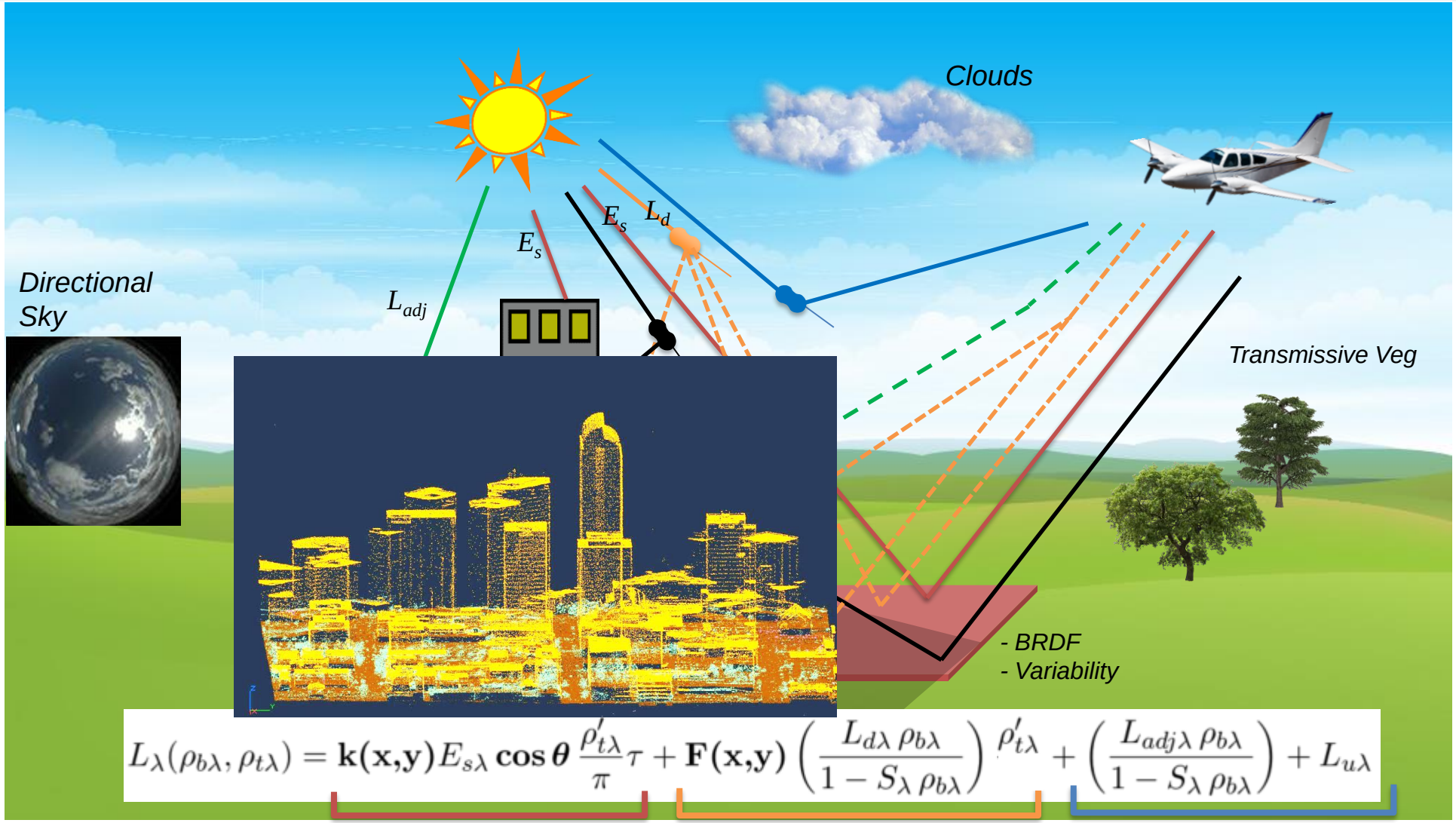
How About Illumination and Shade…



$$L_\lambda(\rho_{b\lambda}, \rho_{t\lambda}) = \mathbf{k(x,y)} E_{s\lambda} \cos\boldsymbol{\theta} \frac{\rho'_{t\lambda}}{\pi} \tau + \mathbf{F(x,y)} \left(\frac{L_{d\lambda}\, \rho_{b\lambda}}{1 - S_\lambda\, \rho_{b\lambda}} \right) \rho'_{t\lambda} + \left(\frac{L_{adj\lambda}\, \rho_{b\lambda}}{1 - S_\lambda\, \rho_{b\lambda}} \right) + L_{u\lambda}$$

$$L_\lambda(\rho_{t\lambda}, \rho_{b\lambda}) = \texttt{GRND_RFLT}(\rho_{t\lambda}, \rho_{b\lambda}) + \texttt{SOL_SCAT}(\rho_{t\lambda}, \rho_{b\lambda})$$

How About Illumination and Shade…



$$L_\lambda(\rho_{b\lambda}, \rho_{t\lambda}) = \mathbf{k(x,y)} E_{s\lambda} \cos\boldsymbol{\theta} \frac{\rho'_{t\lambda}}{\pi} \tau + \mathbf{F(x,y)} \left(\frac{L_{d\lambda}\, \rho_{b\lambda}}{1 - S_\lambda\, \rho_{b\lambda}} \right) \rho'_{t\lambda} + \left(\frac{L_{adj\lambda}\, \rho_{b\lambda}}{1 - S_\lambda\, \rho_{b\lambda}} \right) + L_{u\lambda}$$

$$L_\lambda(\rho_{t\lambda}, \rho_{b\lambda}) = \texttt{GRND_RFLT}(\rho_{t\lambda}, \rho_{b\lambda}) + \texttt{SOL_SCAT}(\rho_{t\lambda}, \rho_{b\lambda})$$

Topographic LADAR

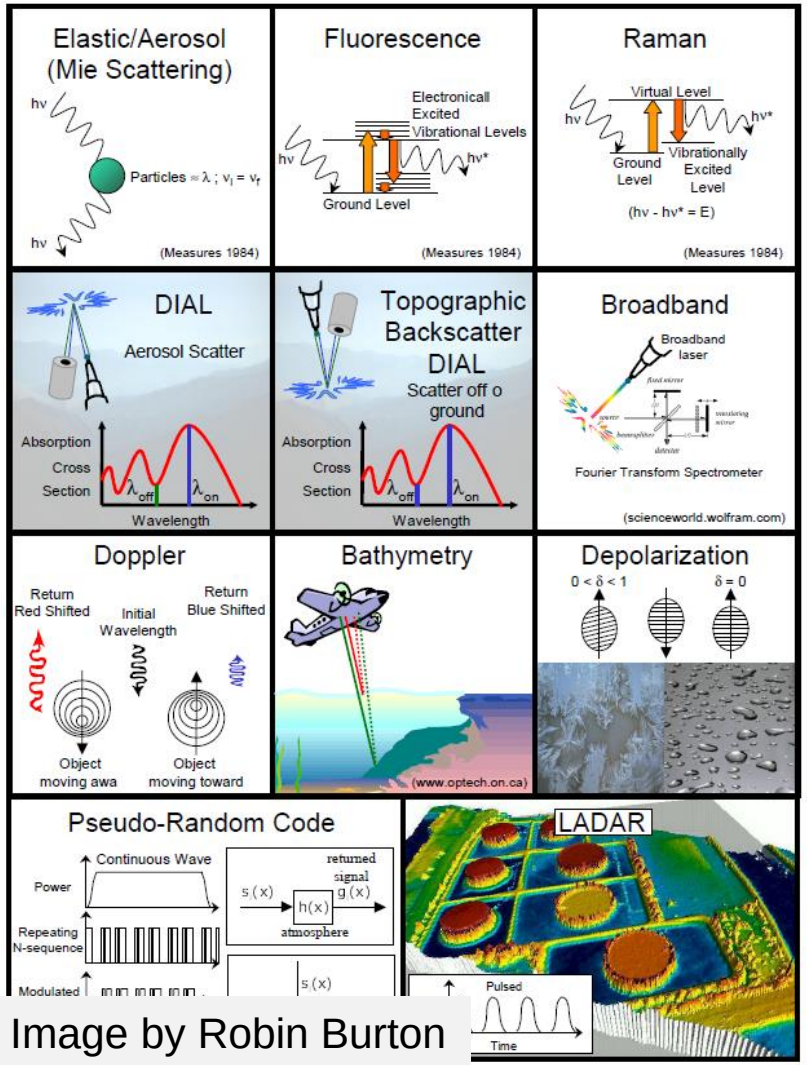
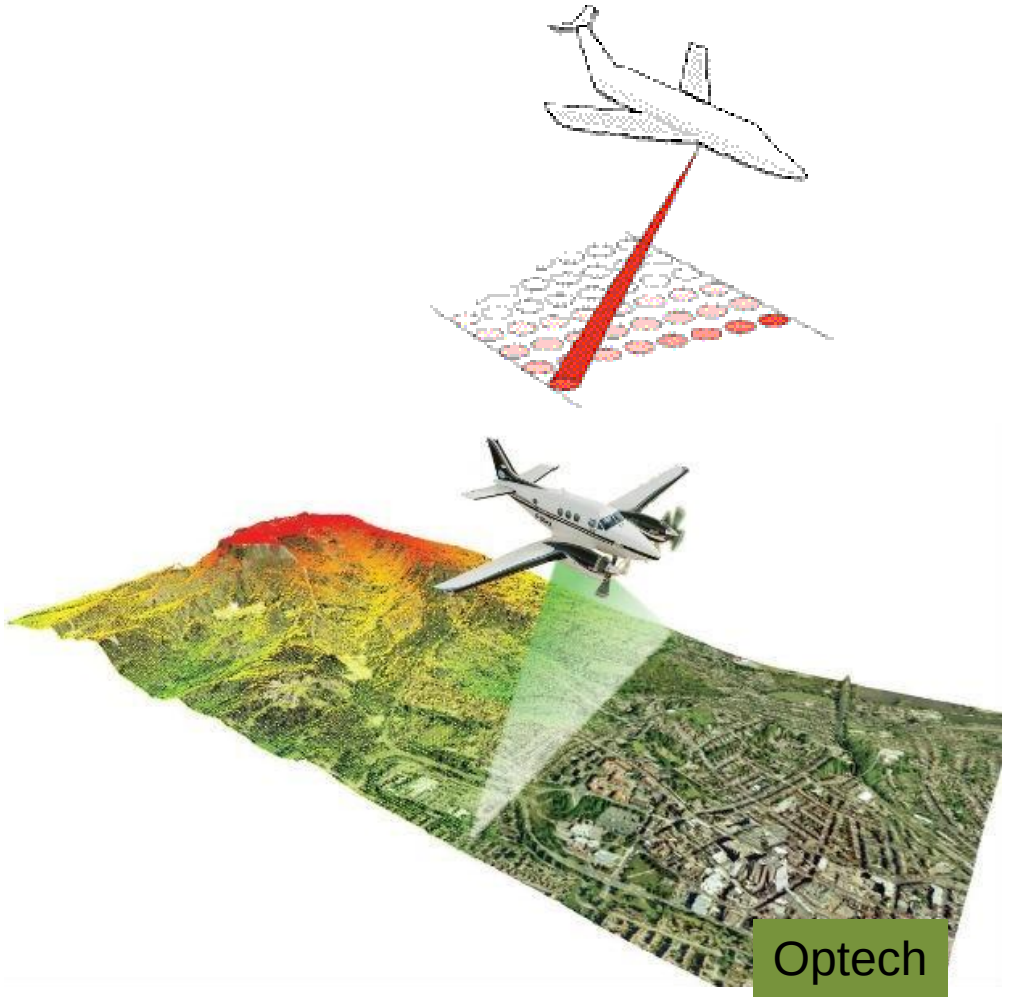
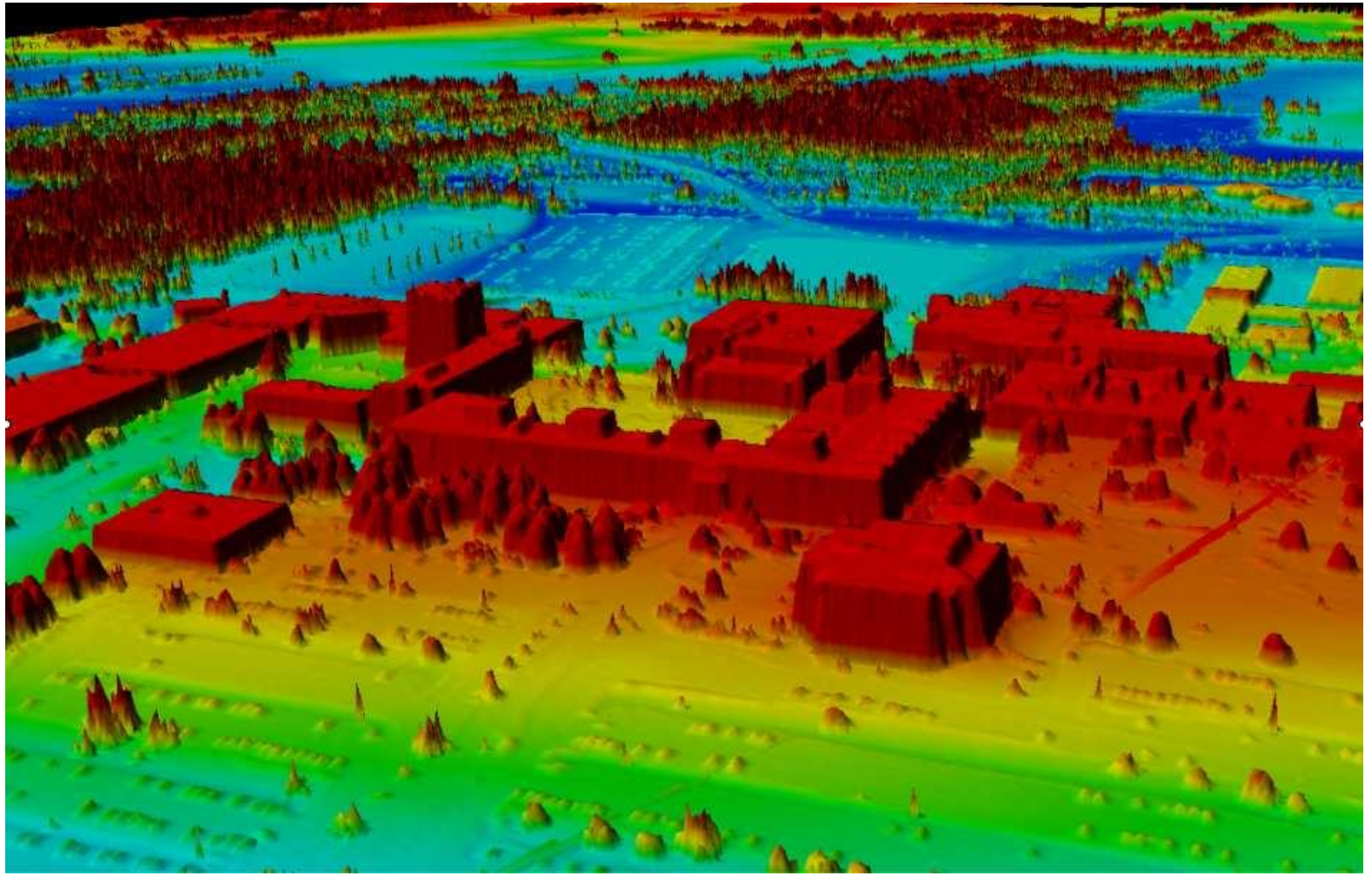


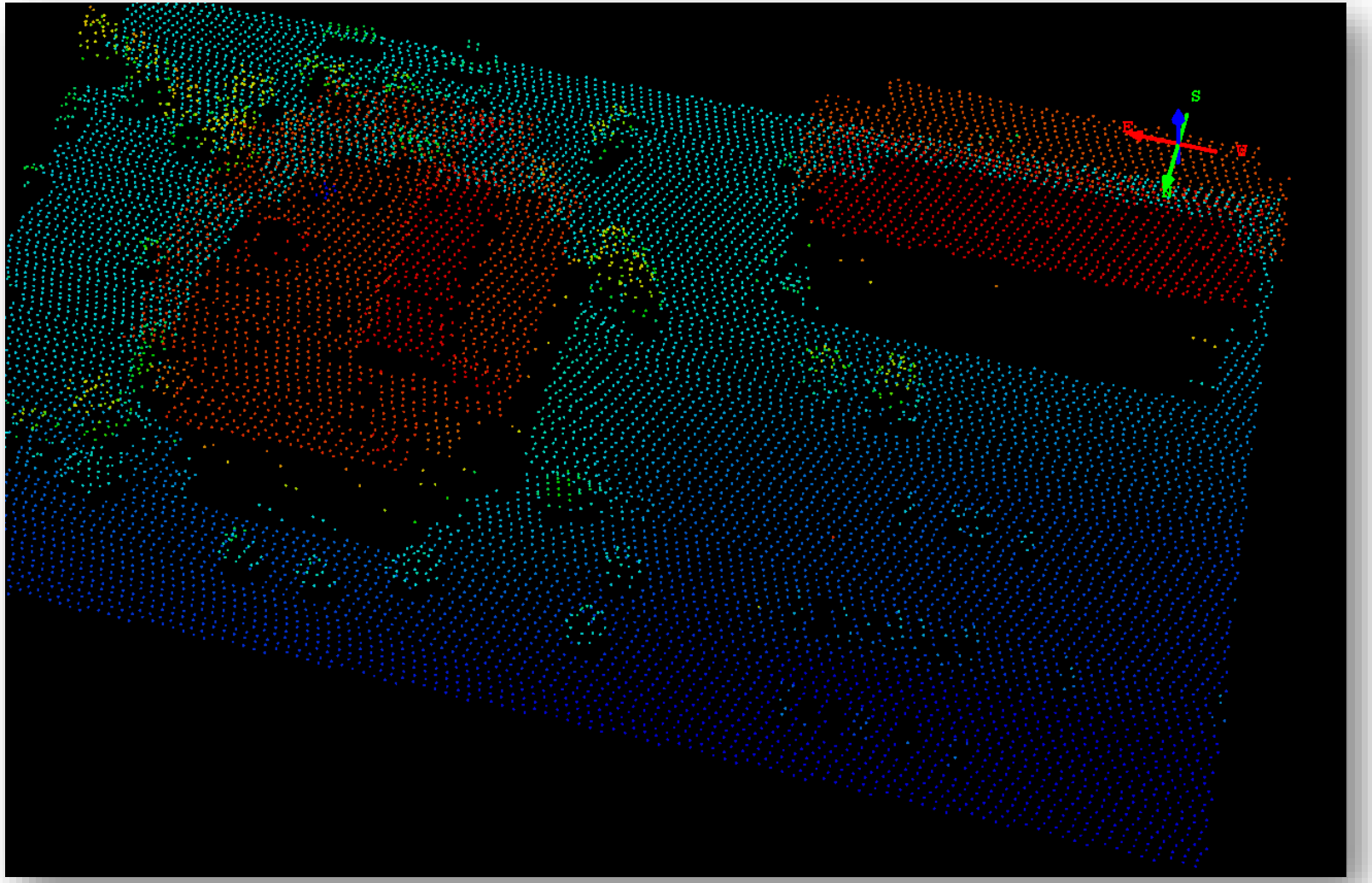
Image by Robin Burton



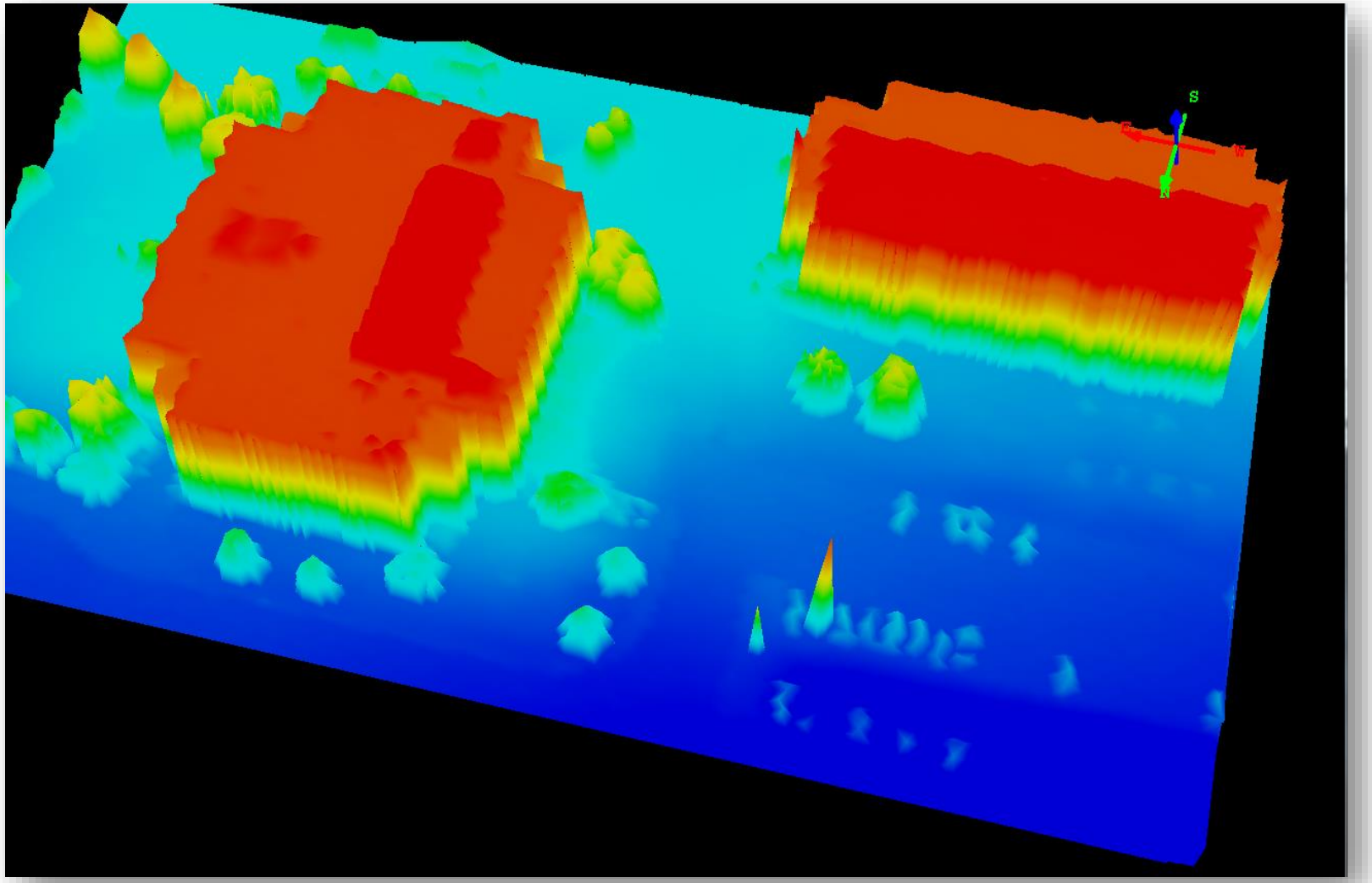
Topographic LADAR: RIT



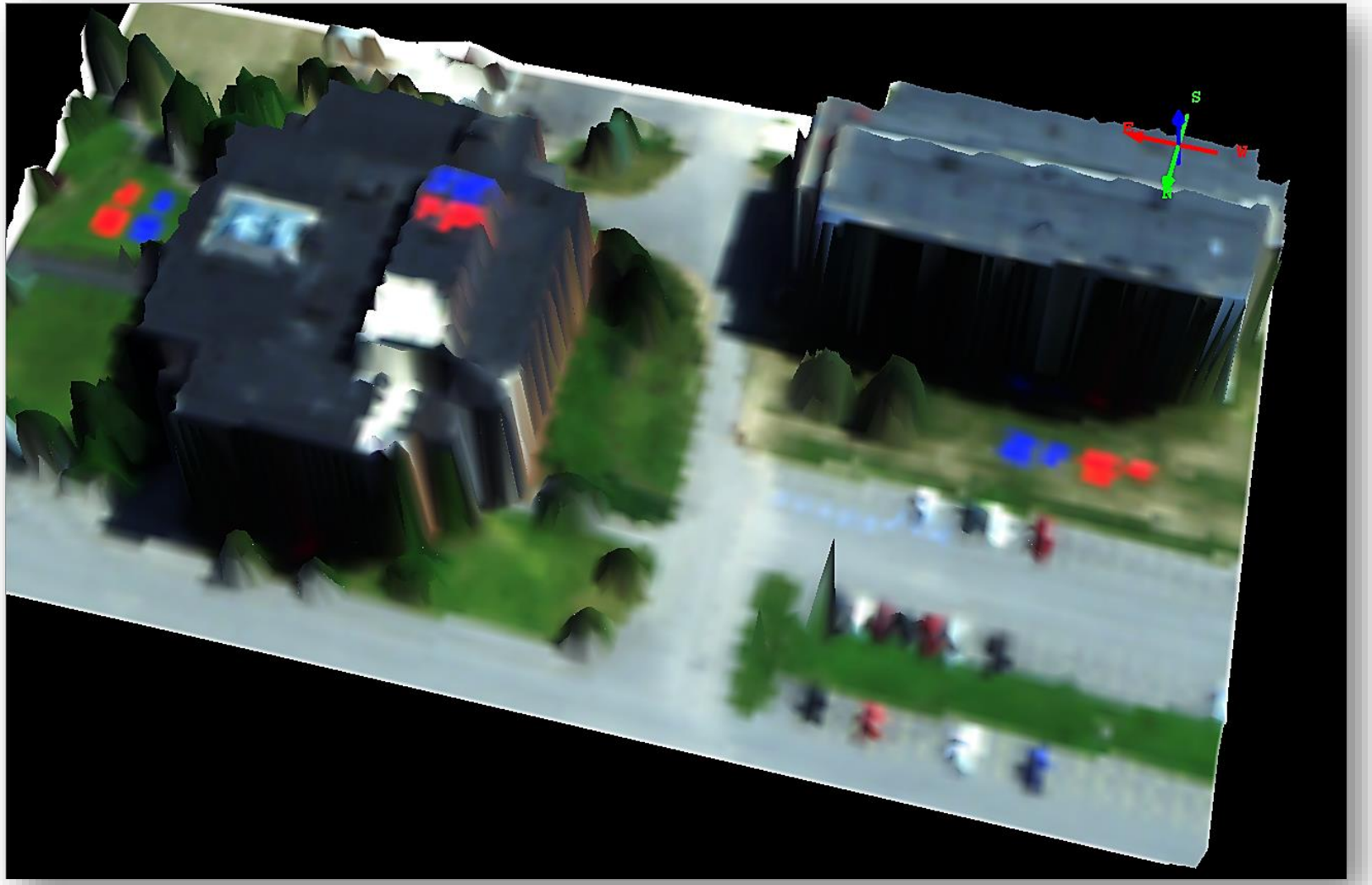
Topographic LADAR: RIT



Topographic LADAR: RIT

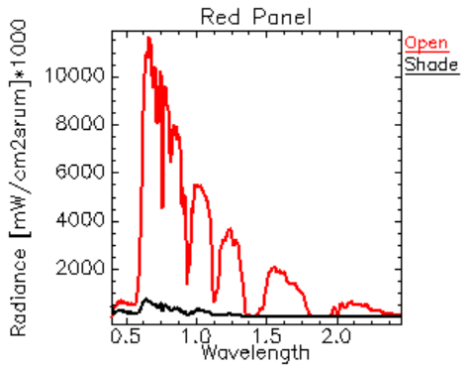


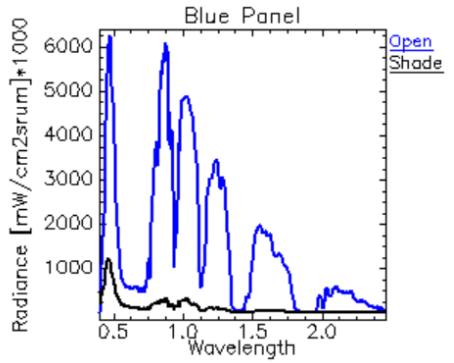
Topographic LADAR + RGB: RIT



Illumination Problem Statement

Lambertian Panel Assumption

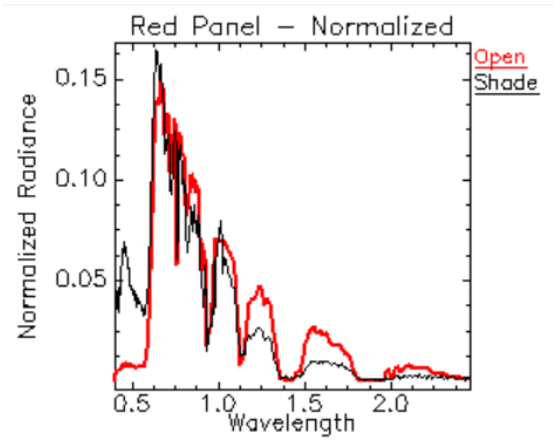


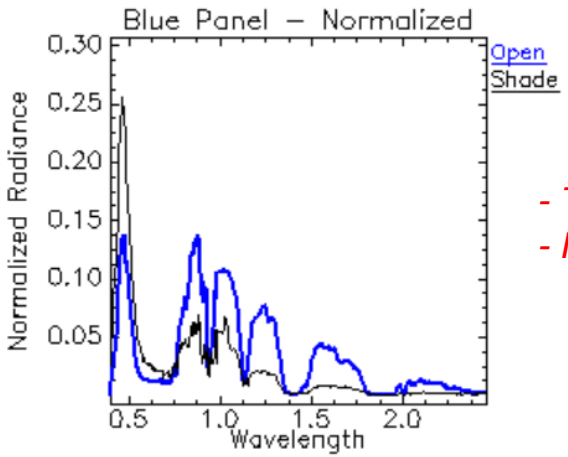


Are the Panels Actually Different in Open vs. Shade?

- Compute *L2-Norm* or *Euclidian Norm* or Simply "*Magnitude*"
- Normalize Spectra by the Norm

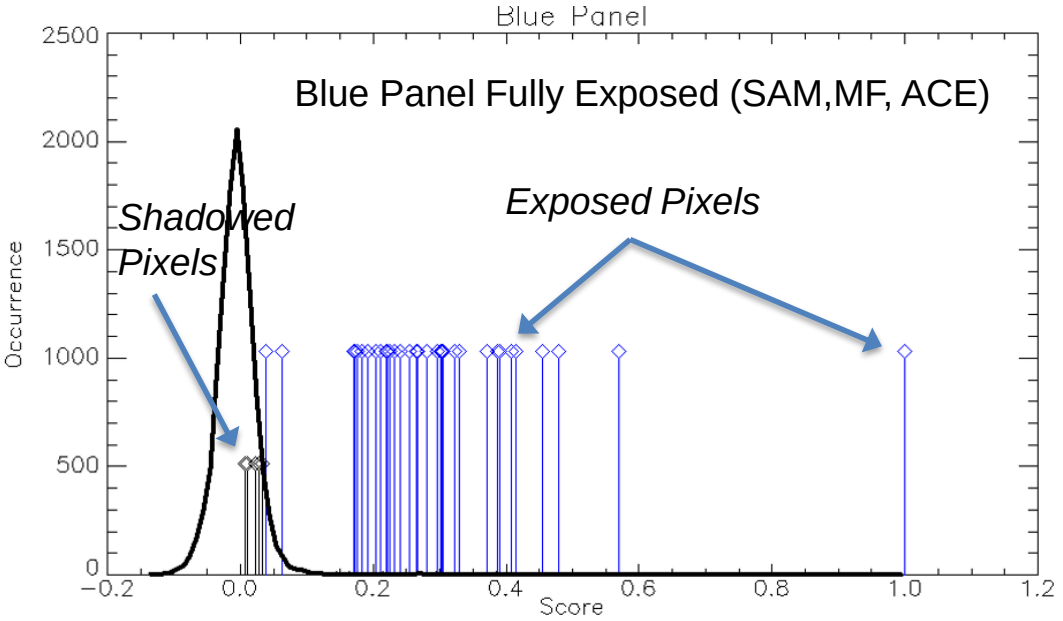
$$|\mathbf{x}|_2 = |\mathbf{x}| = \sqrt{x_1^2 + x_2^2 + \ldots + x_n^2}$$

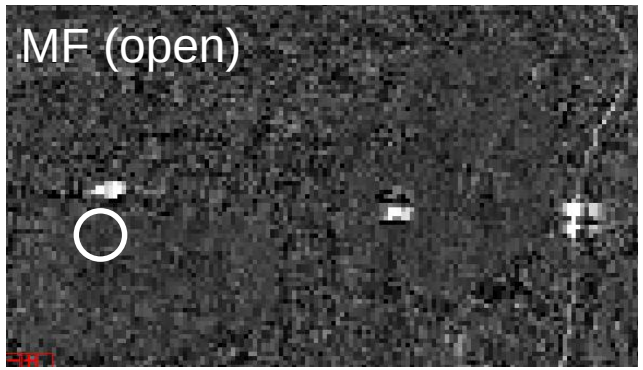


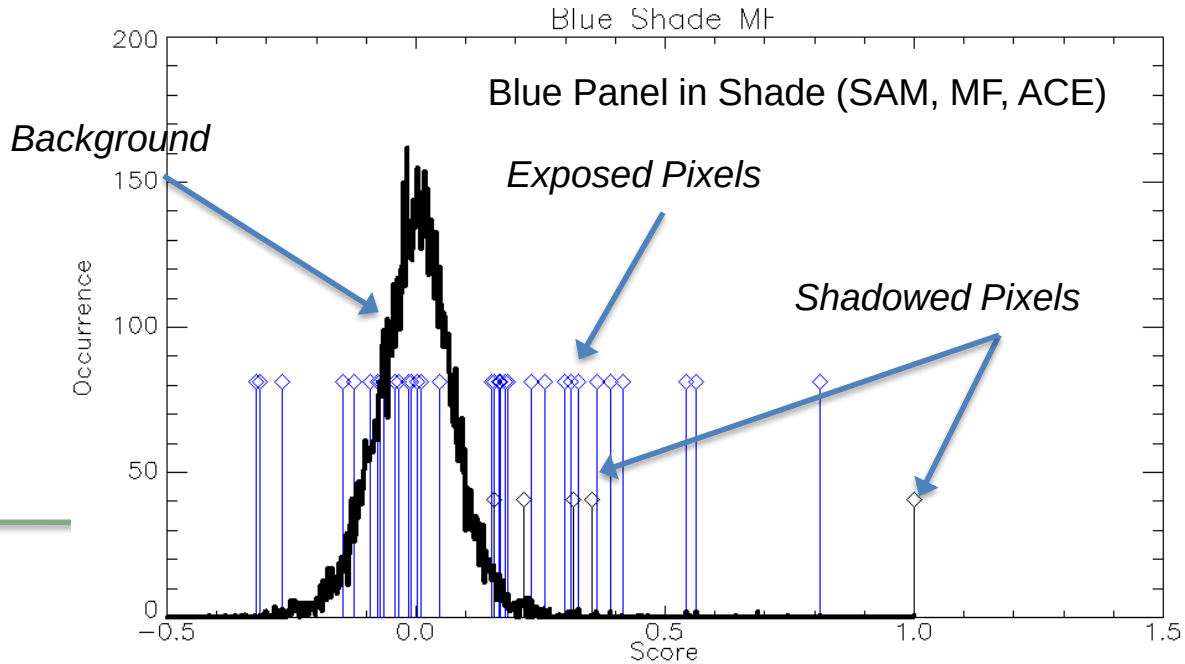


- They Seem to be Spectrally Different.
- It is not just a magnitude Difference

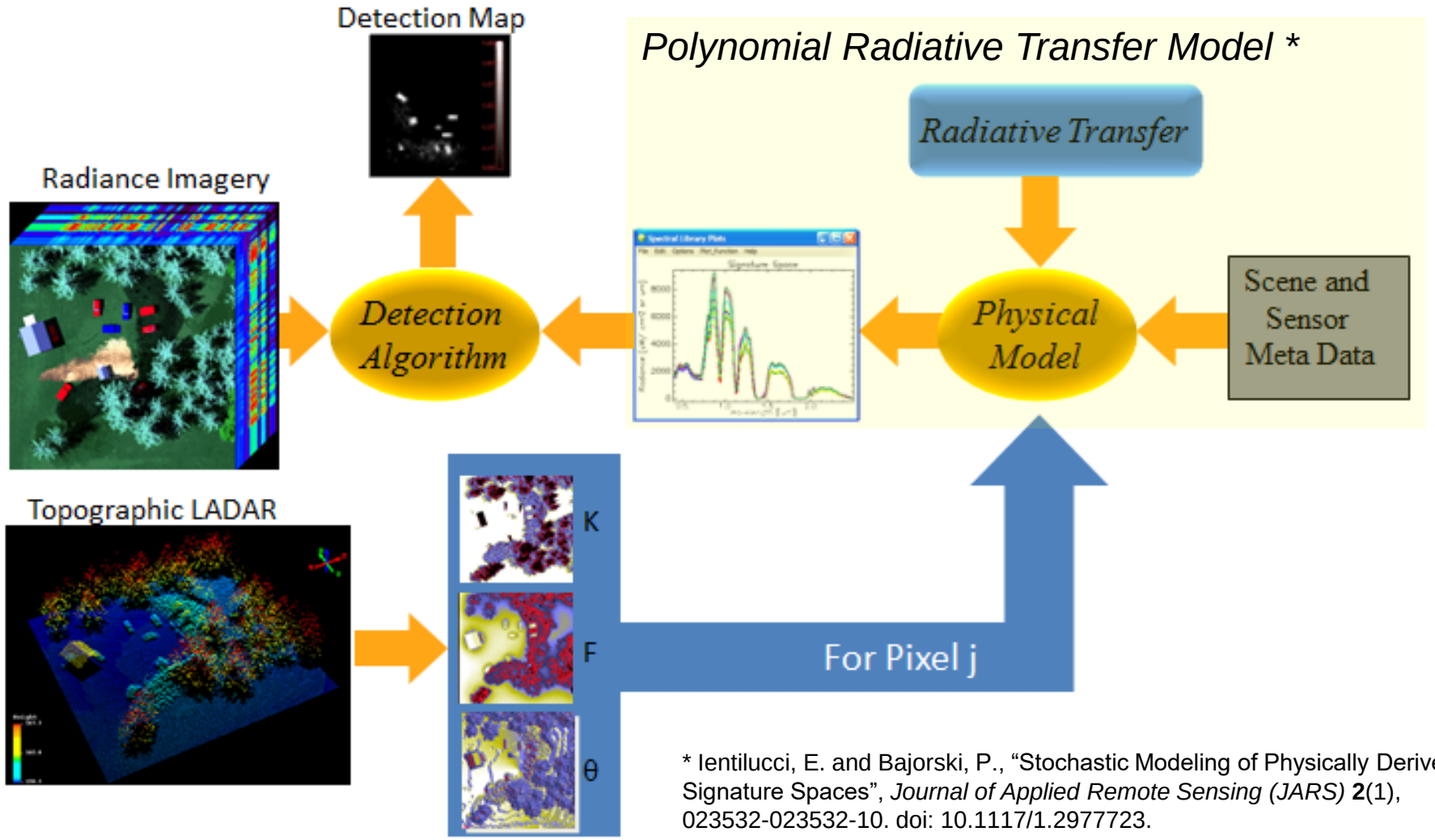
Detection Experiment Using in-Scene Pixels







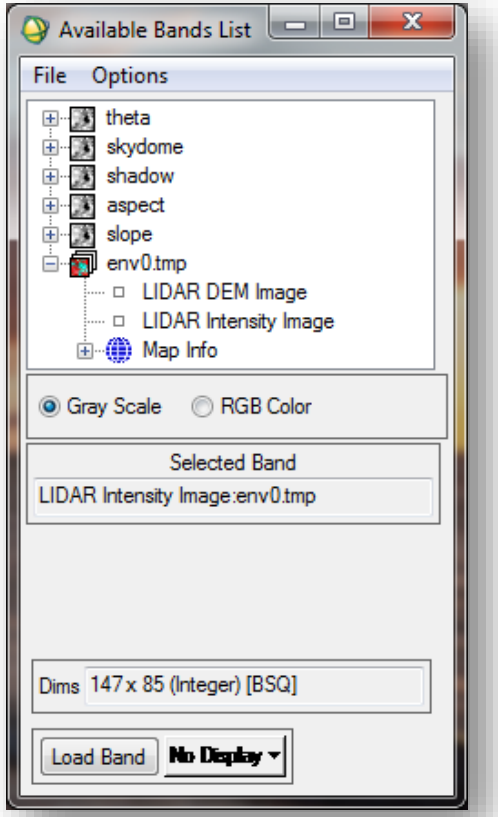
Automated LiDAR Augmented Method: “Local Approach”



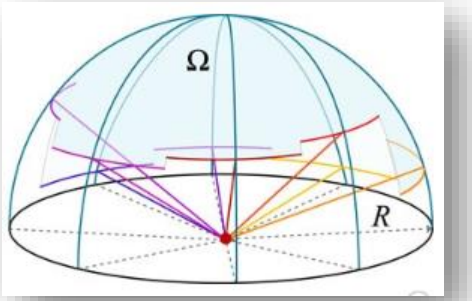
* Ientilucci, E. and Bajorski, P., “Stochastic Modeling of Physically Derived Signature Spaces”, *Journal of Applied Remote Sensing (JARS)* **2**(1), 023532-023532-10. doi: 10.1117/1.2977723.

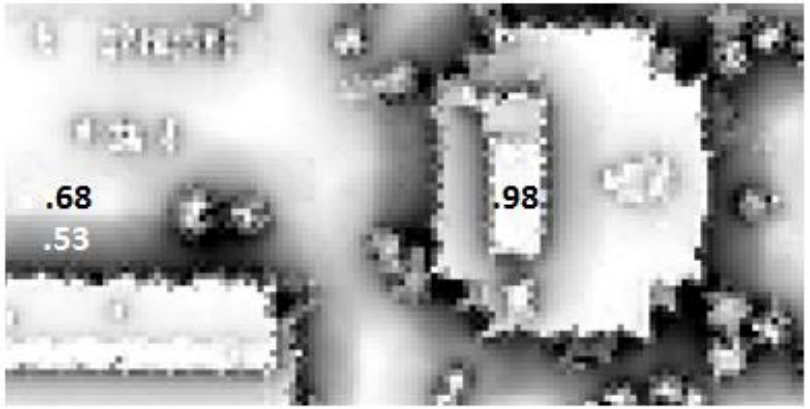
Shadow Map

Metadata comes from LiDAR header (*i.e.*, Solar position).



In-Direct Sky Loading Map





$$\Omega_i = \int_{\theta_1}^{\theta_2} \int_{\phi_1}^{\phi_2} \sin\theta d\theta d\phi$$

$$\Omega_T = \sum_{i=0}^{N-1} \Omega_i$$

$$F = \frac{\sum_{i=0}^{N-1} w_i \Omega_i}{\Omega_T}$$

Solar Angle Map

Angle between two vectors

$$\theta = \arccos\left(\frac{\mathbf{a}\cdot\mathbf{b}}{\|\mathbf{a}\|\,\|\mathbf{b}\|}\right)$$

Angle between two unit vectors

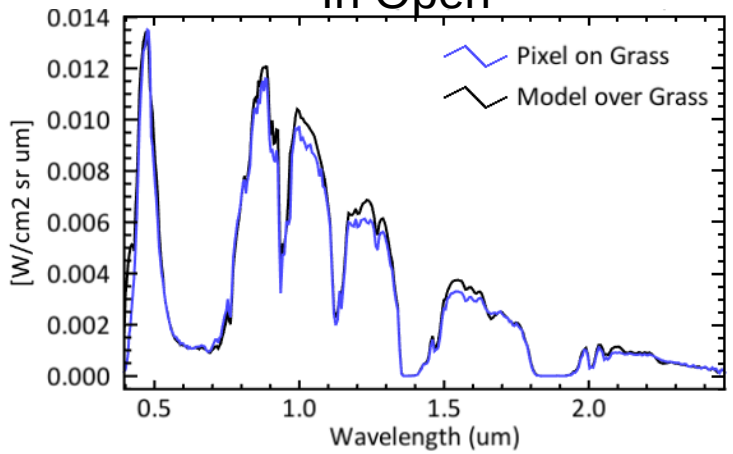
$$\theta = \arccos(\hat{\boldsymbol{a}}\cdot\hat{\boldsymbol{b}})$$

a = unit vector towards sun
b = unit normal vector of surface at pixel “i”

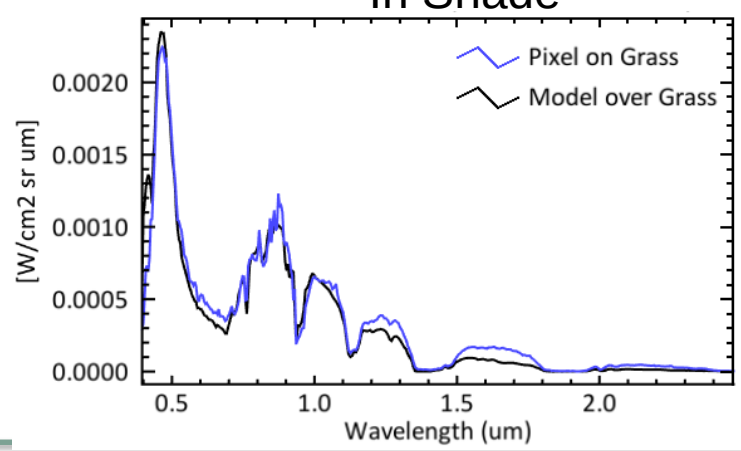
$$\begin{aligned} x &= r\,\cos\phi\,\sin\theta \\ y &= r\,\sin\phi\,\sin\theta \\ z &= r\,\cos\theta \end{aligned}$$

Map Values in Blue Panel Region

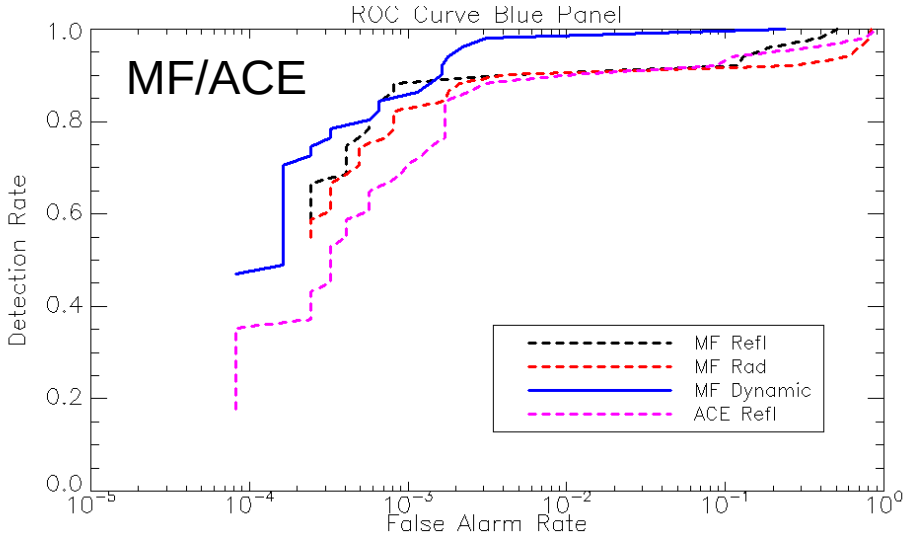
In Open



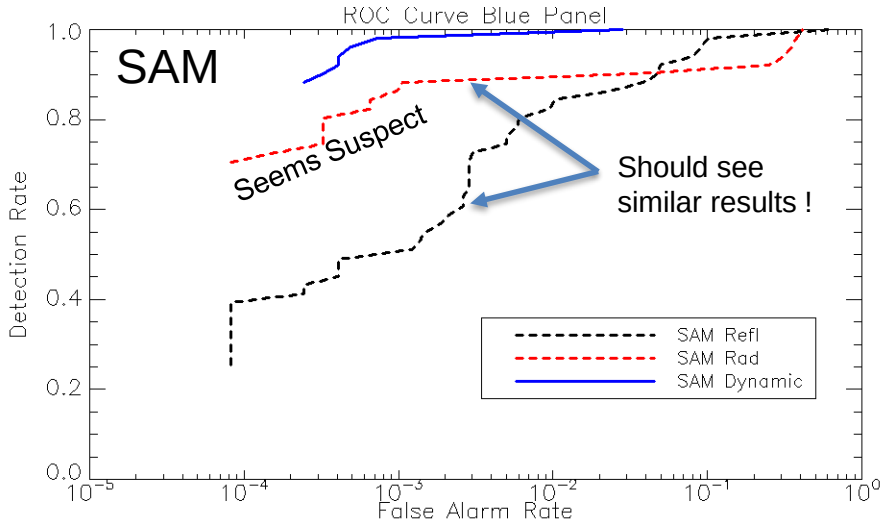
In Shade



Results of Physically Modeling Blue Panel



- MF (ATCOR Reflectance Data)
- MF (Radiance Data, Model Target Radiance)
- MF Local (Radiance per pixel dynamic)
- ACE (Reflectance Data)

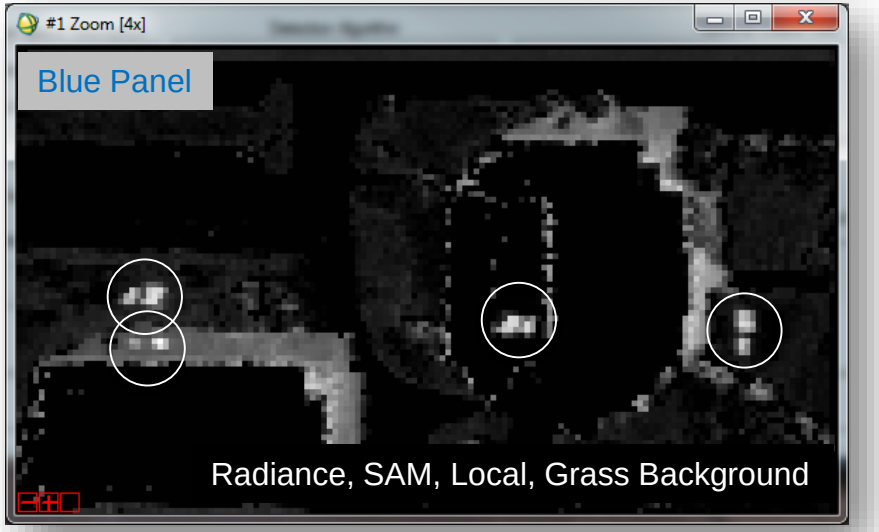


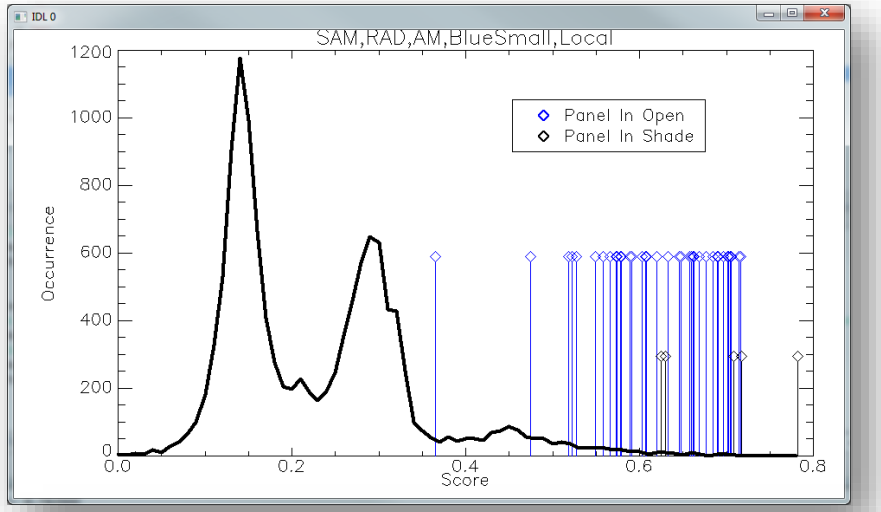
- SAM (ATCOR Reflectance Data)
- SAM (Radiance Data, Model Target Radiance)
- SAM Local (Radiance per pixel dynamic)

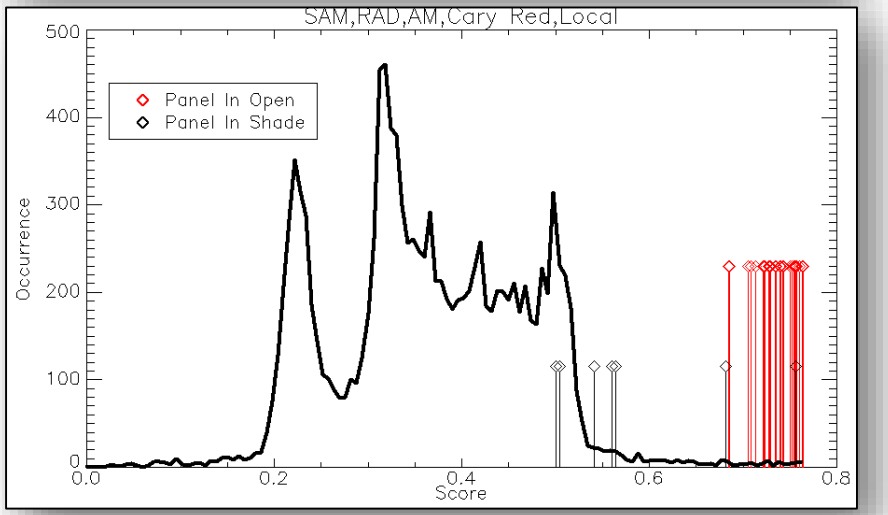
VISUAL Results of Physically Modeling Blue and Red Panels

Usage of forward modeling with LiDAR information (and the same MF / SAM detectors) improved results rather than using the detectors as is

- SAM
- MF
- MF + PBM
- SAM + PBM







Summary and Remarks

- Hyperspectral target detection has seen much growth and success since the introduction of the ACE detector.
  - As seen over the years in various (detection) publications

- The community has solved the full target pixel / uniformly illuminated pixel problem. And to some degree, the fractional target pixel problem

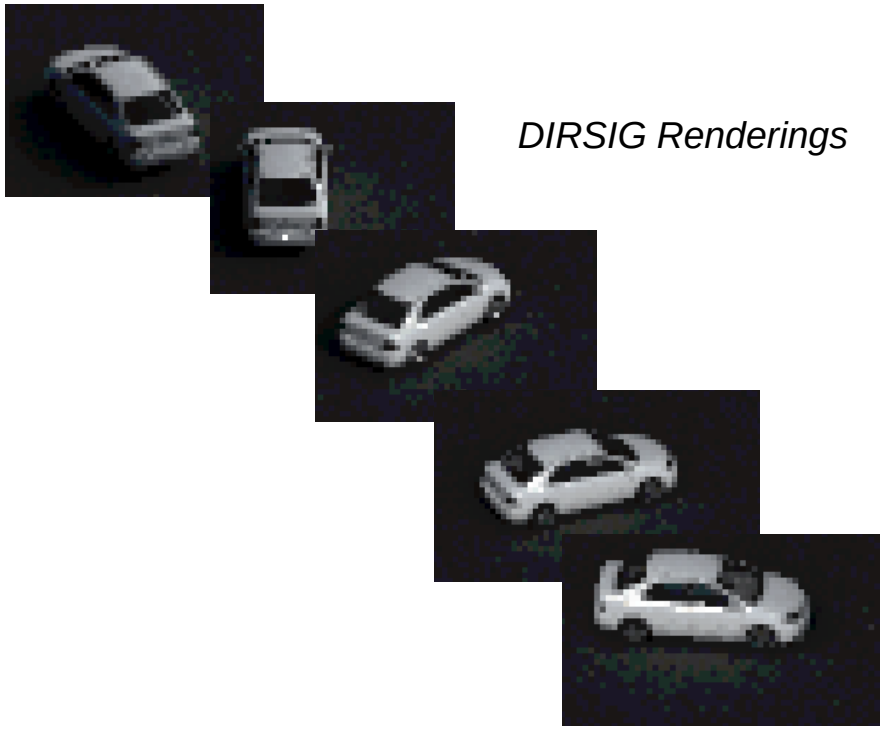
- However, there are still some gaps in our understanding of the phenomenology, data processing, and their impacts on target detection, for certain problem sets.

- Today we simply focused our energy on better understanding the phenomenology associated with illumination as a mean to 'help' the detector

- What about approaches using Machine Learning, training, Deep Learning, CNN?

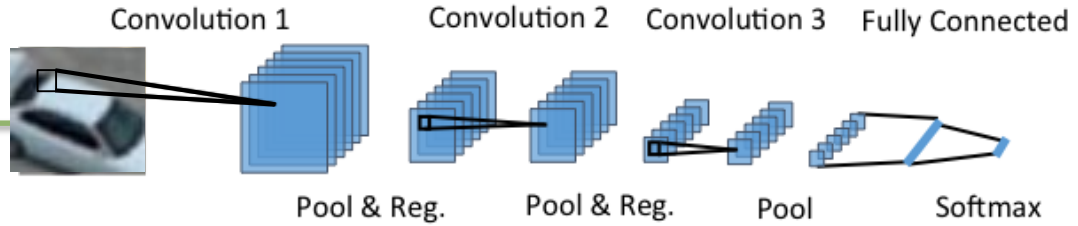
Looking Ahead: Deep Learning and Training for Detection?

- Full image simulations with ground truth
  - It is known that CNN / Deep Learning (DL) requires training
  - How would we implement DL network for target detection?
  - How would this work “Big” Remote Sensing Data?
    - Which is large, spatially (3000 x 3000) and spectrally (350 channels)
    - Pixel level ? Object level?



DIRSIG Renderings

- Training
  - Perhaps we can use DIRSIG for training?
  - Model changes in illumination, orientation, shadow, atmosphere, etc. ?
  - Hundreds of examples to be used for deep-learning and other algorithm training



Thank you

PART I
- Background on:
  - Rochester, RIT, CIS, DIRS

PART II
- DIRS Research Focus Areas
- Growth and Management of Data
- WNY GRSS

PART III
- Hyperspectral Imaging
- Target Detection w/ HSI and LiDAR
- Where do we go from hear?

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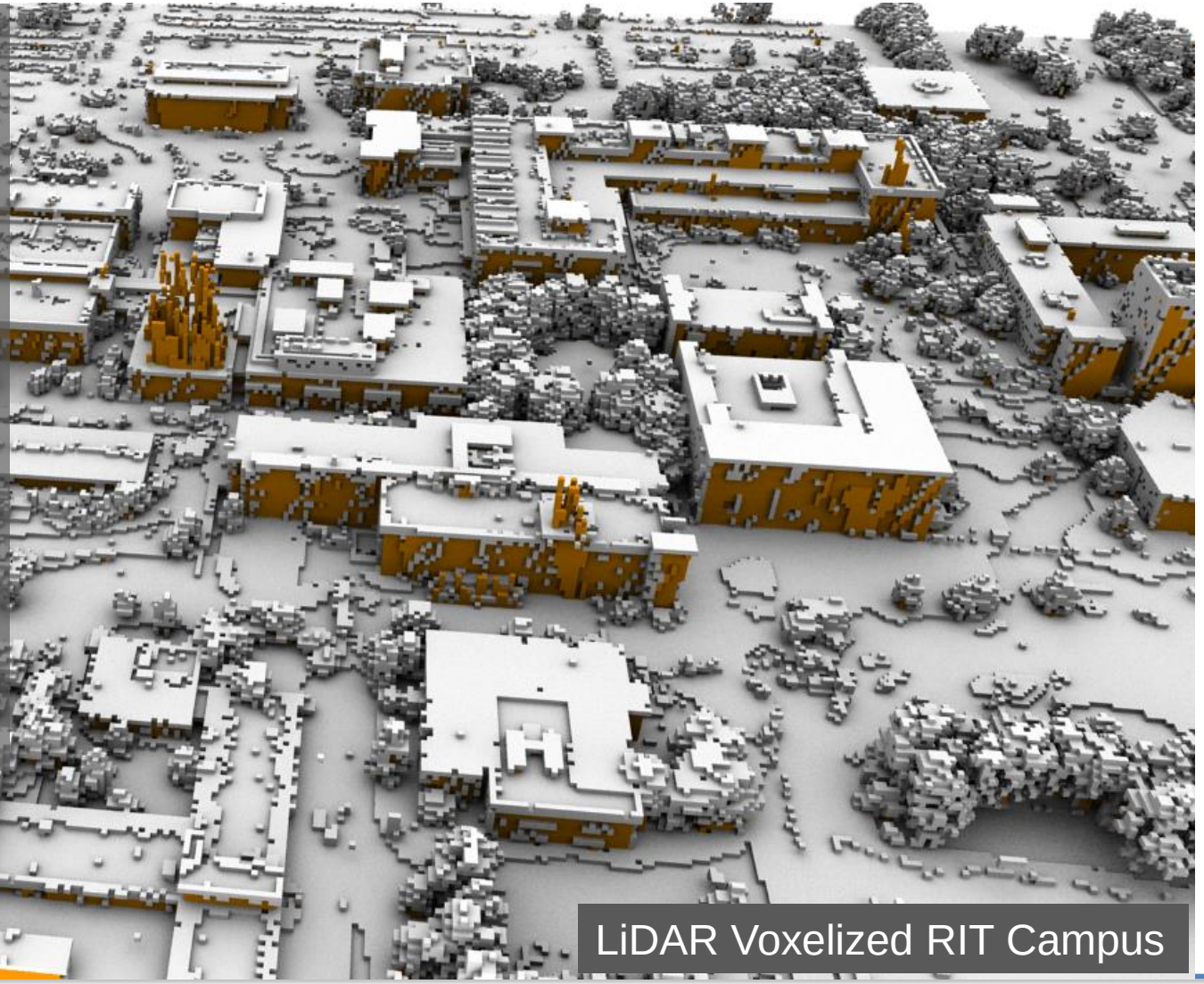

LiDAR Voxelized RIT Campus