FFI Forsvarets forskningsinstitutt

Hyperspectral systems and image processing at FFI

Trym Vegard Haavardsholm

NTNU smallsat seminar
06.09.2017

Hyperspectral activities at FFI

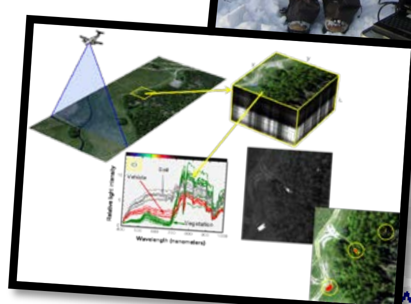
- Objective: Give scientifically based advice to the Norwegian defence regarding use of spectral imaging techniques

- FFI group embraces the hyperspectral value chain:
  - Scene phenomenology and field trials
  - Sensor technology, design and testing
  - Hyperspectral image processing
  - Application studies

- Comprehensive experience with hyperspectral imaging systems
  - VNIR, SWIR, MWIR, LWIR
  - Ground-based, airborne, satellites
  - Military applications








SYSIPHE - the world's best hyperspectral imaging system

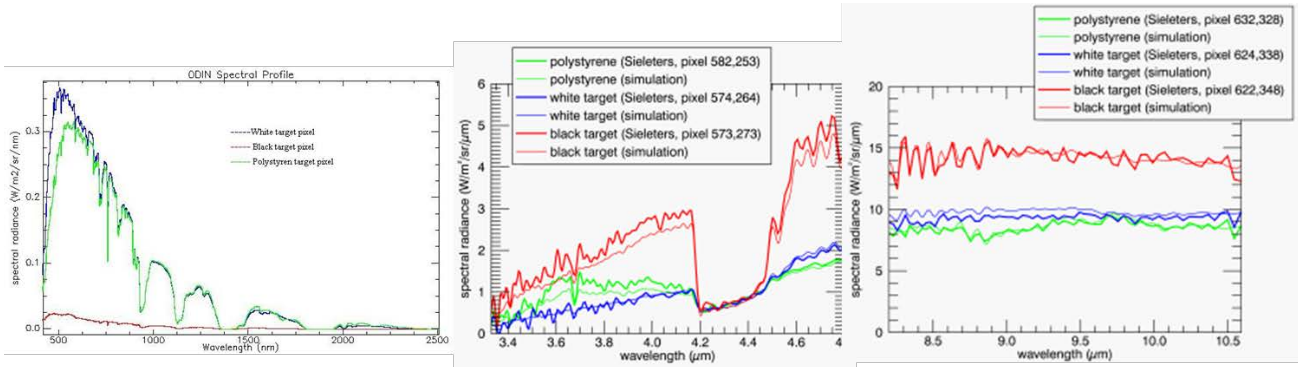
- French-Norwegian collaboration
- Covers all bands, from 0.4 to 11.8 µm
- Open to third-party users
- France: thermal IR (ONERA)
- Norway: daylight bands (NEO) +real-time processing (FFI)

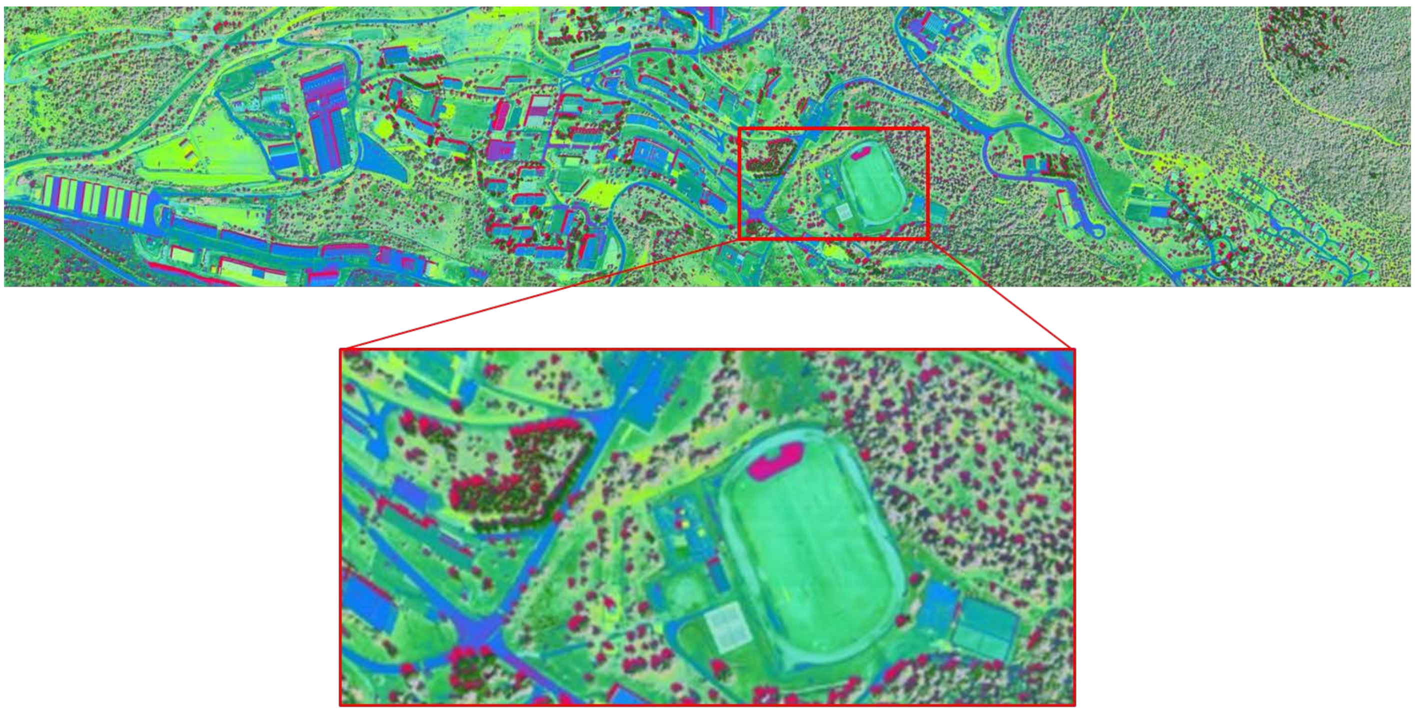
SIELETERS (France)

Odin (Norway)

Rousset-Rouviere et al, «SYSIPHE system: A state of the art airborne hyperspectral imaging system. Initial results from the first airborne campaign», Proc. SPIE 9249, 92490V, 2014

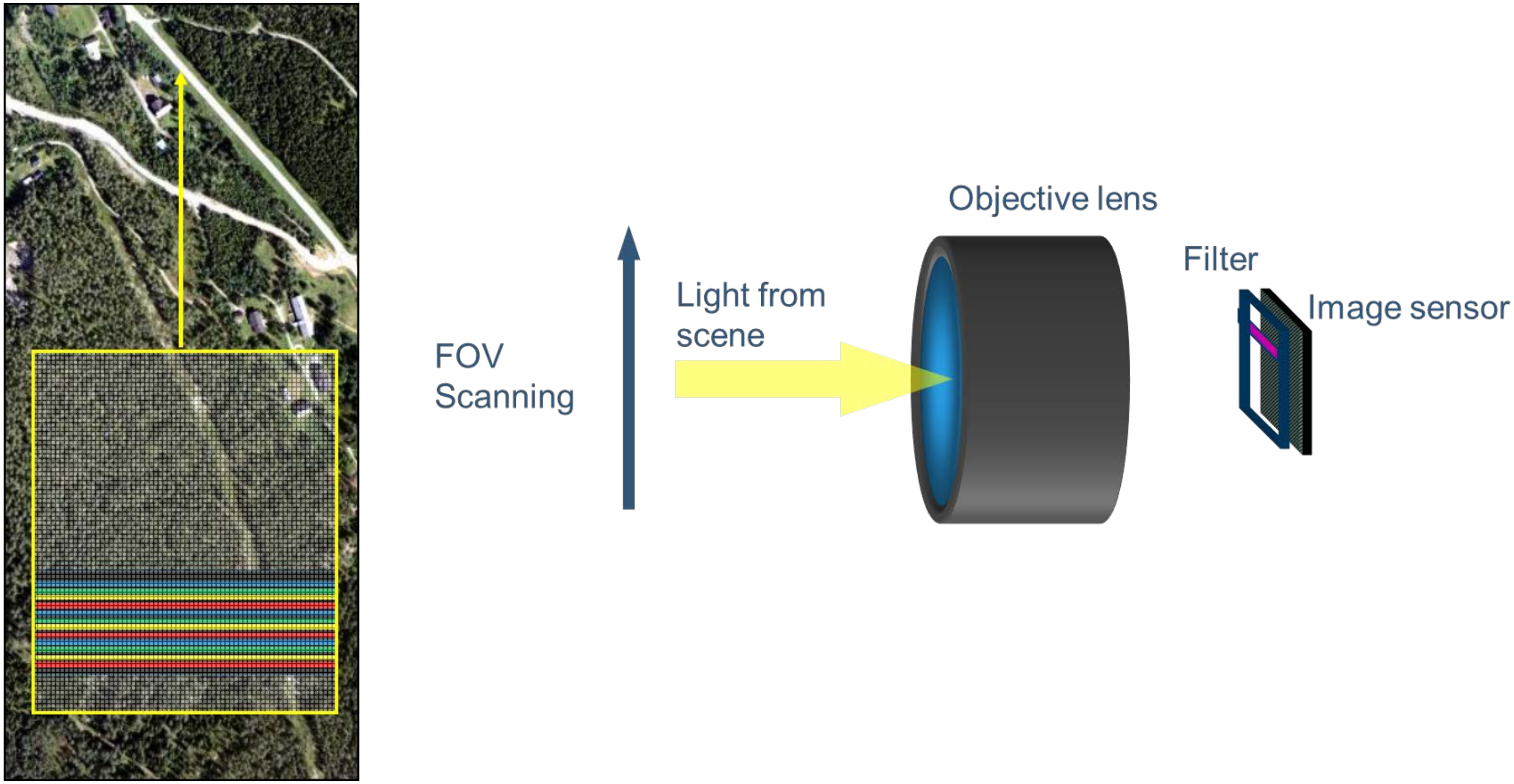
Very large wavelength range, excellent quality





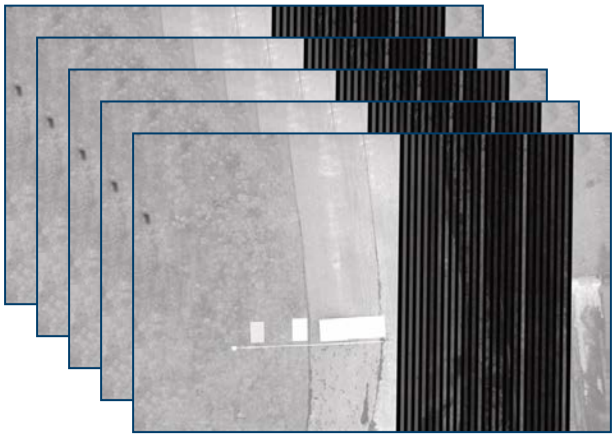
Selected principal components, 0.5 m resolution, 0.4 til 2.5 um wavelength

Compact spectral imaging concept

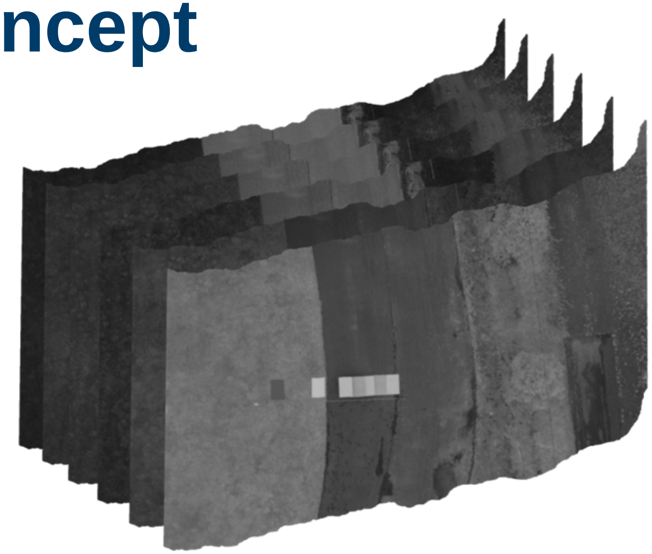


Skauli, Torkildsen, Nicolas, Opsahl, Haavardsholm, Kåsen, Rognmo: «Compact camera for multispectral and conventional imaging based on patterned filters», Applied Optics, Vol 53, Issue 13, 2014

Compact spectral imaging concept

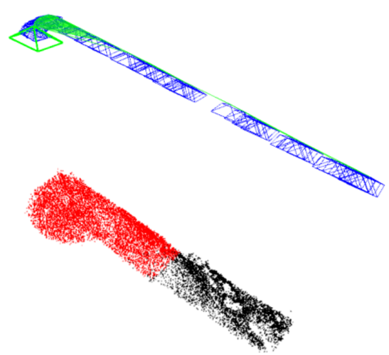


Raw image sequence

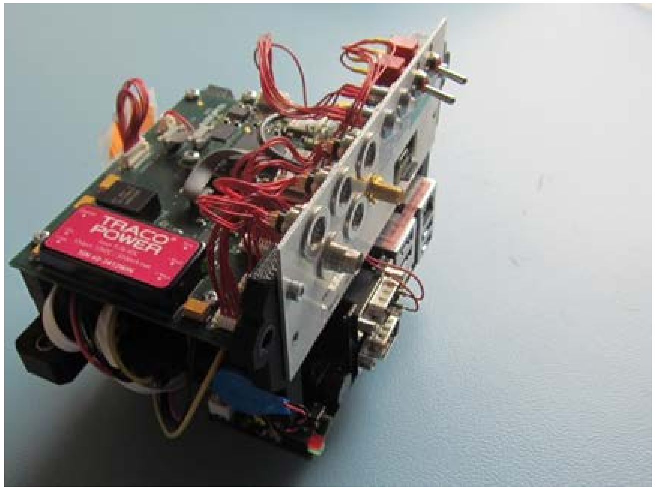


Spectral band images

Image-based navigation



Wide Field UAV Sensor Package



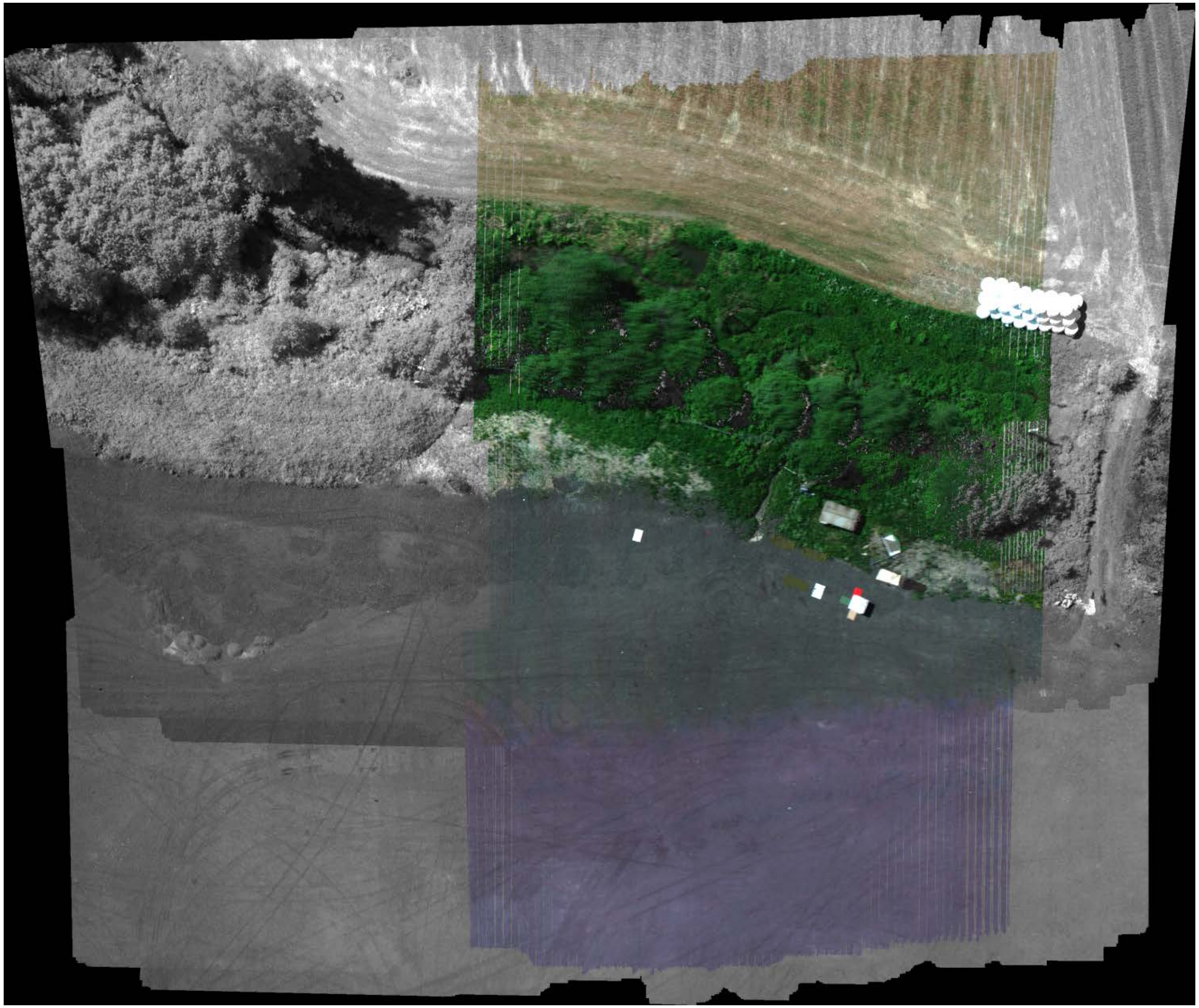
- 3 CMOS cameras with 1920x1200 pixels
  - Total across Field of View ~43° at ~3000 pixels
  - Frame rate up to 163 fps

- A Pico 880 microcomputer for camera control and logging
- GPS and MEMS IMU with FPGA-based synchronization and logging

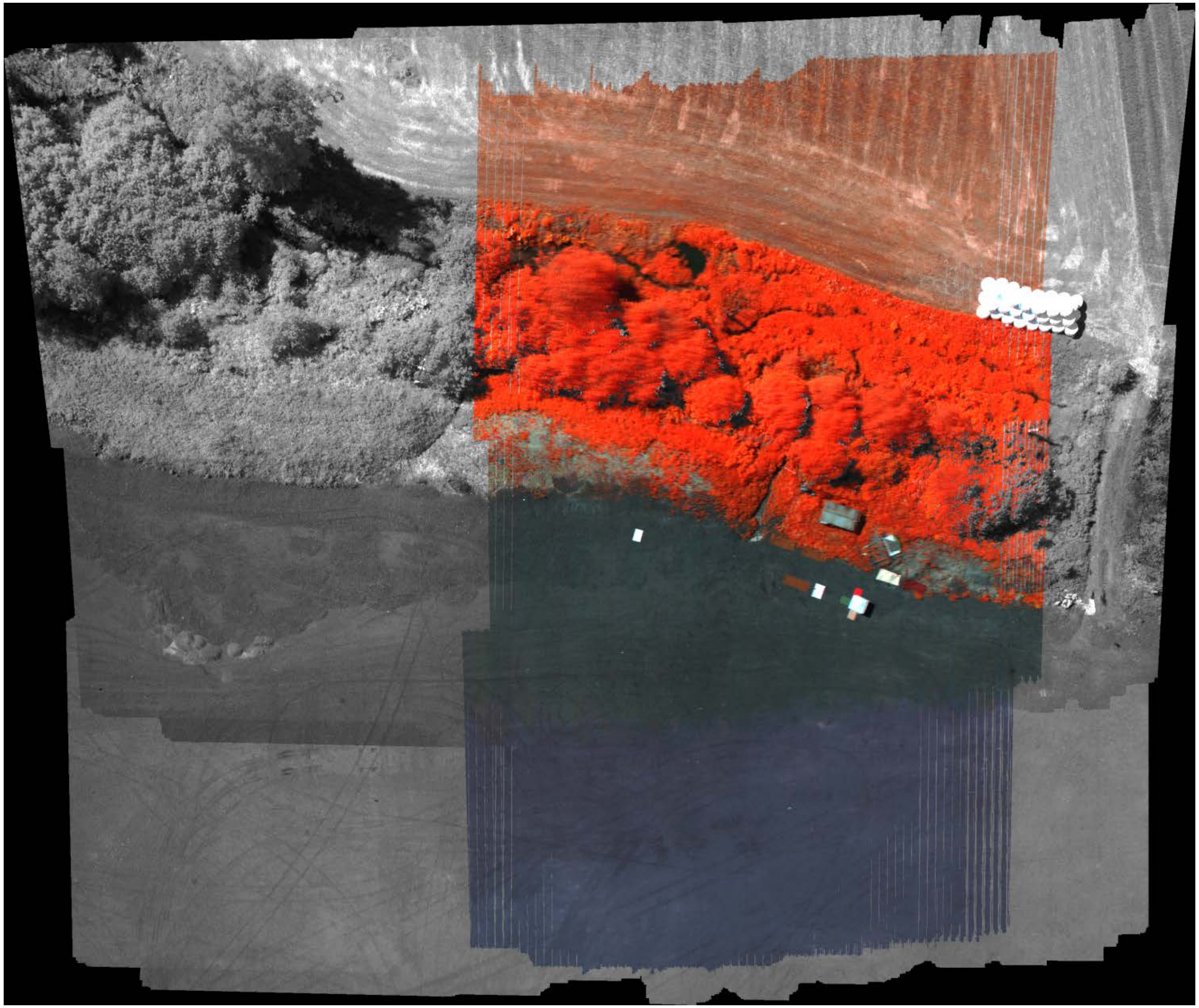
- Total mass < 1 kg

Torkildsen, Haavardsholm, Opsahl, Datta, Skaugen, Skauli, «Compact multispectral multi-camera imaging system for small UAVs», Proc. SPIE 9840, 98401U, 2016

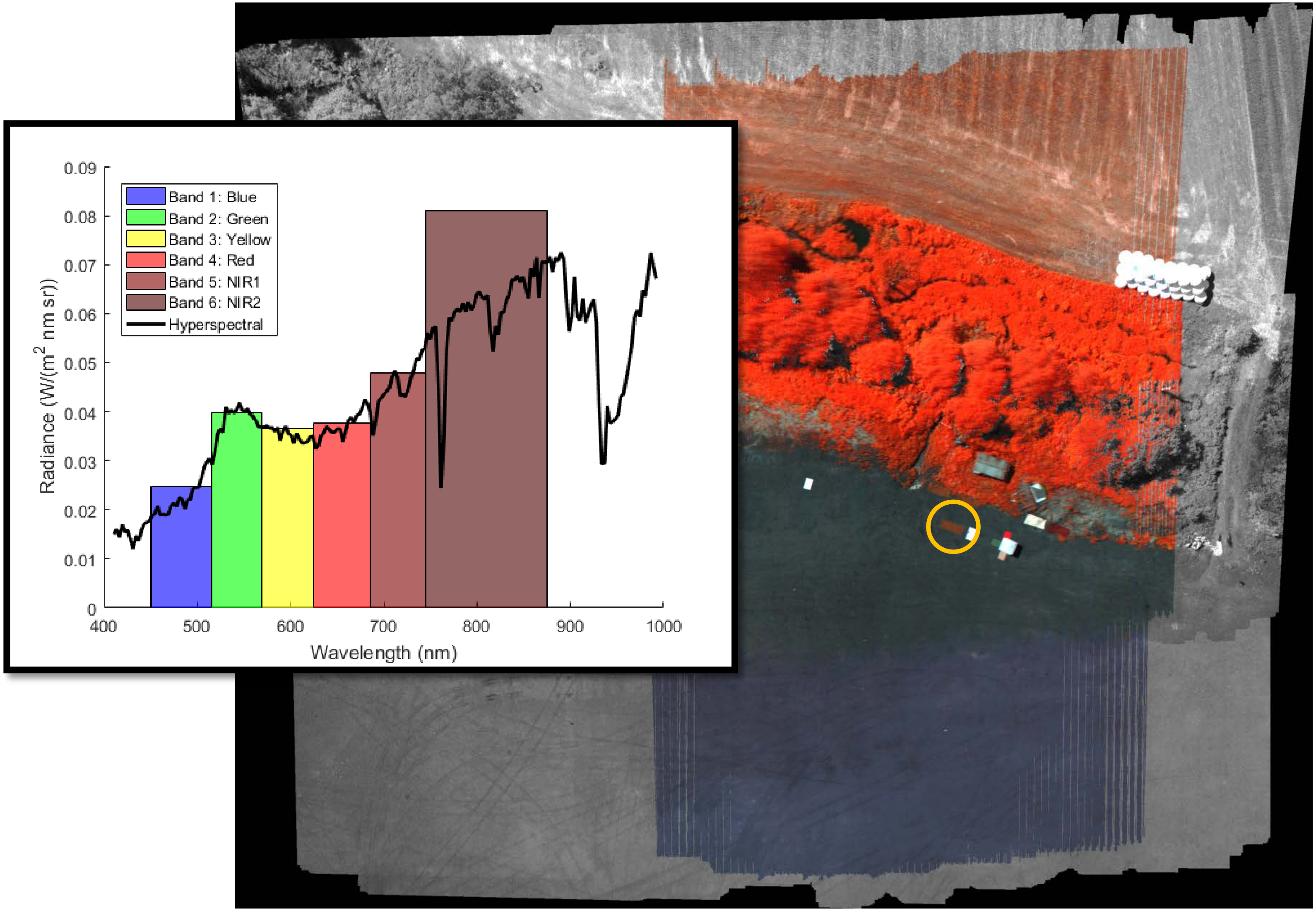
Example spectral reconstruction



Example spectral reconstruction



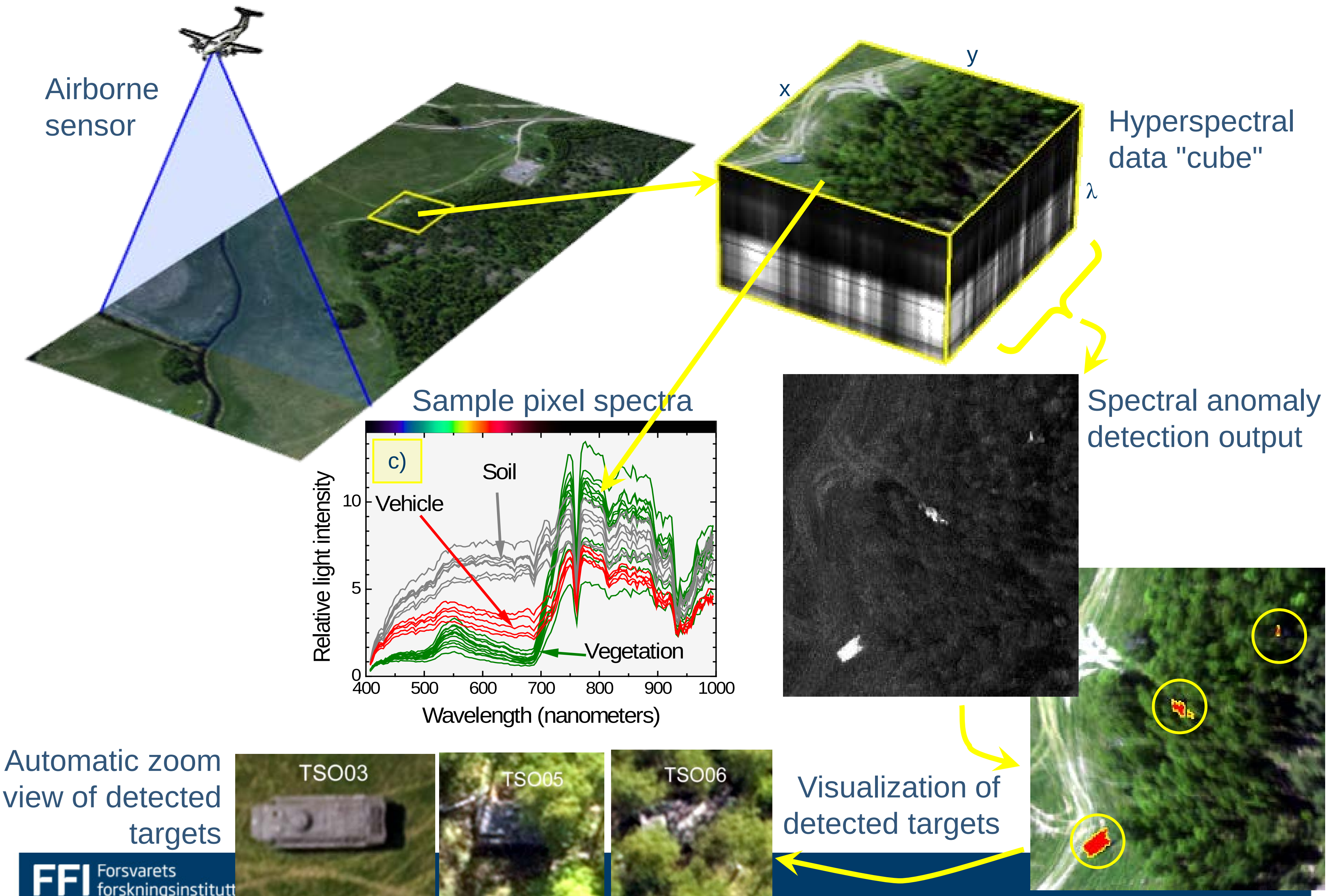
Example spectral reconstruction



The airborne target detection demonstrator system

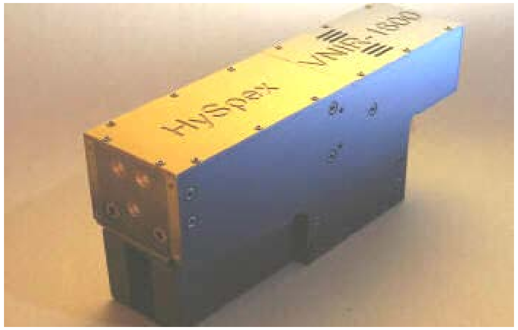
Skauli, Haavardsholm, Kåsen, Arisholm, Kavara, Opsahl, Skaugen, «An airborne real-time hyperspectral target detection system», Proc. SPIE 7695, 76950A, 2010

Hyperspectral airborne reconnaissance



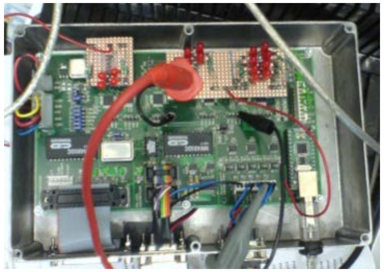
Sensors

- Hyperspectral camera: NEO HySpex VNIR-1600
  - 0.4 to 1 µm in 160 bands
    (binned to 40 bands for processing)
  - 1600 spatial pixels, pushbroom scan
  - 17-degree FOV, high spatial resolution:
    0.18 x 0.36 mrad pixel IFOV
  - Approx. 100 lines/s (autoset)



- High-resolution panchromatic camera: Dalsa Piranha2 8k
  - 8192 square pixels, same FOV as HySpex
  - Nominally 5 x 10 hi-res pixels for each hyperspectral pixel

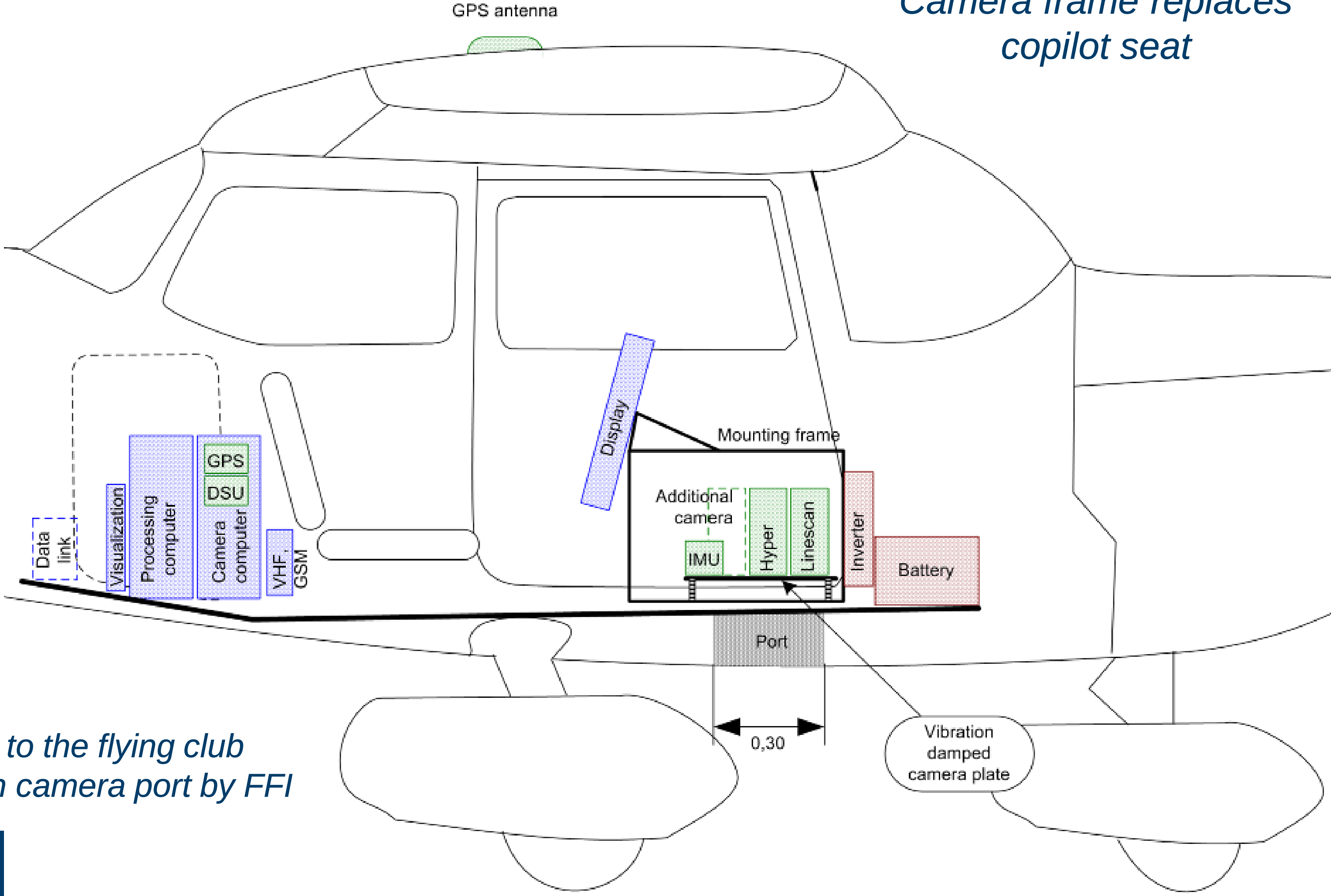
- Navigation
  - dual-frequency GPS receiver
  - navigation-grade IMU
  - data synchronization unit



Installation in a Cessna 172

Computers in baggage compartment

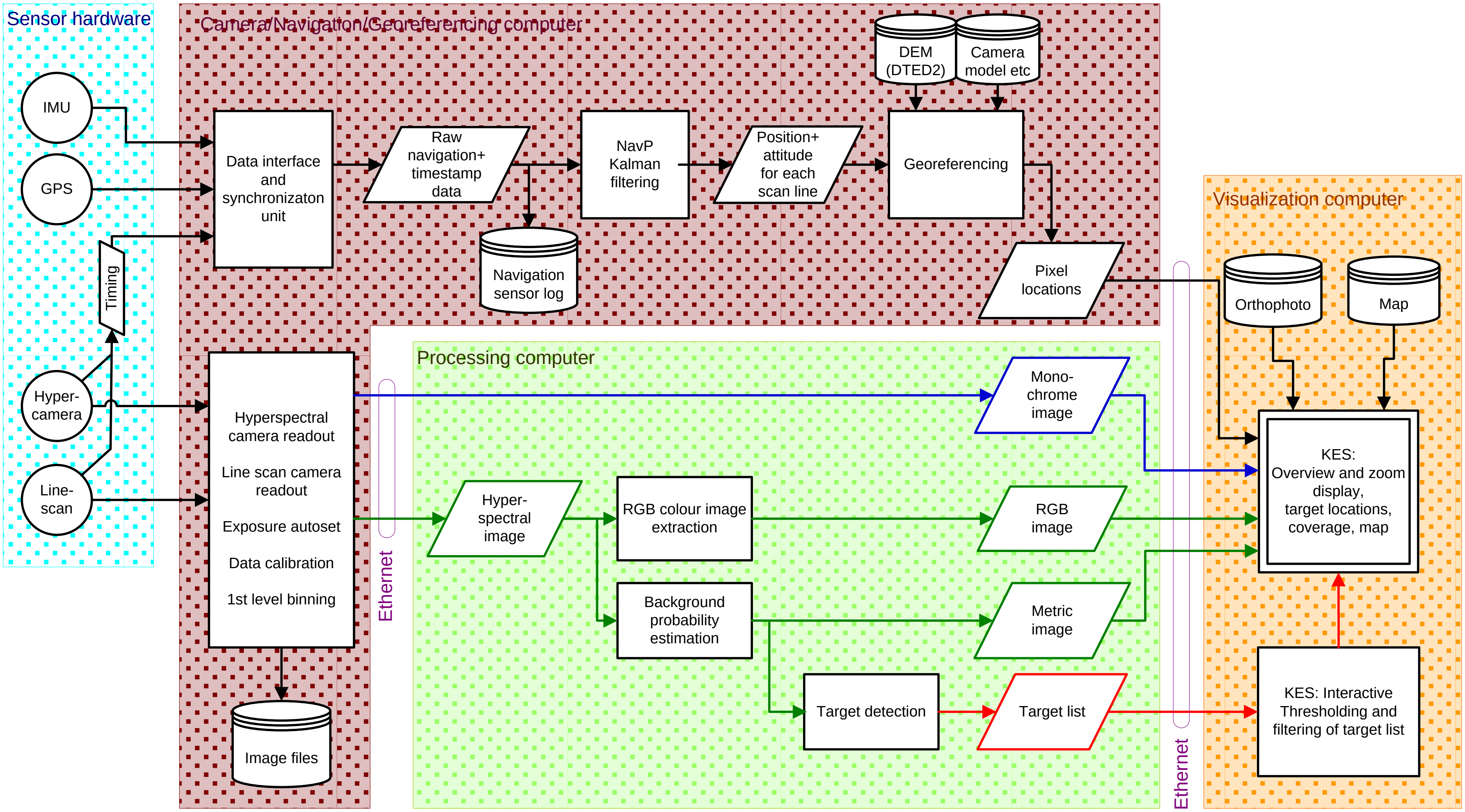
Camera frame replaces copilot seat



Cessna 172 belonging to the flying club at Kjeller, modified with camera port by FFI

FFI Forsvarets forskningsinstitutt

Data flow



3 separate computers, for engineering convenience

Software framework for processing

- Design drivers
  - Large data rate: ~20 MB/s
  - Computationally intensive algorithms

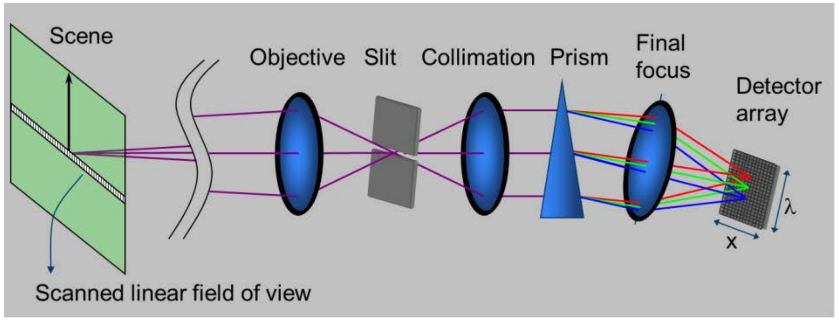
- Data rate is handled by nonlinear pipeline architecture implemented in C++

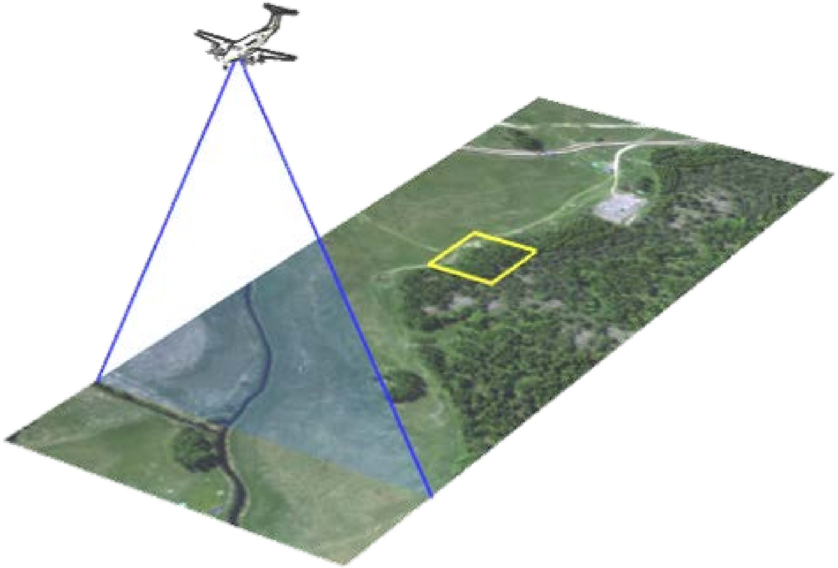
- For high compute performance, various techniques are available within each processing stage:
  - processor-specific numerical libraries
  - multicore processing (OpenMP)
  - Graphics processing unit (CUDA)

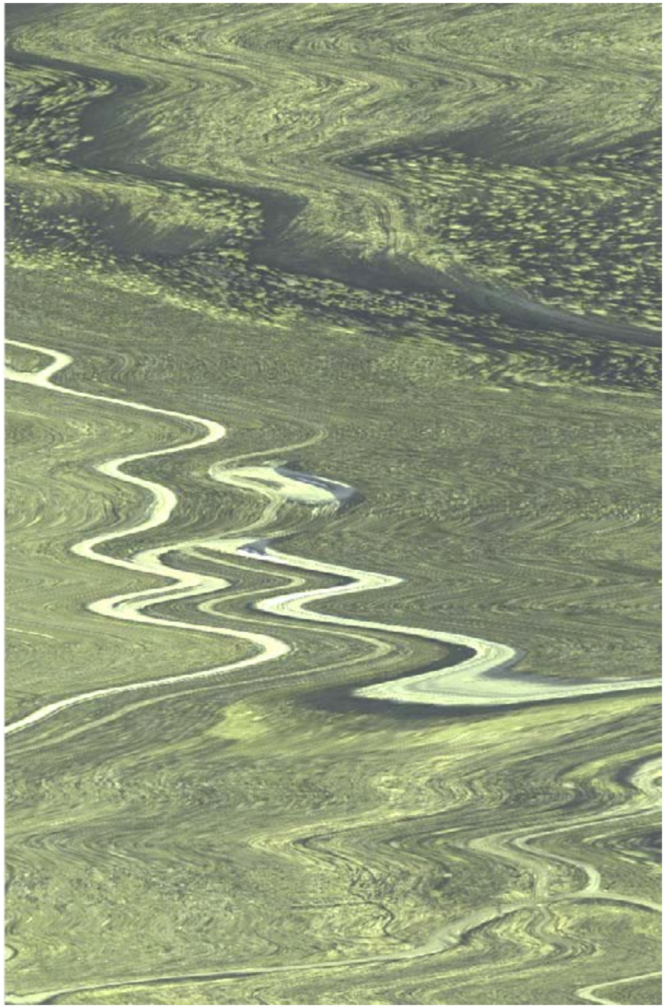
Haavardsholm, Arisholm, Kavara, Skauli: «Architecture of the real-time target detection processing in an airborne hyperspectral demonstrator system», IEEE WHISPERS, 2010

Tarabalka, Haavardsholm, Kåsen, Skauli: «Real-time anomaly detection in hyperspectral images using multivariate normal mixture models and GPU processing», Journal of Real-Time Image Processing, Vol 4, Issue 3, pp 287-300, 2009

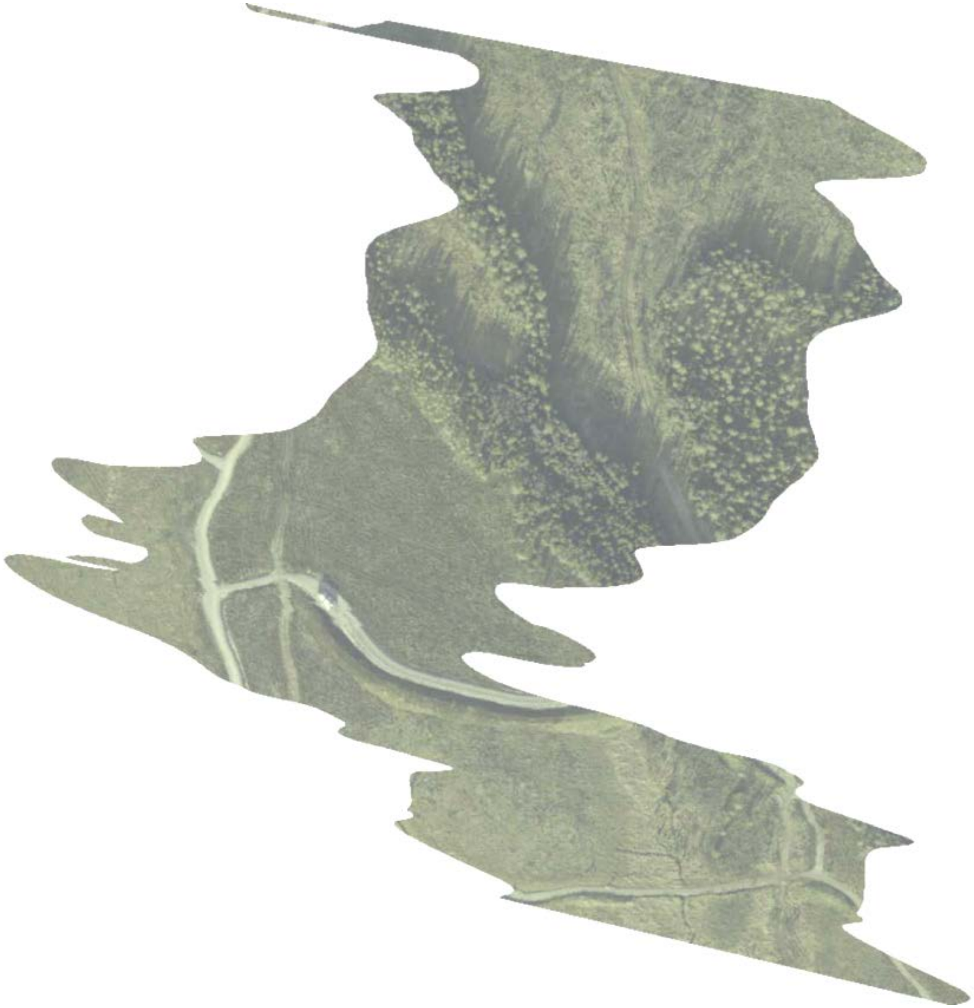
Direct real-time georeferencing of push-broom cameras

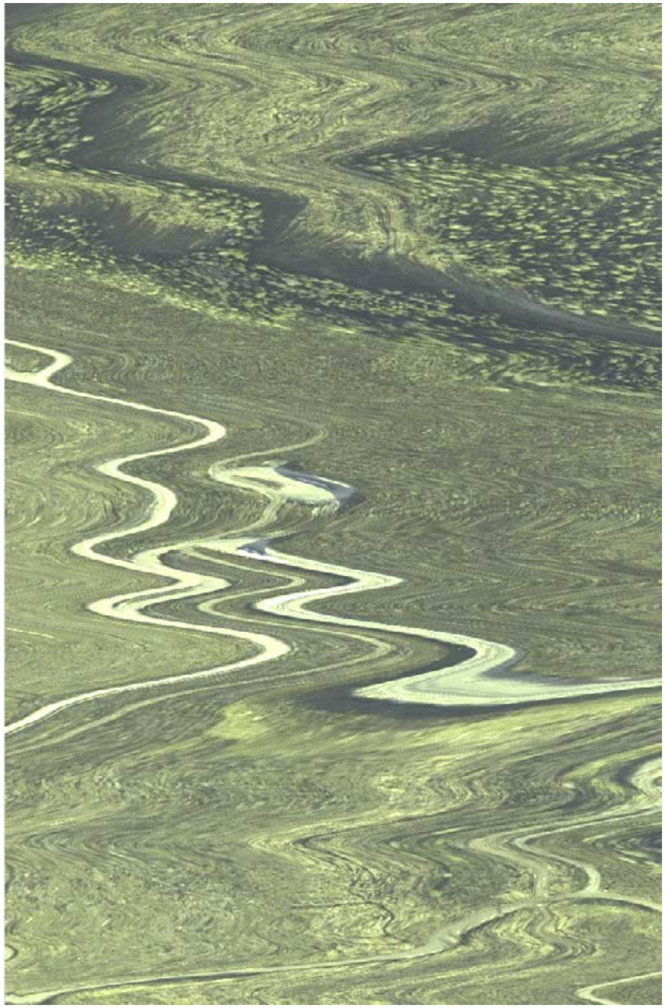




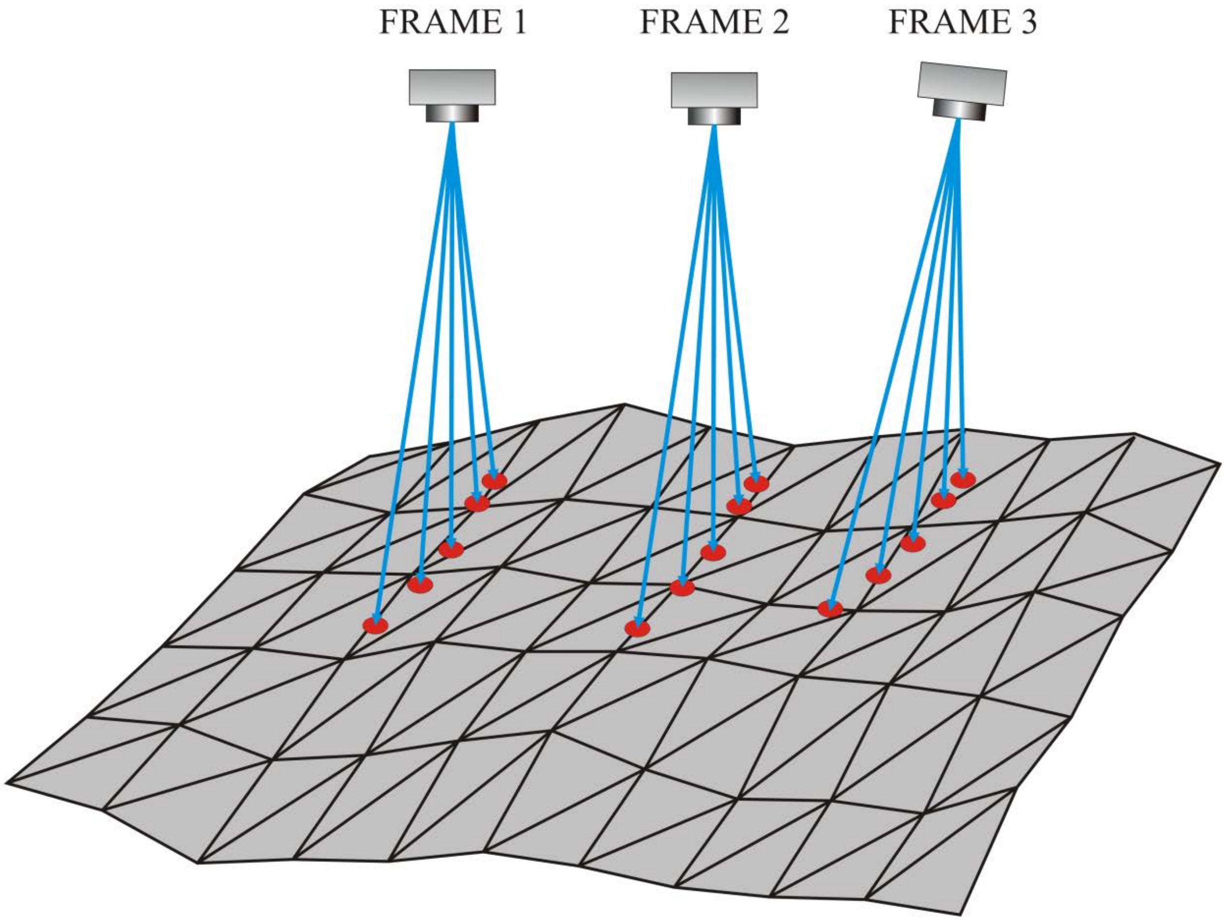


Direct real-time georeferencing of push-broom cameras



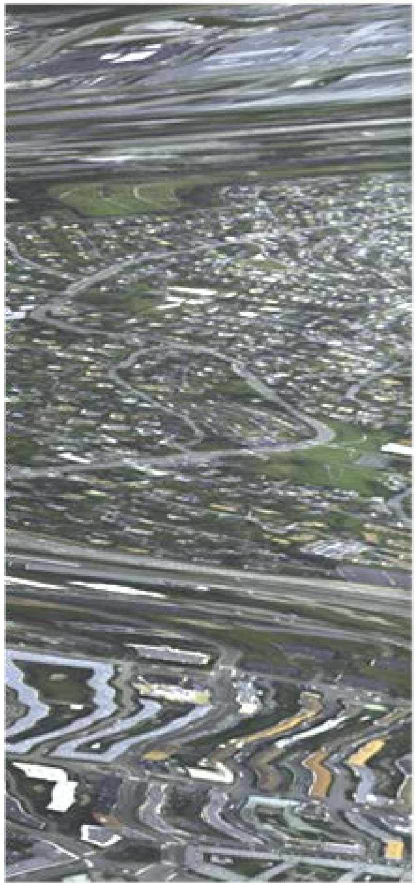


Representing georeferencing as a ray-tracing problem



Opsahl, Haavardsholm, Winjum: «Real-time georeferencing for an airborne hyperspectral imaging system», Proc. SPIE 8048, 80480S, 2011

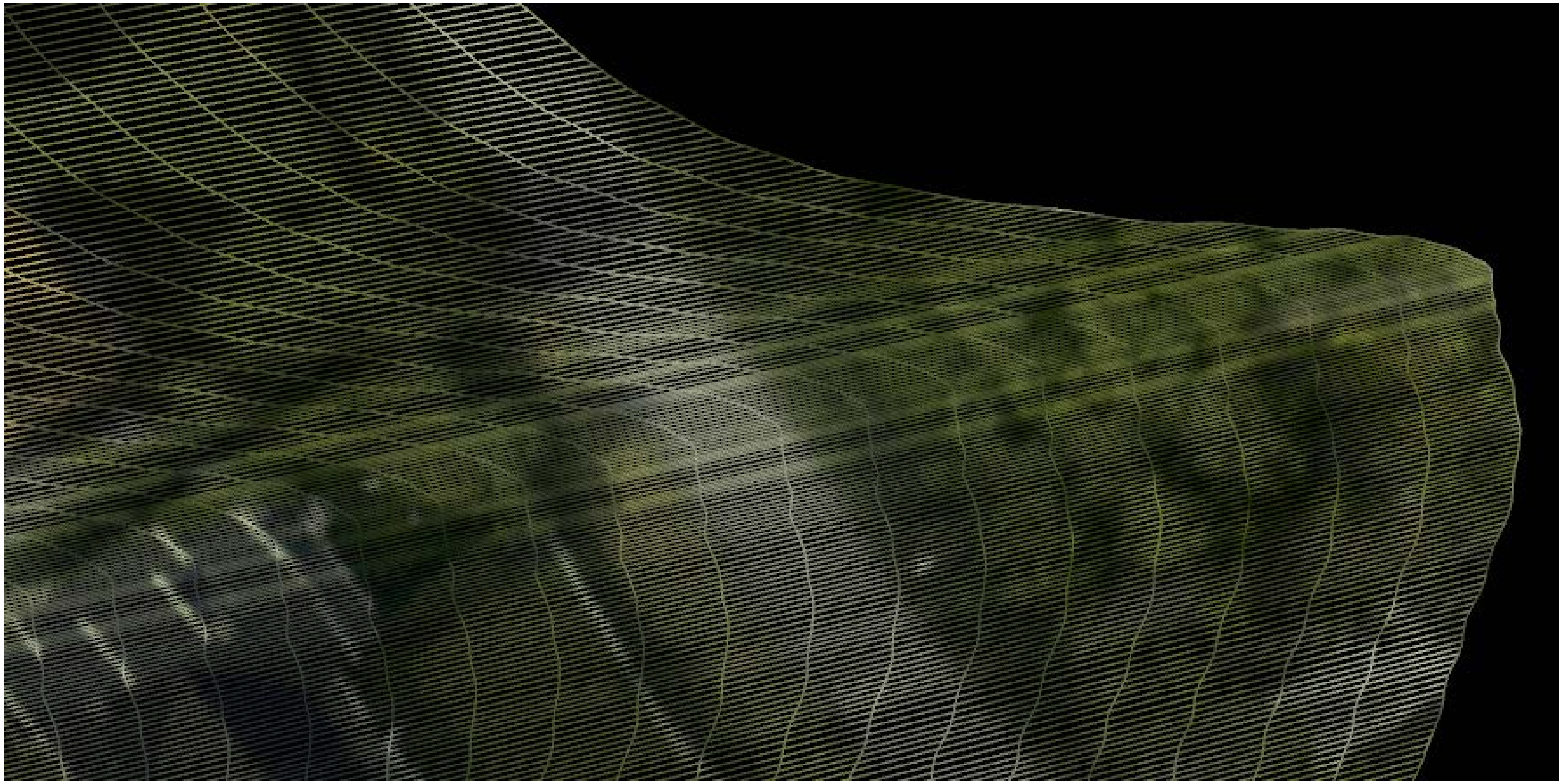
Orthorectification example



- On-the-fly orthorectification

Rectification using the graphics hardware

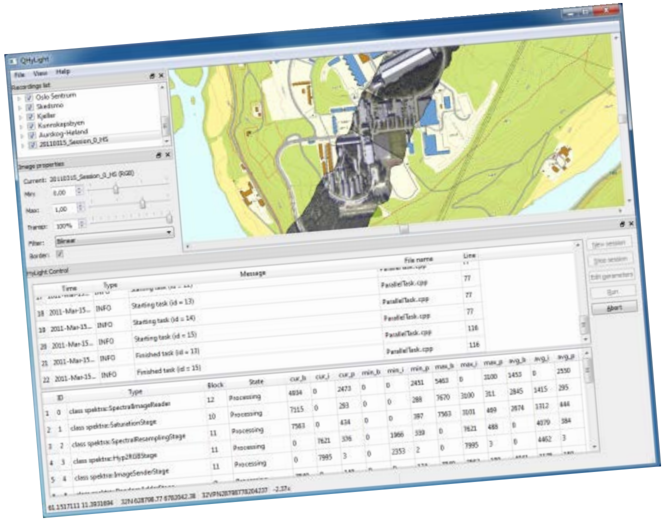
- The georeference describes a 3D surface (or a 2D grid)
- The image is mapped onto the georeference surface
- Very efficient when using the graphics hardware



GUI for visualization and control

- GUI for FFIs airborne demonstrator system
  - Implemented using Qt (C++)
  - Runs the real-time processing
  - Displays processing status

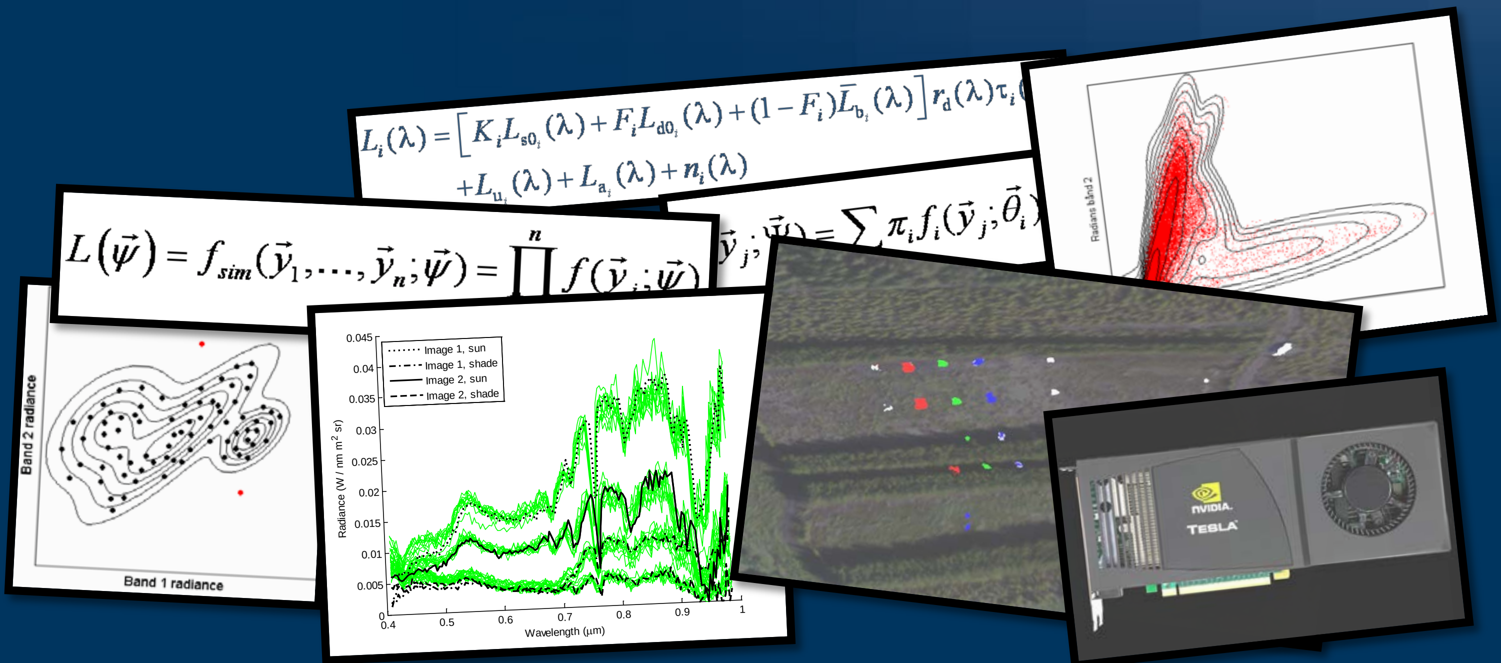
- Real-time rectification of push-broom images
  - Resolution is not fixed,
    but images are resampled in real-time
  - Based on texture mapping with OpenGL
  - Real-time adjustment of brightness and contrast



- Geographic data
  - Georeferenced maps and photos
  - Points: Waypoints/Tracks/Routes/detections

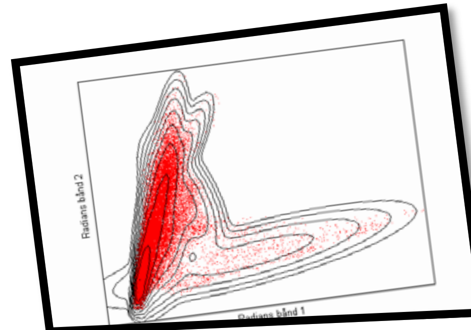
FFI Forsvarets forskningsinstitutt

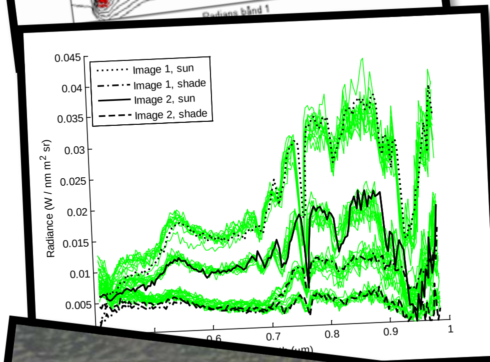
Hyperspectral image processing

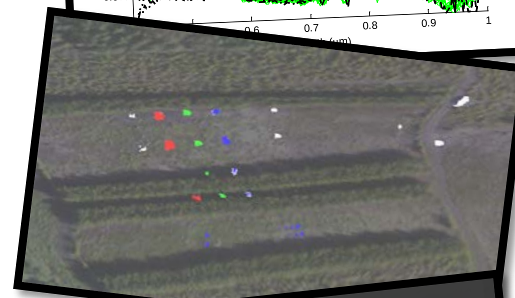


Hyperspectral image processing

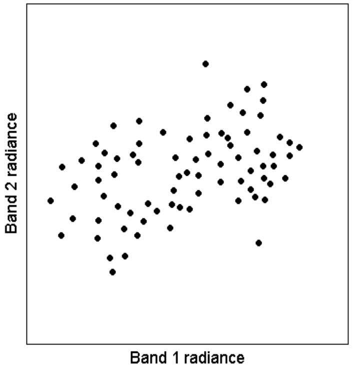
- Work mainly focused on target detection methods
- Research and development of methods
  - Anomaly detection
  - Signature detection
  - Change detection
- Focus areas
  - High resolution hyperspectral images
  - Exploit knowledge about the physical processes
  - Statistical mixture models
  - Forward modelling
  - Use of computational geometry rather than resampling
  - Real-time implementations, GPGPU programming

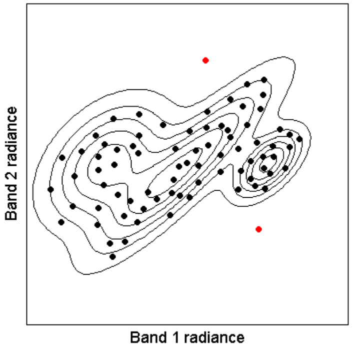






Anomaly detection
based on multinormal mixture models





- Task: identify anomalous, "interesting" pixels

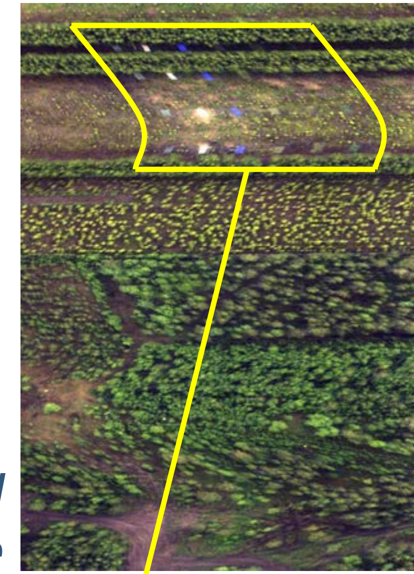
- Statistical approach:
  Estimate a probability distribution for the data
  ≈ background model

- Method used here:
  1. Mixture of Gaussian distribution model for the background using an iterative stochastic parameter estimation method
  2. An image indicating how well each pixel fits with the background model is calculated
  3. Thresholding selects "interesting" pixels with low likelihood of being background

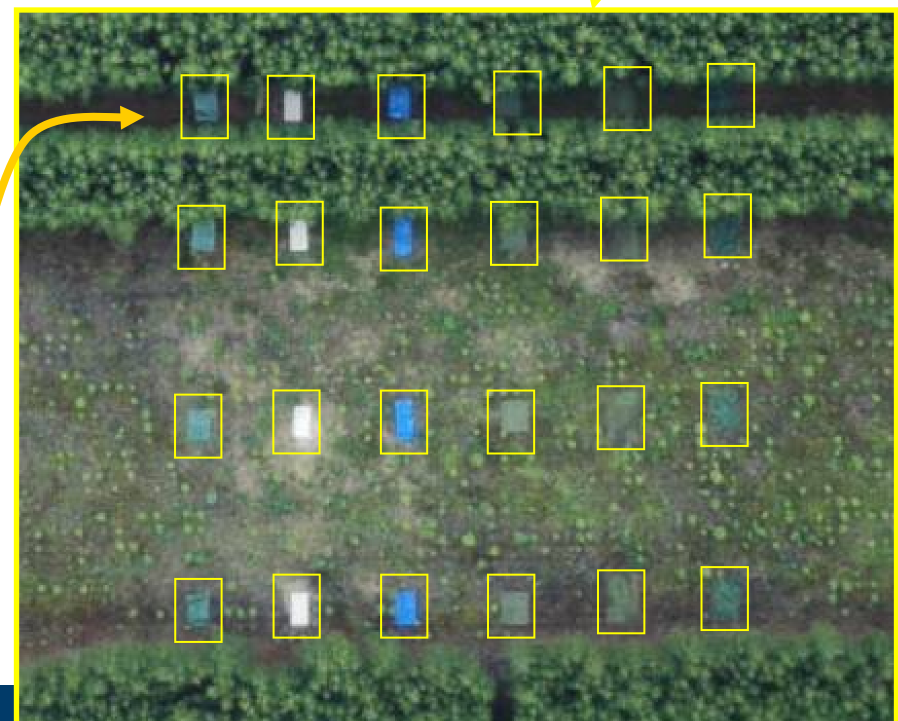
Kåsen, Goa, Skauli: «Target detection in hyperspectral images based on multicomponent statistical models for representation of background clutter», Proc. SPIE 5612, 2004

Example: Spectral anomaly detection

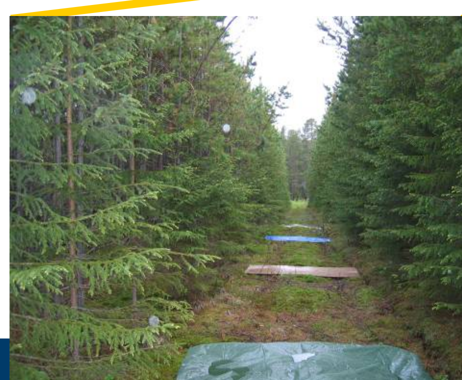
- Background: mixed forest, sand
- Targets: sheets of different materials with varying spectral properties and mostly low visual contrast
- Target layout in a matrix configuration:
  - columns of identical material
  - rows of similar illumination conditions



spectral image

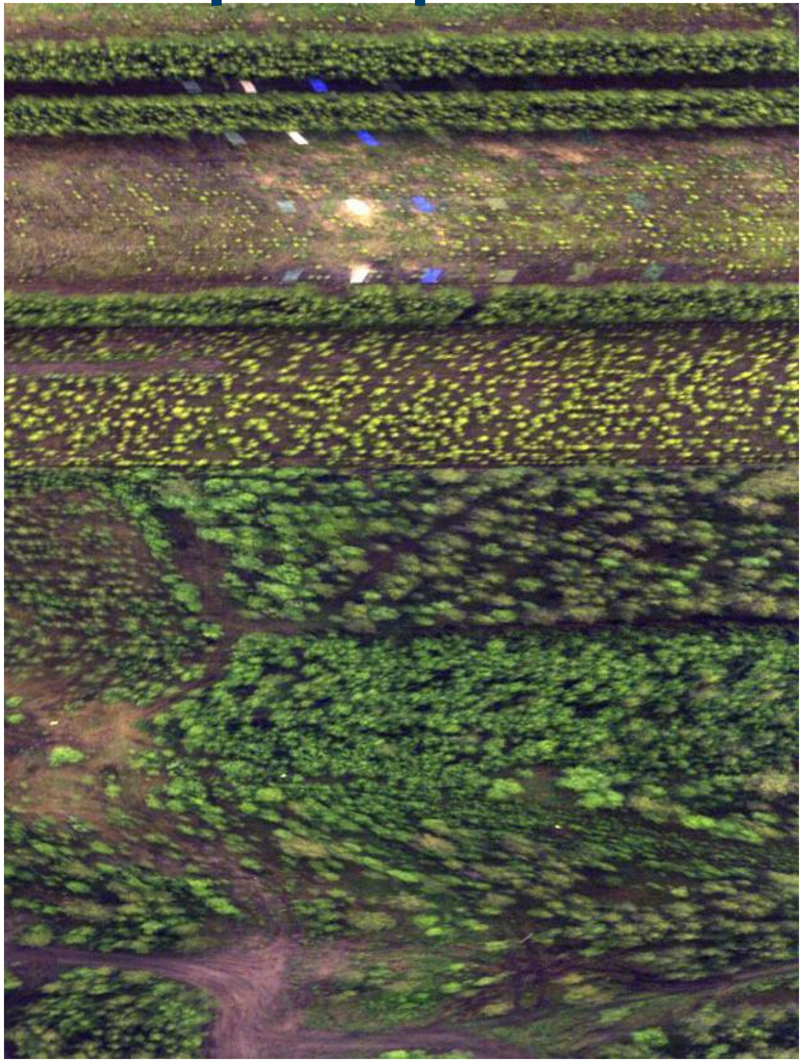


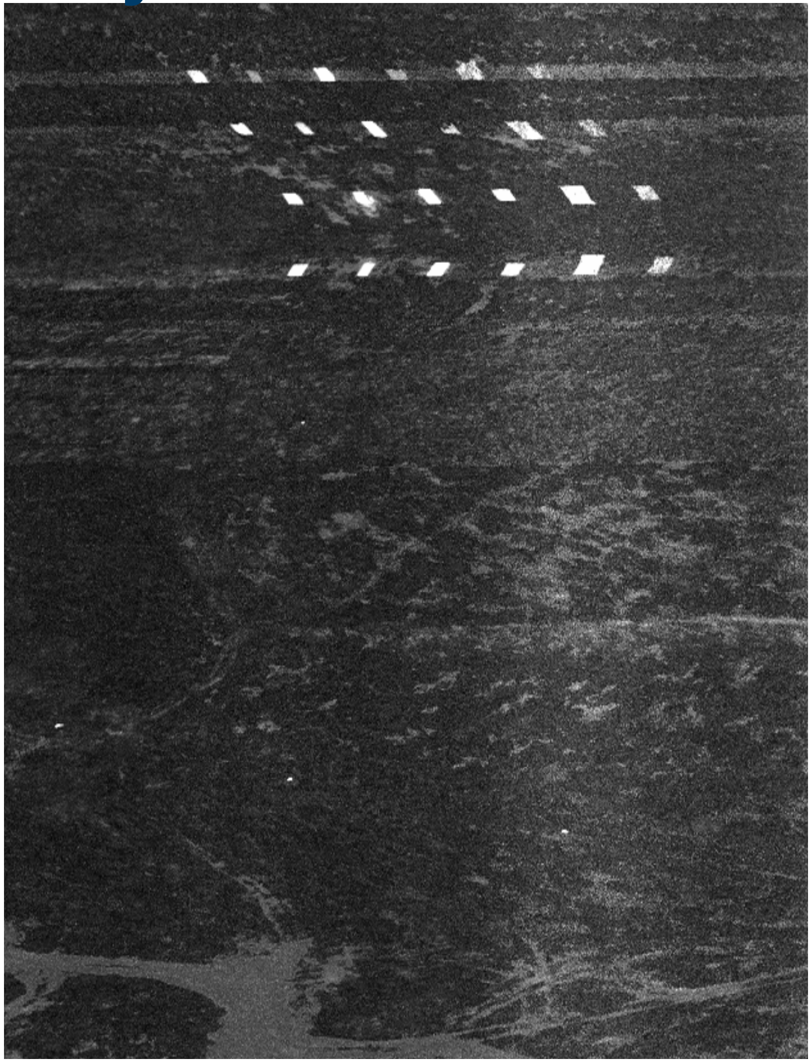
RGB image



Ground image

Example: Spectral anomaly detection

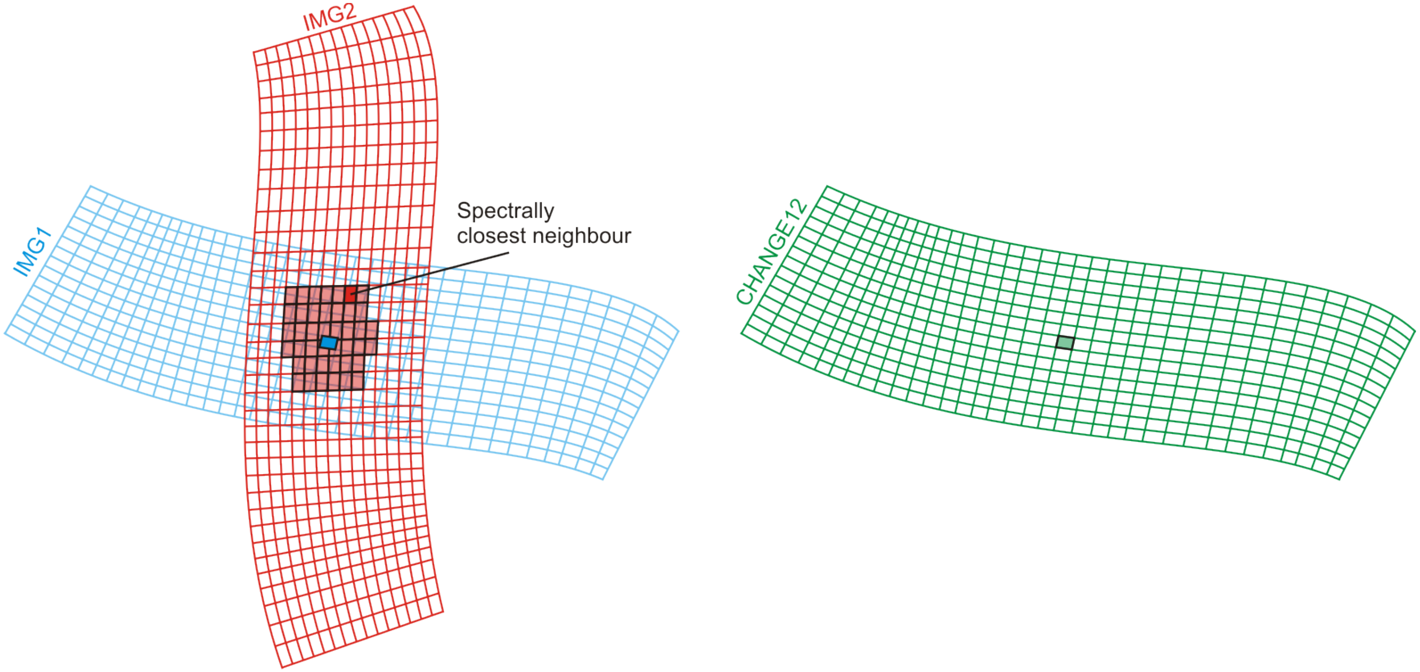




- All targets detectable as spectral anomalies
- Background clutter strongly suppressed

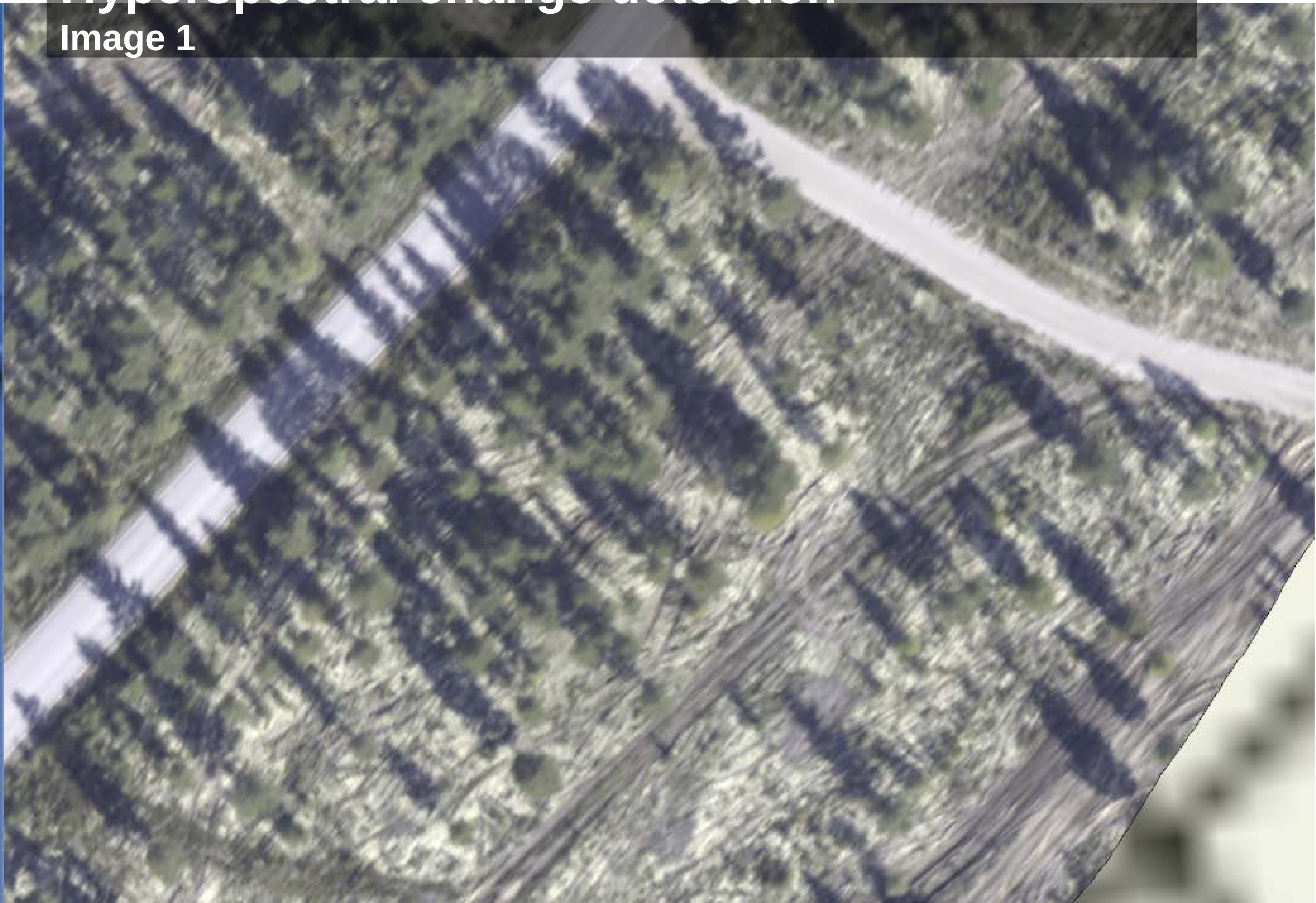
Hyperspectral anomalous change detection

1. Estimate spectral change based on corresponding pixels
   - Uncertainties in registration, pixel footprint, …
2. Model typical changes
3. Detect anomalous changes



Hyperspectral change detection

Image 1

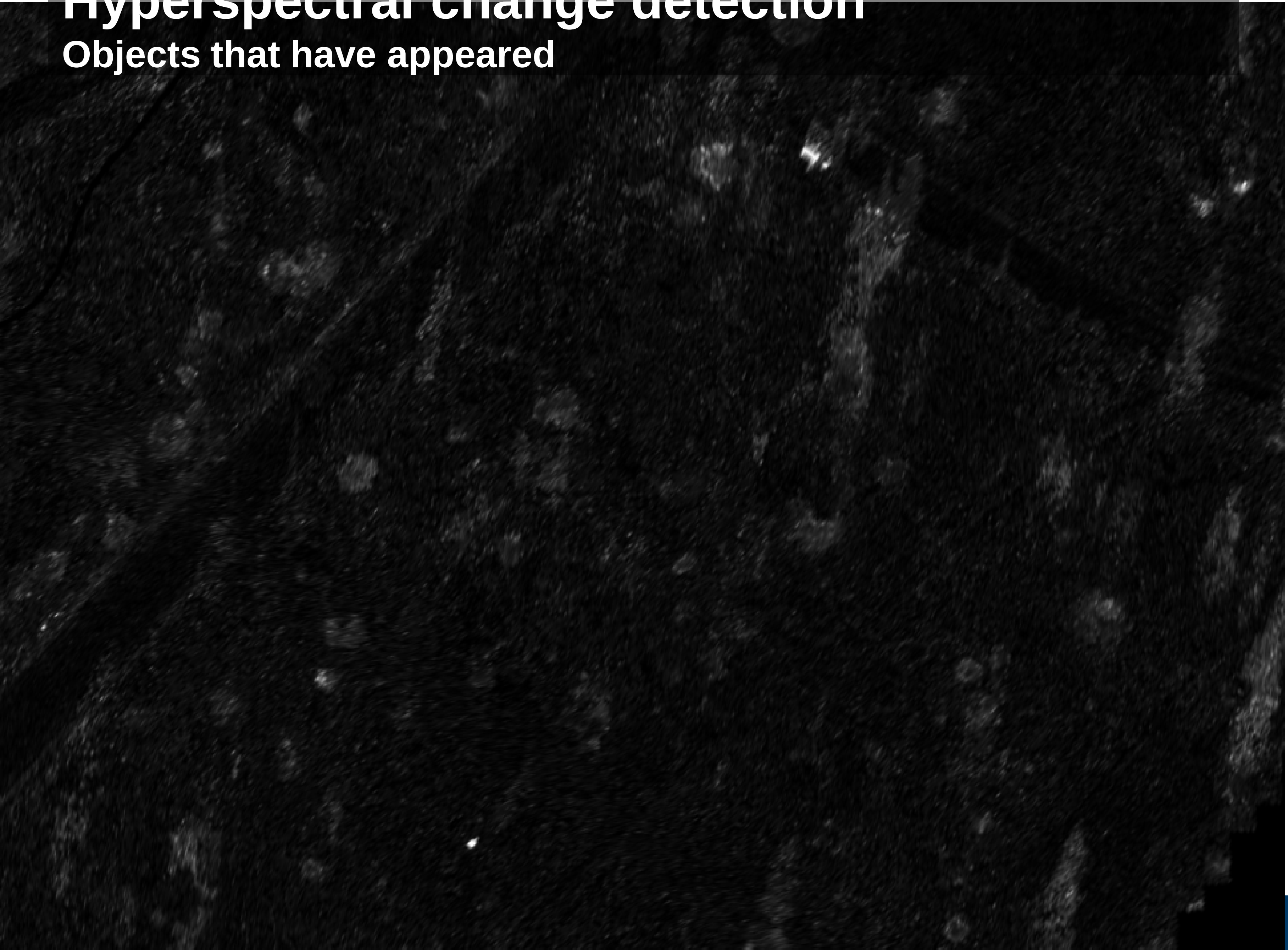


Hyperspectral change detection

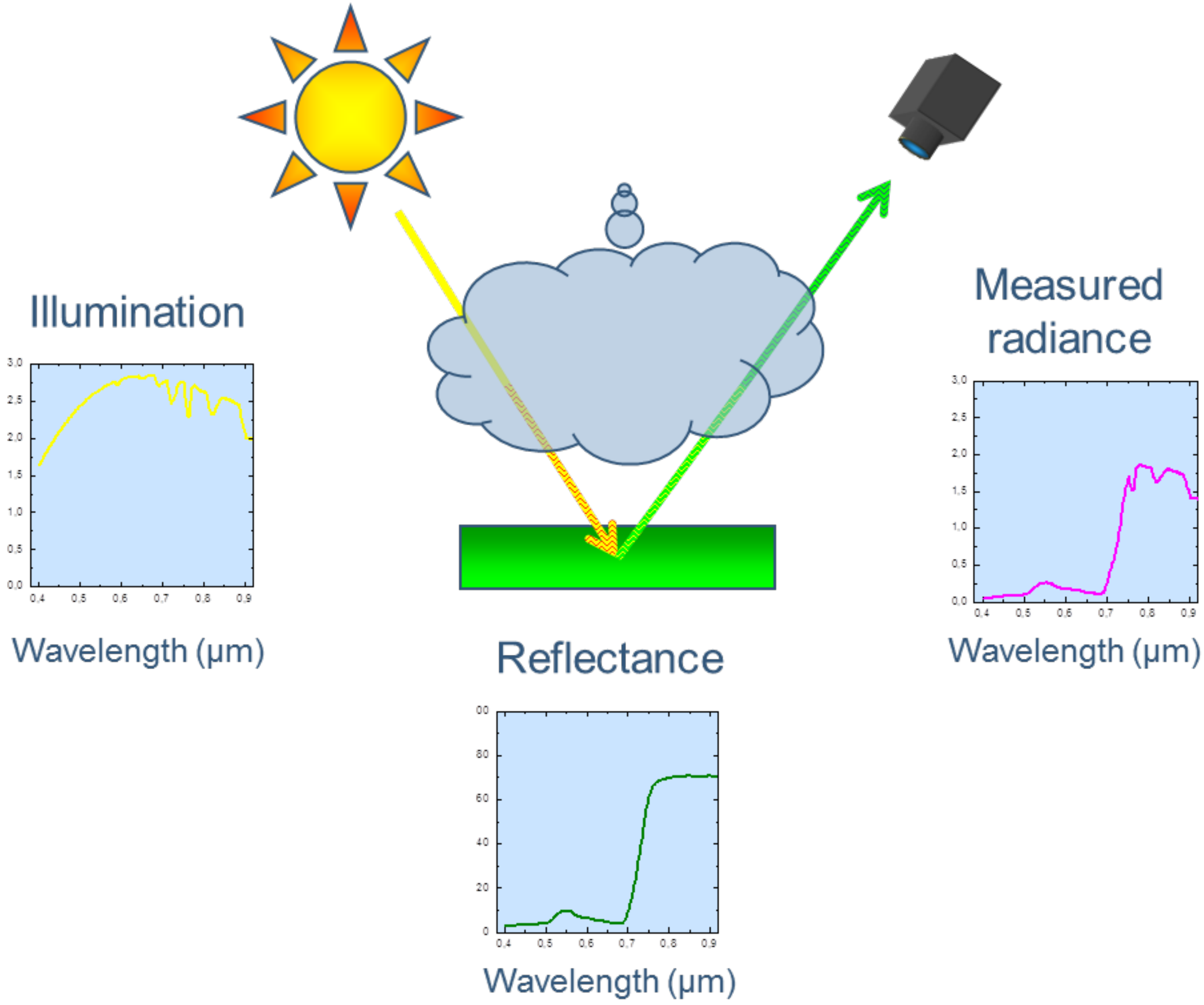
Image 2 (1 month later)

Hyperspectral change detection

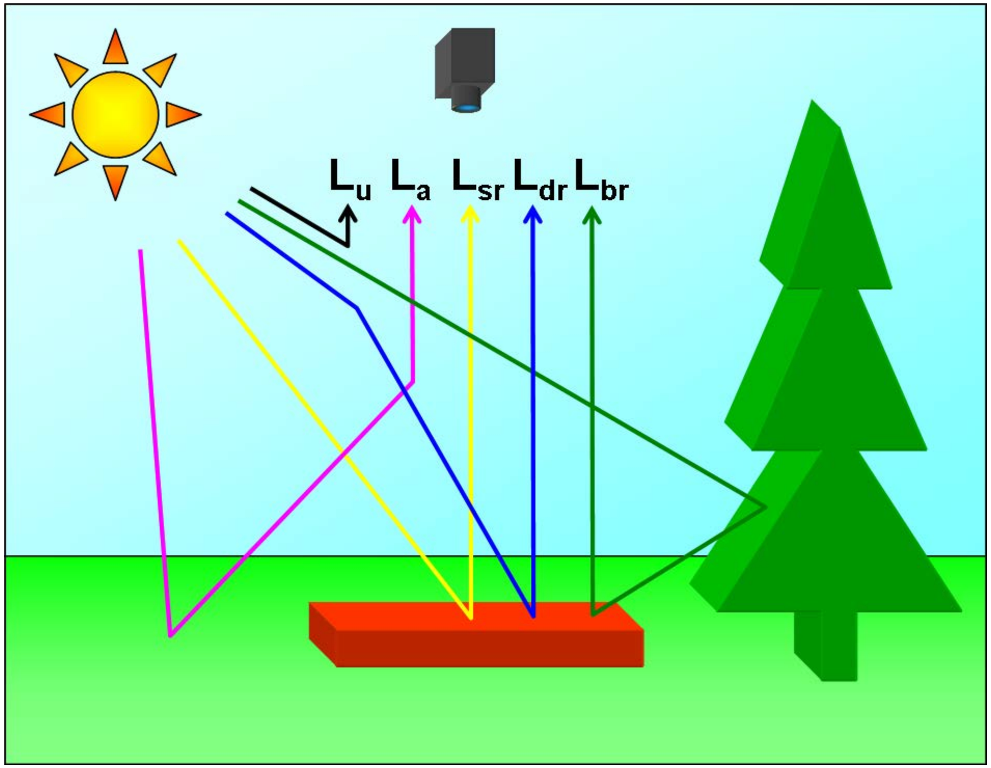
Objects that have appeared



Spectral signatures



Signature-specific detection
Estimating radiance from reflectance

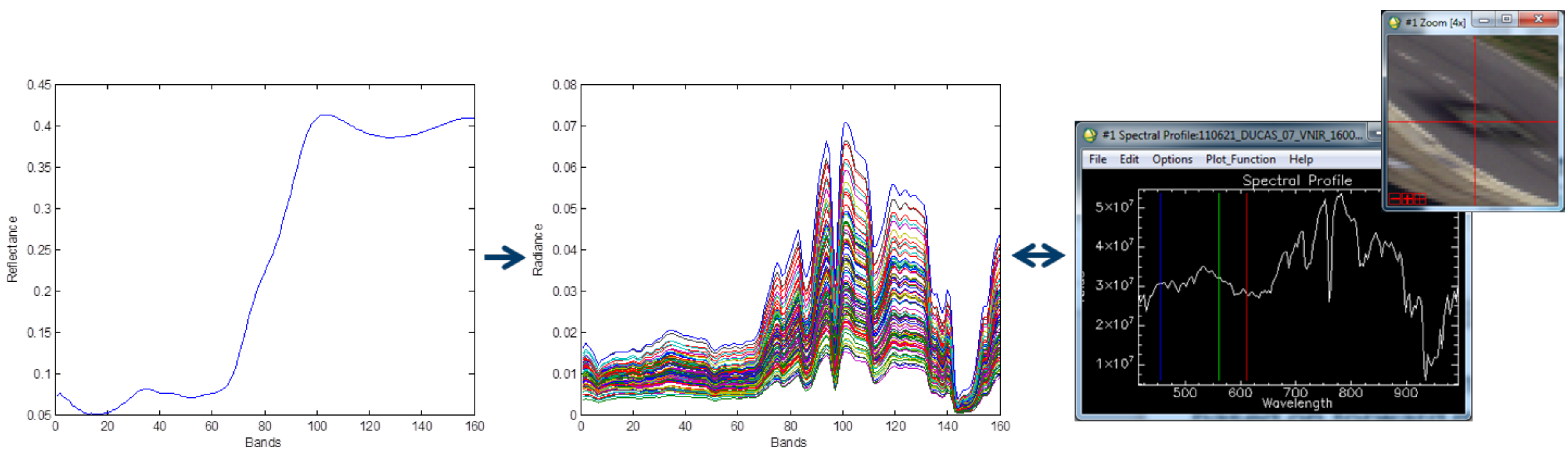


$$L(\lambda) = L_{sr}(\lambda) + L_{dr}(\lambda) + L_{br}(\lambda) + L_{u}(\lambda) + L_{a}(\lambda)$$

Signature-specific detection based on forward modelling

- Methods for atmospheric compensation are often inaccurate, especially for high resolution images and in areas that are not sunlit
  - Radiance image → Reflectance image ↔ Reflectance signature

- An alternative approach is to model the variability of the received radiance given the reflectance signature (forward modelling)
  - Reflectance signature → Radiance signature model ↔ Radiance image

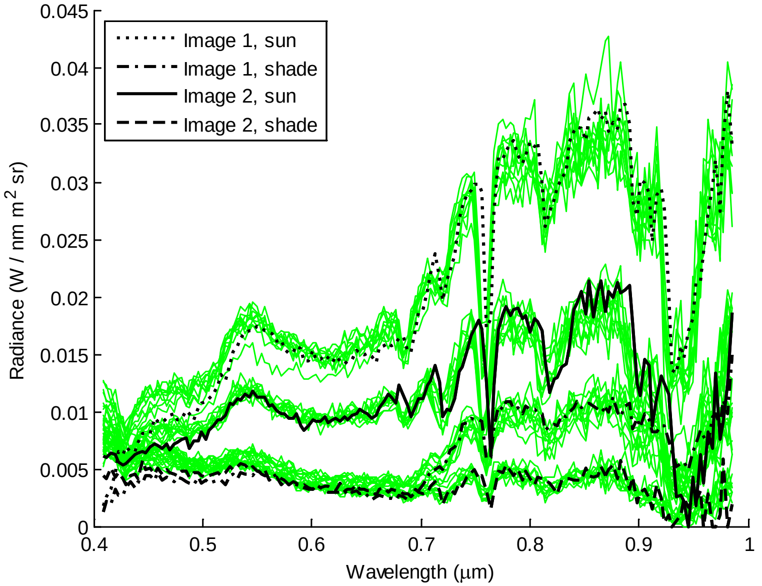


Signature-specific detection
Modelling radiance signature variability

- Parameters that cause signature variability: $\vec{\theta}$
  - Imaging geometry
  - Time and place
  - Meteorological and atmospheric conditions
  - Background characteristics and scene geometry
  - …

- Monte Carlo simulations of variability:
  - Draw parameters $\vec{\theta}_i$ from probability densities that are adapted to the current imaging scenario
  - Simulate the radiance signature using the physical model
  - The result is a set of simulated radiance signatures:

$$\left\{ L_1(\lambda \mid \vec{\theta}_1, r_\mathrm{d}), \ldots, L_N(\lambda \mid \vec{\theta}_N, r_\mathrm{d}) \right\}$$

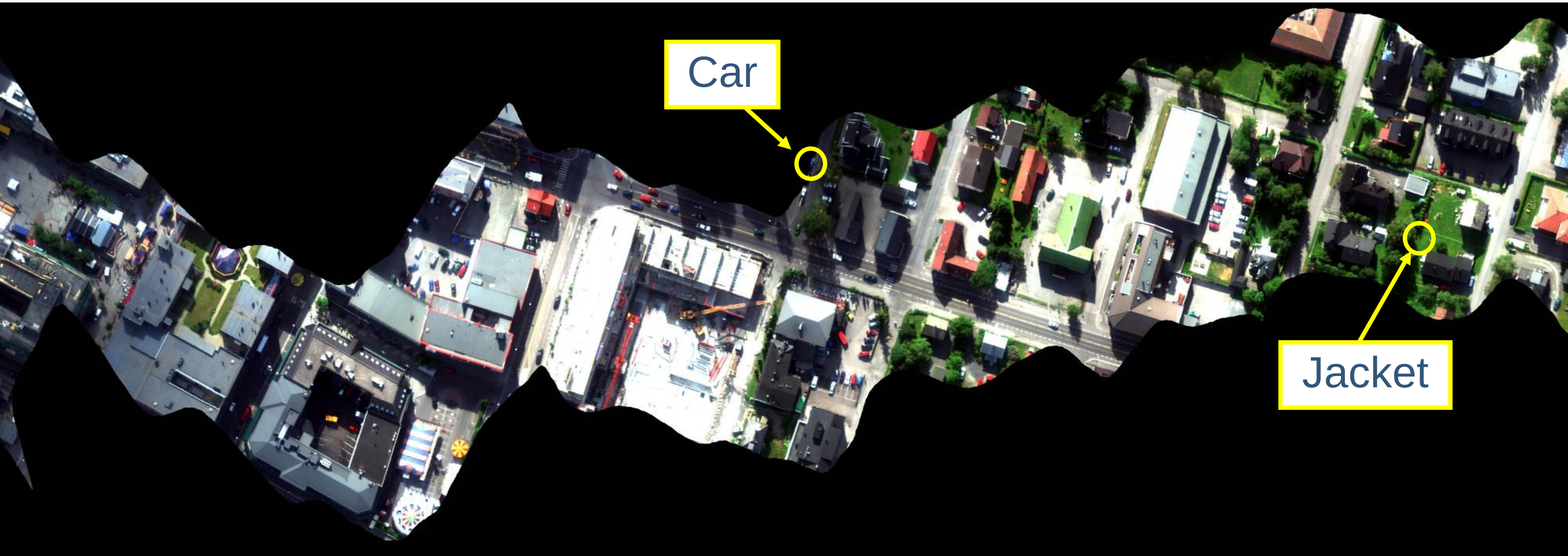


Haavardsholm, Skauli, Kåsen: «A physics-based statistical signature model for hyperspectral target detection», IEEE IGARSS, 2007

Example: Detection in an urban scene

- Urban background with high spectral complexity
- A few controlled target objects
- Target reflectance spectra are not taken from the image itself, but collected in an <u>independent measurement</u> of spectral reflectance

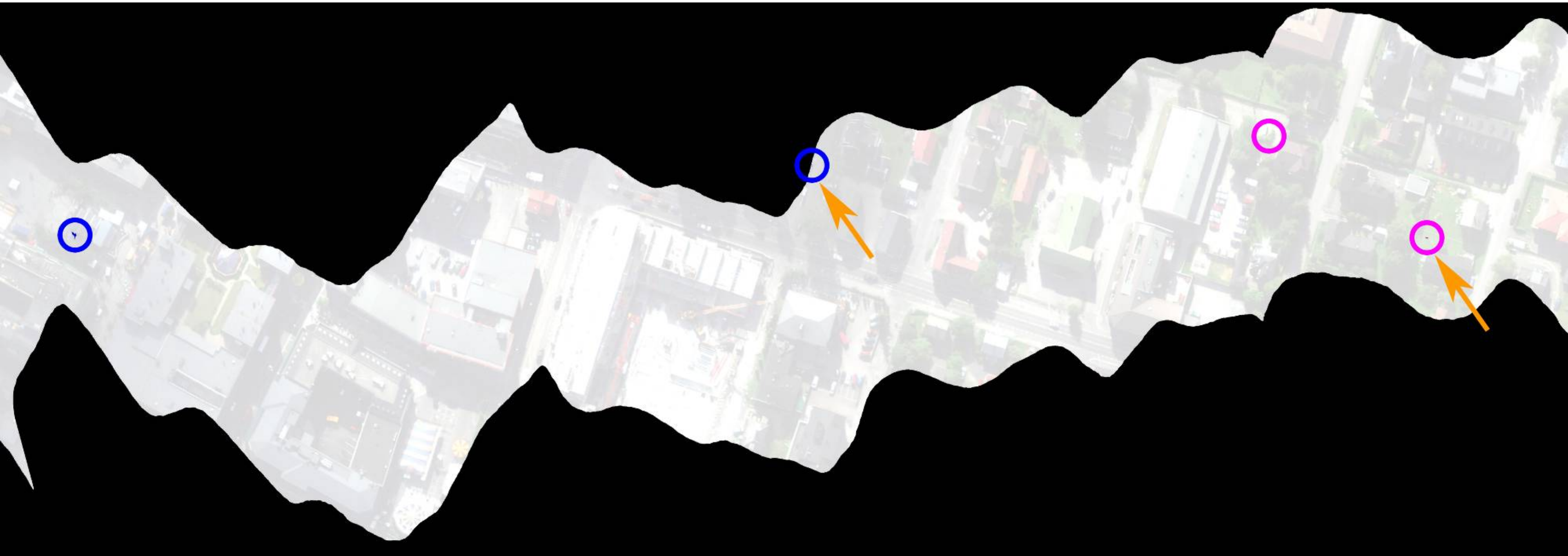
RGB image extracted from spectral image



Example: Detection in an urban scene

- Using independently measured spectral signatures, most of the background can be suppressed
- The blue car is detectable with only one falsely detected object
- A green jacket is detectable with zero false alarm
- Using a common detection threshold, each target class yields one falsely detected object

Result from signature-specific detection

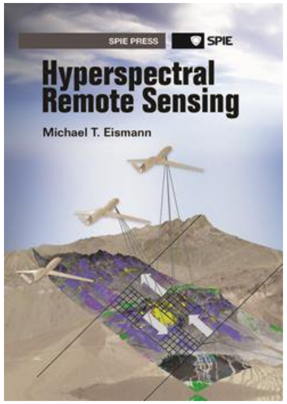


Finally…

- A few hyperspectral systems, image processing methods

- By the way:
  - Masters student and Research Council project proposal «Combining Human and Machine Vision - a Multidisciplinary Approach» on appliying deep neural nets on hyperspectral image data together with MR-Physics Group, Dept. of Physics, NTNU
  - FFI is currently working with micro satellites, and optical systems meant for these

- Good books:



Reserve

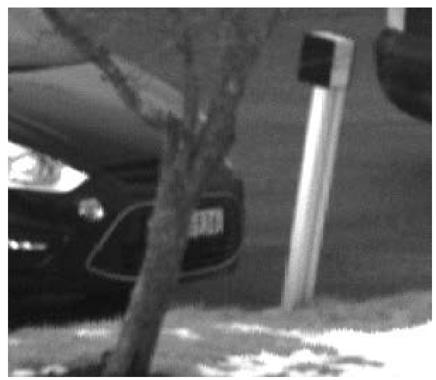
Detail images from each band: sharpness difference

Band 1, blue

Band 2, green

Band 3, yellow

Band 4, red



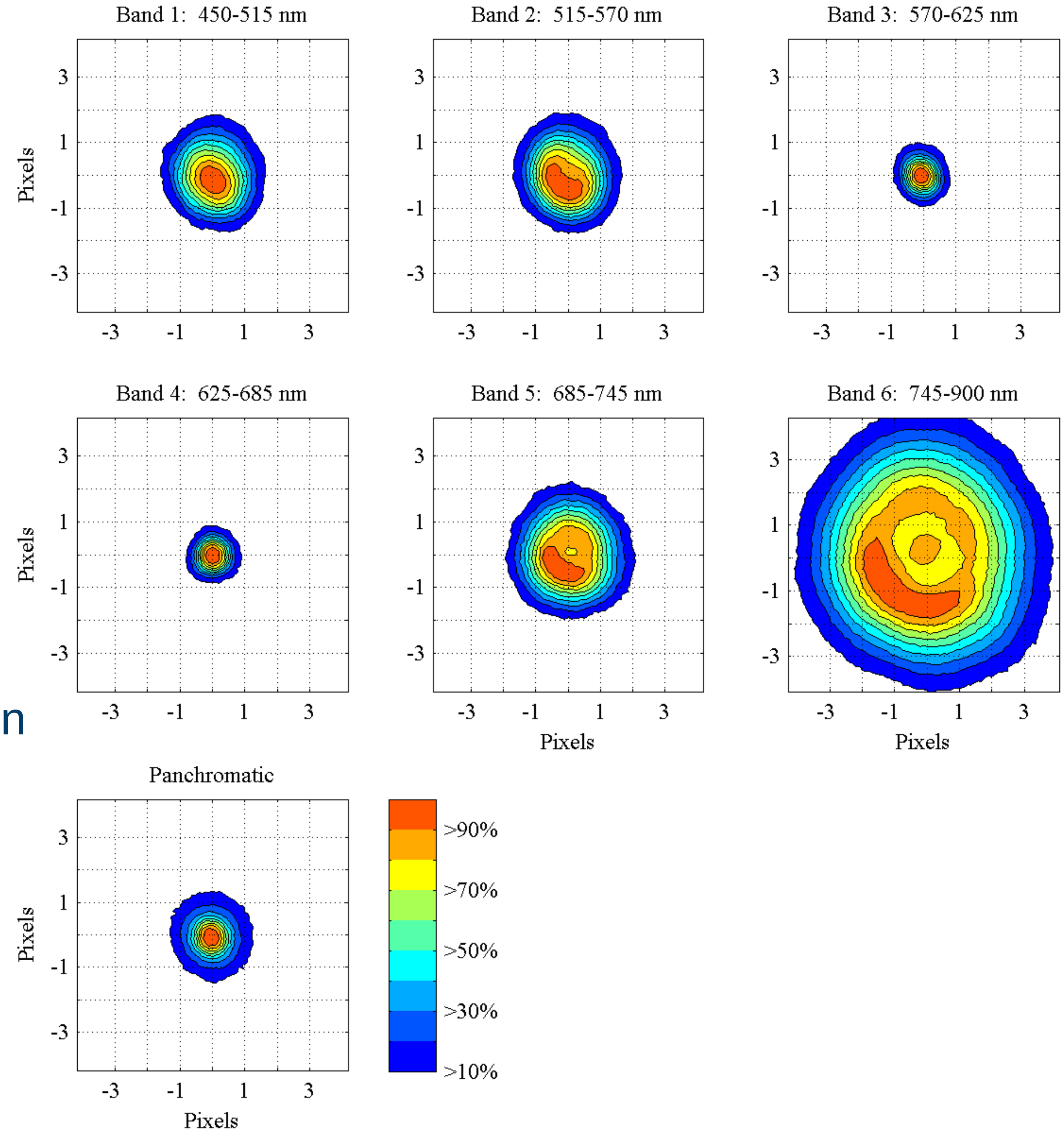
Band 5, NIR1

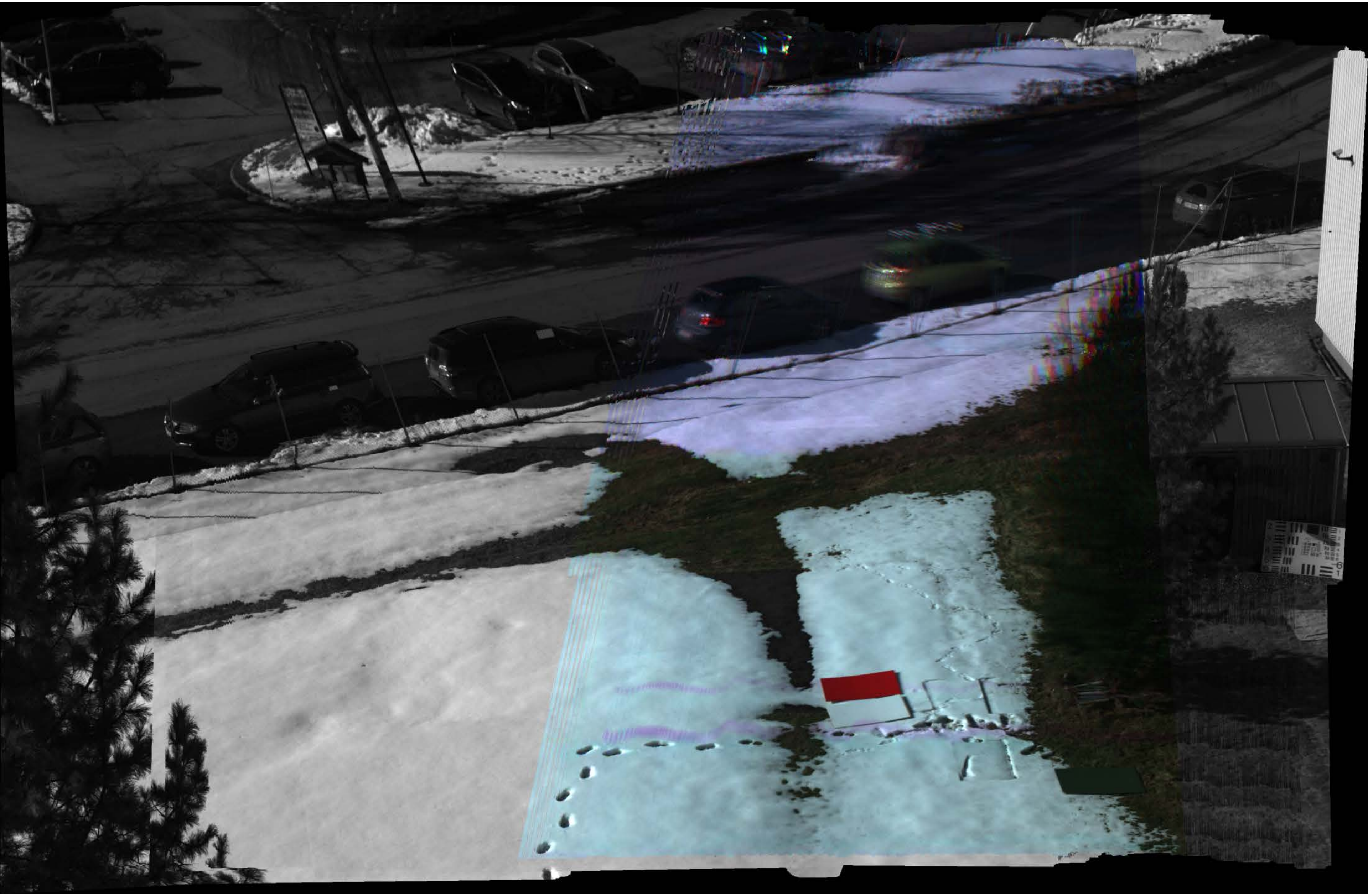
Band 6, NIR2

- Strong differences in focus between bands
- Lens properties must be taken into account in image reconstruction

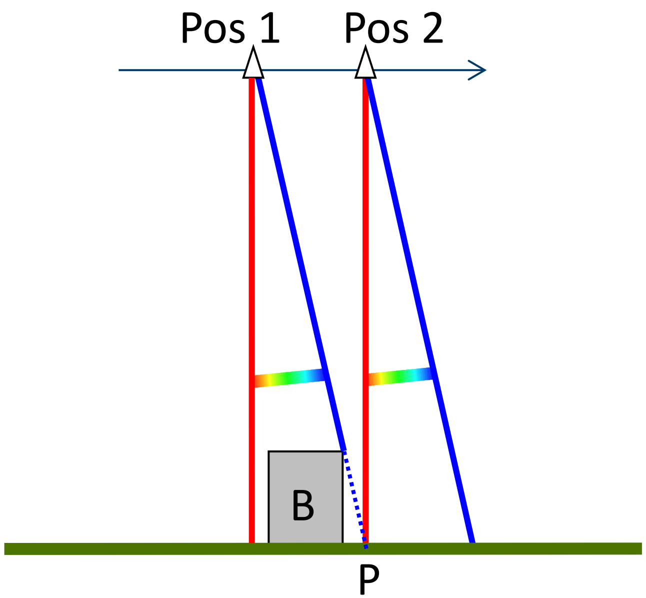
PSF for all bands

- Clear differences in degree of focus
- Result of chromatic errors in lens
- Can be exploited in image reconstruction

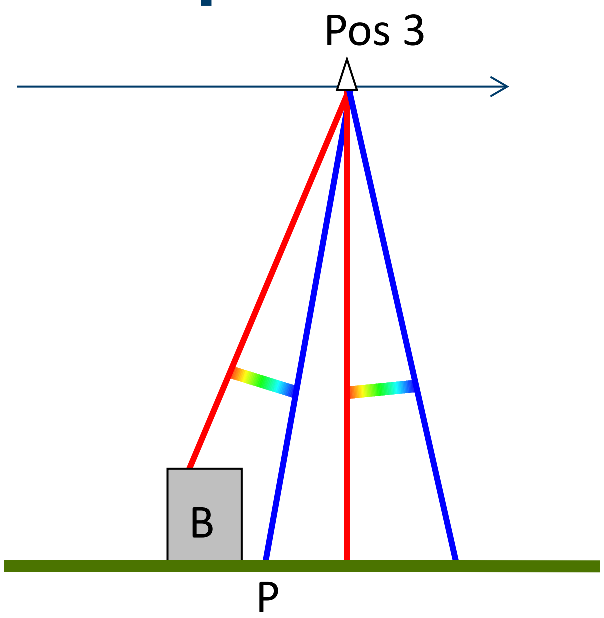




Repeated sampling can overcome parallax

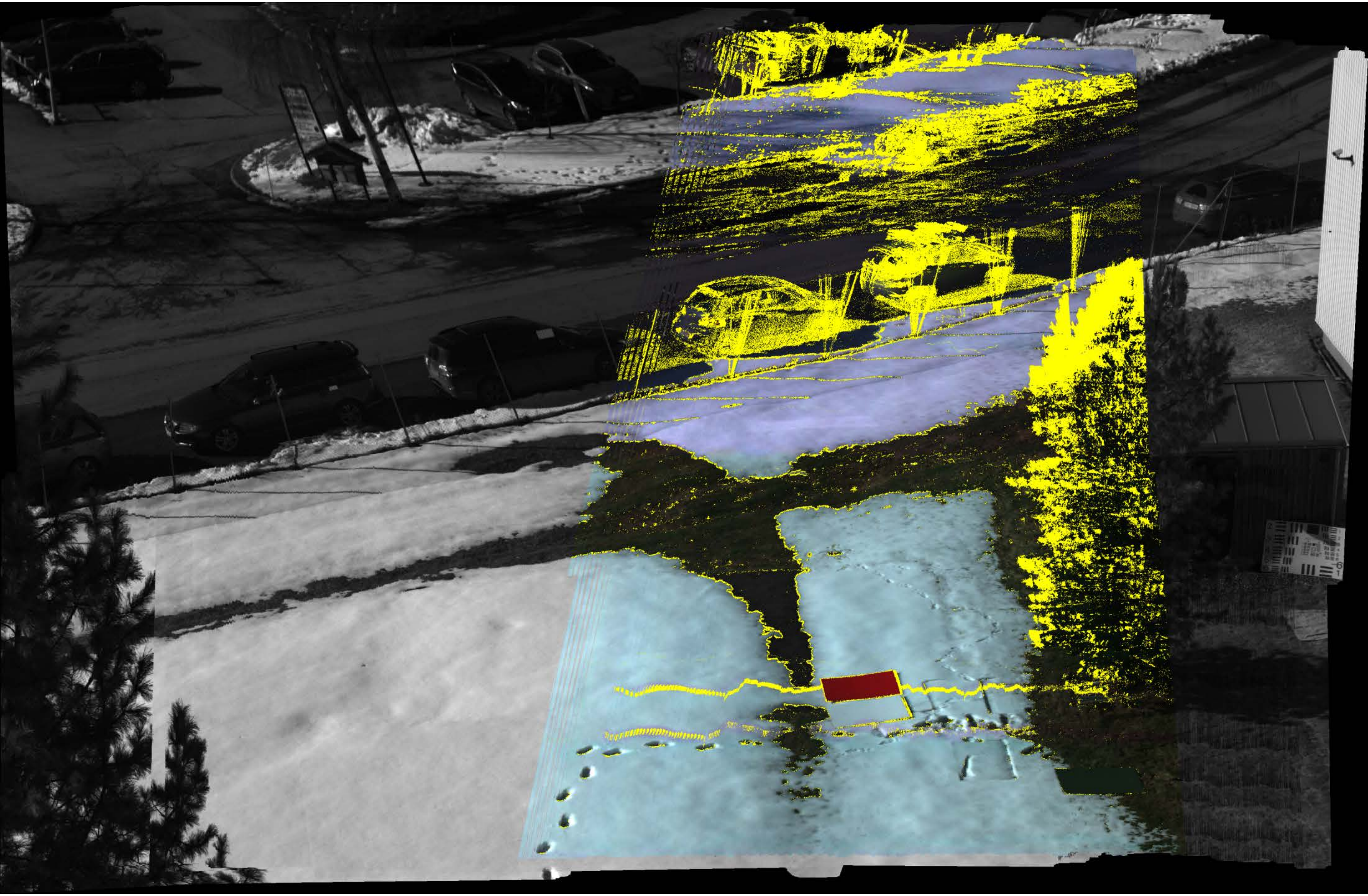


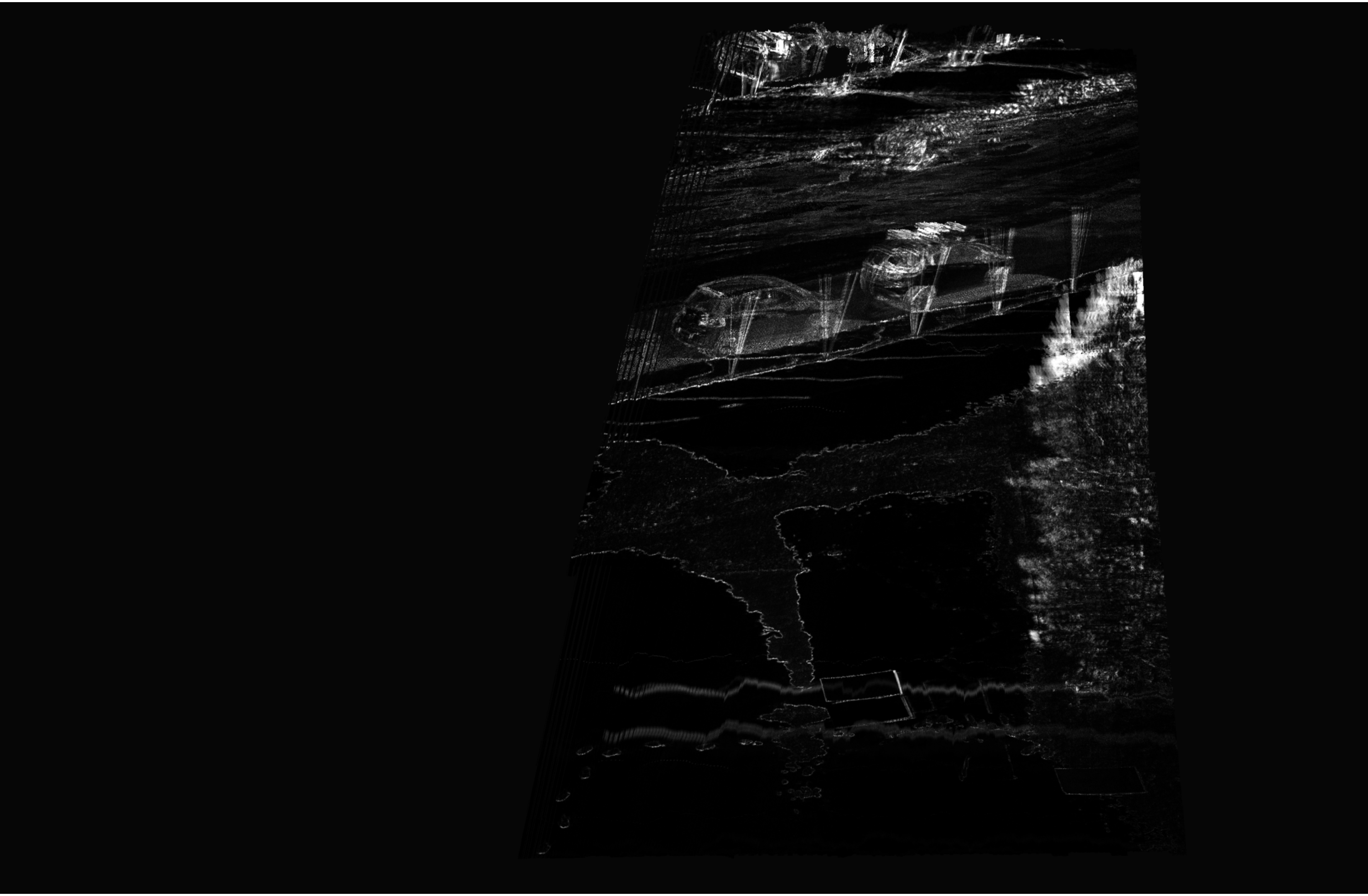
One sample per band



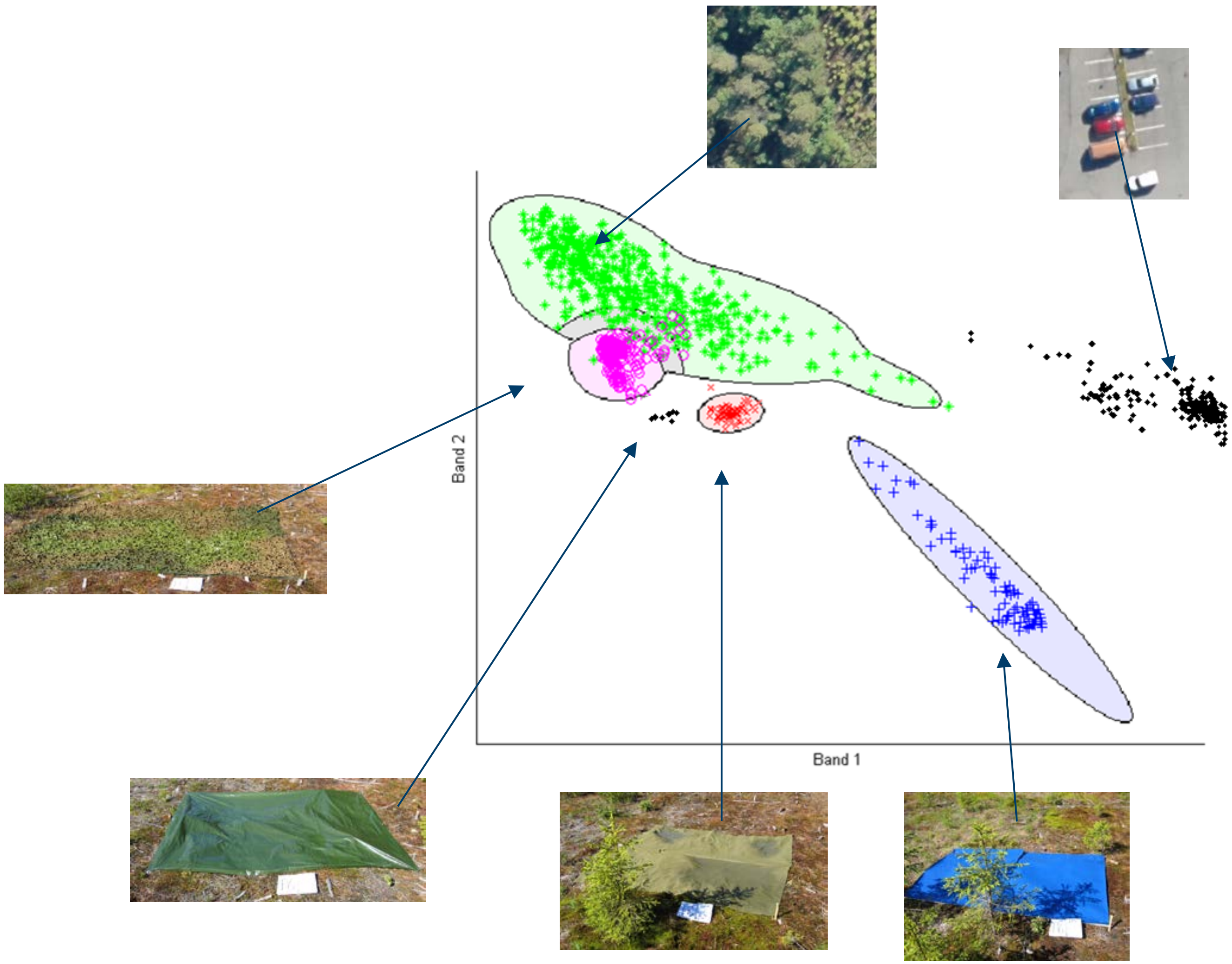
Two samples per band

- Point P can be correctly measured if 3D structure is known
- Or, inconsistency can be detected in point P, data flagged as invalid
- With more samples, additional correction strategies are possible



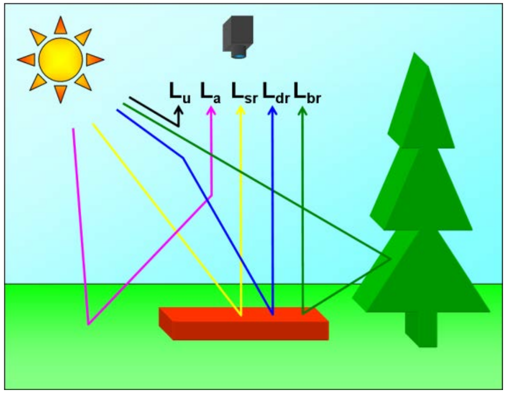


Example: Combined signature-specific and anomaly detection



Signature-specific detection
Estimating radiance from reflectance

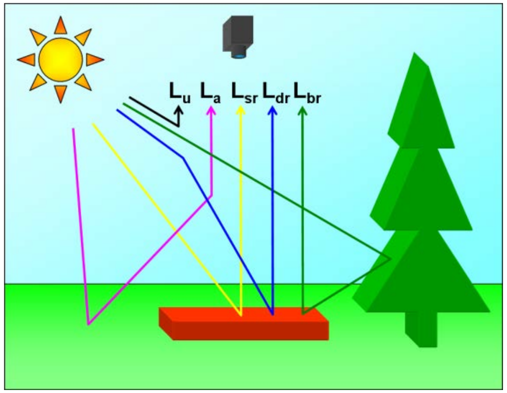
The radiance signature measured
by a hyperspectral sensor:



$$L_i(\lambda) = \left[K_i L_{s0_i}(\lambda) + F_i L_{d0_i}(\lambda) + (1 - F_i)\bar{L}_{b_i}(\lambda) \right] r_d(\lambda)\tau_i(\lambda)$$
$$+ L_{u_i}(\lambda) + L_{a_i}(\lambda) + n_i(\lambda)$$

Signature-specific detection
Estimating radiance from reflectance

The radiance signature measured
by a hyperspectral sensor:

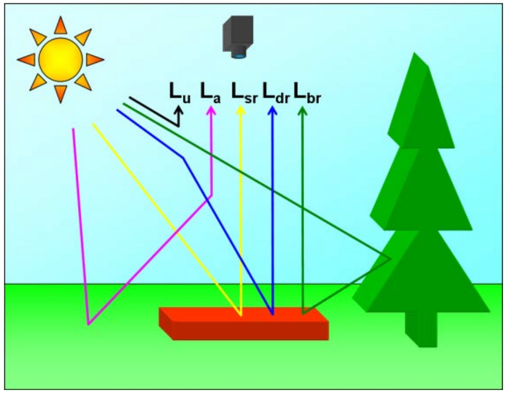


$$L_i(\lambda) = \left[K_i L_{\mathrm{s0}_i}(\lambda) + F_i L_{\mathrm{d0}_i}(\lambda) + (1 - F_i)\bar{L}_{\mathrm{b}_i}(\lambda) \right] r_{\mathrm{d}}(\lambda)\tau_i(\lambda) + L_{\mathrm{u}_i}(\lambda) + L_{\mathrm{a}_i}(\lambda) + n_i(\lambda)$$

The radiance from reflected direct sunlight
(if the target had been a 100% reflector)

Signature-specific detection
Estimating radiance from reflectance

The radiance signature measured
by a hyperspectral sensor:

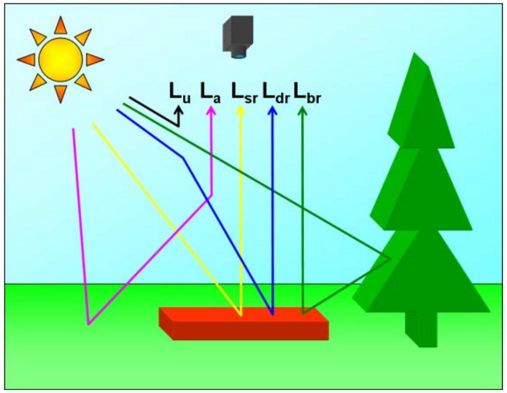


$$L_i(\lambda) = \left[K_i L_{s0_i}(\lambda) + F_i L_{d0_i}(\lambda) + (1 - F_i)\bar{L}_{b_i}(\lambda) \right] r_d(\lambda)\tau_i(\lambda)$$
$$+ L_{u_i}(\lambda) + L_{a_i}(\lambda) + n_i(\lambda)$$

The radiance from reflected skylight
(if the target had been a 100% reflector)

Signature-specific detection
Estimating radiance from reflectance

The radiance signature measured
by a hyperspectral sensor:

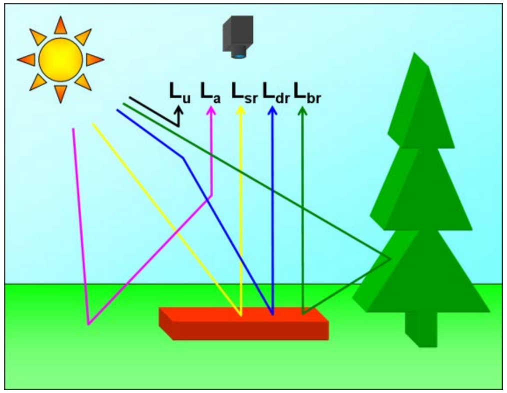


$$L_i(\lambda) = \left[K_i L_{s0_i}(\lambda) + F_i L_{d0_i}(\lambda) + (1 - F_i)\bar{L}_{b_i}(\lambda) \right] r_d(\lambda)\tau_i(\lambda) + L_{u_i}(\lambda) + L_{a_i}(\lambda) + n_i(\lambda)$$

The radiance from reflected background illumination
(if the target had been a 100% reflector)

Signature-specific detection
Estimating radiance from reflectance

The radiance signature measured
by a hyperspectral sensor:

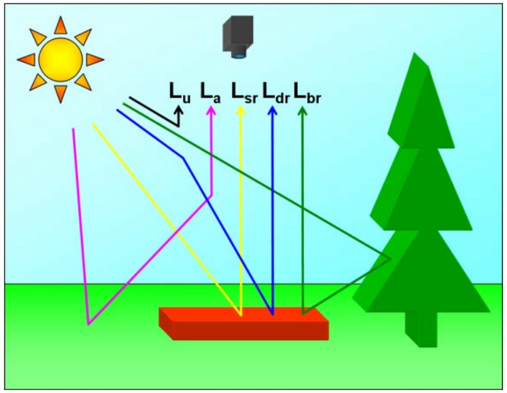


$$L_i(\lambda) = \left[K_i L_{s0_i}(\lambda) + F_i L_{d0_i}(\lambda) + (1 - F_i)\bar{L}_{b_i}(\lambda) \right] r_d(\lambda) \tau_i(\lambda)$$
$$+ L_{u_i}(\lambda) + L_{a_i}(\lambda) + n_i(\lambda)$$

The reflectance signature

Signature-specific detection
Estimating radiance from reflectance

The radiance signature measured
by a hyperspectral sensor:

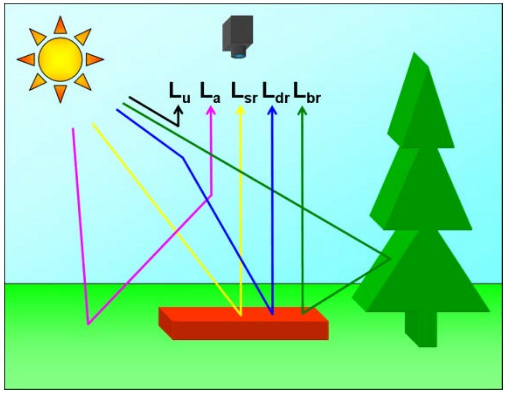


$$L_i(\lambda) = \left[K_i L_{s0_i}(\lambda) + F_i L_{d0_i}(\lambda) + (1 - F_i)\bar{L}_{b_i}(\lambda) \right] r_d(\lambda) \tau_i(\lambda)$$
$$+ L_{u_i}(\lambda) + L_{a_i}(\lambda) + n_i(\lambda)$$

The atmospheric transmission

Signature-specific detection
Estimating radiance from reflectance

The radiance signature measured
by a hyperspectral sensor:

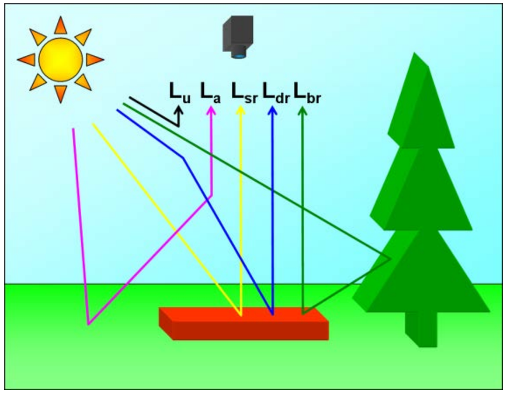


$$L_i(\lambda) = \left[K_i L_{s0_i}(\lambda) + F_i L_{d0_i}(\lambda) + (1-F_i)\bar{L}_{b_i}(\lambda)\right] r_d(\lambda)\tau_i(\lambda) + L_{u_i}(\lambda) + L_{a_i}(\lambda) + n_i(\lambda)$$

Radiance from up-welled skylight and the adjacency effect

Signature-specific detection
Estimating radiance from reflectance

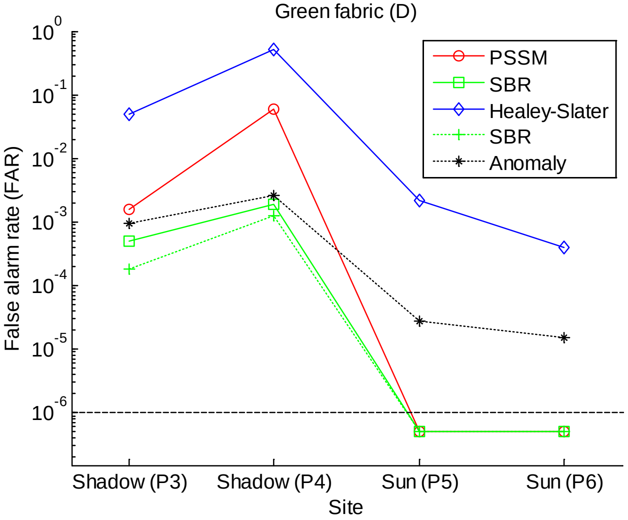
The radiance signature measured
by a hyperspectral sensor:

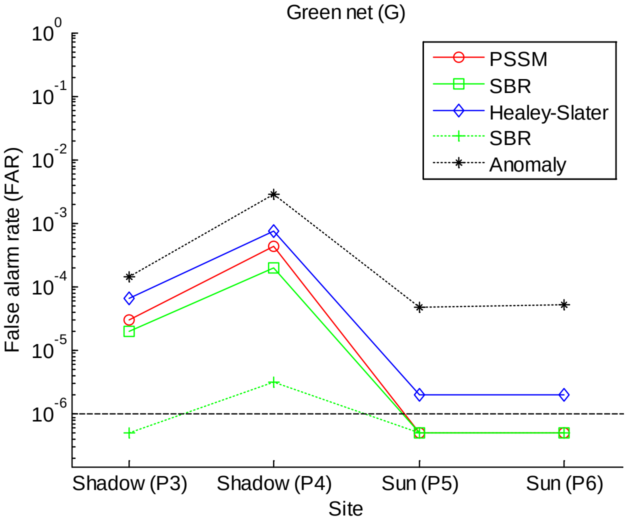


$$L_i(\lambda) = \left[K_i L_{s0_i}(\lambda) + F_i L_{d0_i}(\lambda) + (1 - F_i)\bar{L}_{b_i}(\lambda) \right] r_d(\lambda) \tau_i(\lambda) + L_{u_i}(\lambda) + L_{a_i}(\lambda) + n_i(\lambda)$$

Sensor noise

Example: Signature-specific detection with extreme signature variability





Example: Signature-specific classification with extreme signature variability

Mål	B	D	G	T
P3-B	0	2	13	0
P4-B	3	0	20	0
P5-B	43	0	2	0
P6-B	34	0	6	0
P3-D	0	26	4	0
P4-D	0	23	0	0
P5-D	0	31	0	0
P6-D	0	39	0	0
P3-G	0	0	40	0
P4-G	0	12	12	0
P5-G	0	0	114	0
P6-G	0	0	75	0
Sunlit T	0	0	0	9

Example: Combined signature-specific and anomaly detection