Model Predictive Control Architecture for Optimizing Earth Science Data Collection (PCAES) - Challenges and Testing

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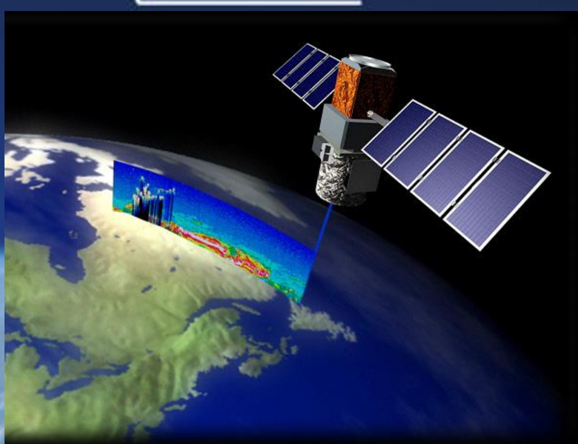


PCAES Overview

- ESTO/ AIST funded with start on May 1 2015 and completion on April 30 2017. Extended to May 31 2017.
- Start at TRL 2, end at TRL 4.
- Demonstrate through simulation and hardware validation that the MPC architecture, borrowed from control theory, can optimize adaptive lidar for remote sensing data collection.
- The software product, using a data driven control and prediction approach, will provide autonomous, rapid and adaptive data collection by creating a science optimized, time-evolving power map.
- Software approach relies on Matlab environment and associated toolboxes, and furthermore leverages community developed software for certain targeted applications.
- Year 1 – Requirements, modeling & simulation and optimization development.
- Year 2 – Hardware implementation and model validation.

Significance of PCAES Work to Future Earth Science Missions

- Tightening NASA budgets require new missions to:

(1) Address the issue of data collection efficiency

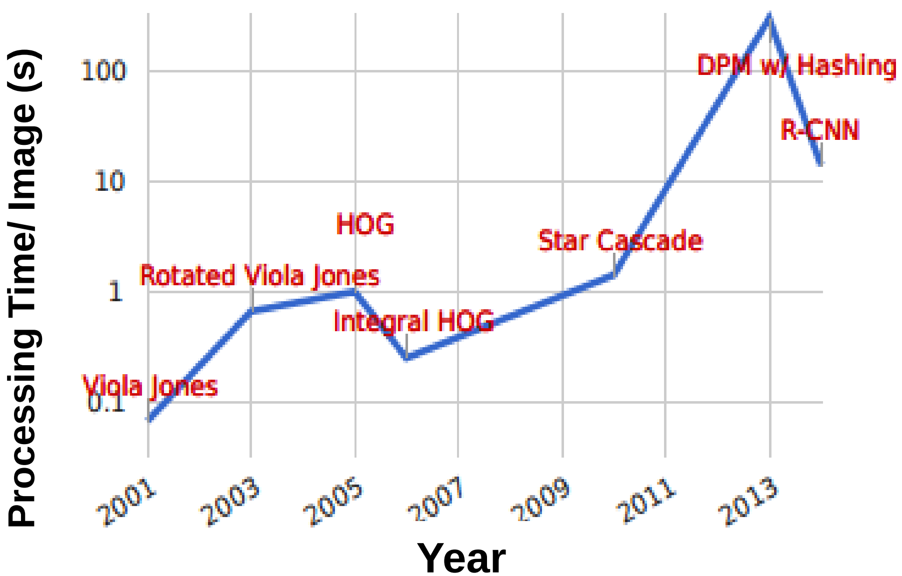
(2) Consider smaller payloads which can still provide high quality science.

- PCAES project is developing an on-board autonomous software architecture that addresses both these areas.
- Sensor platforms can collect much more data of importance for Earth science by optimally targeting areas of interest.
- The PCAES MPC architecture is based on successful ground-based control of complex, hierarchical and sometimes distributed subsystems which can be used for other type of complex space missions.
- We chose a target application to **adaptive multi-beam lidar**.

The Real World is a Rich Environment, Fraught with Complexity [Desnoyer2015]

- Even in the simplest case, an algorithm must operate on all of the pixels in an image, while the trend in vision is to increase the computational complexity further.
- Processing time of algorithms proposed for the well-studied problem of object detection (see below)
- Scene understanding, pose estimation and others, newer techniques rely on modeling the relationships between portions of images and objects, adding extra dimensions to the search space.

Moore's law is not sufficient to overcome this increasing complexity because the same process that increases the transistor density on chips is increasing the number of pixels in camera sensors [Desnoyer2015]



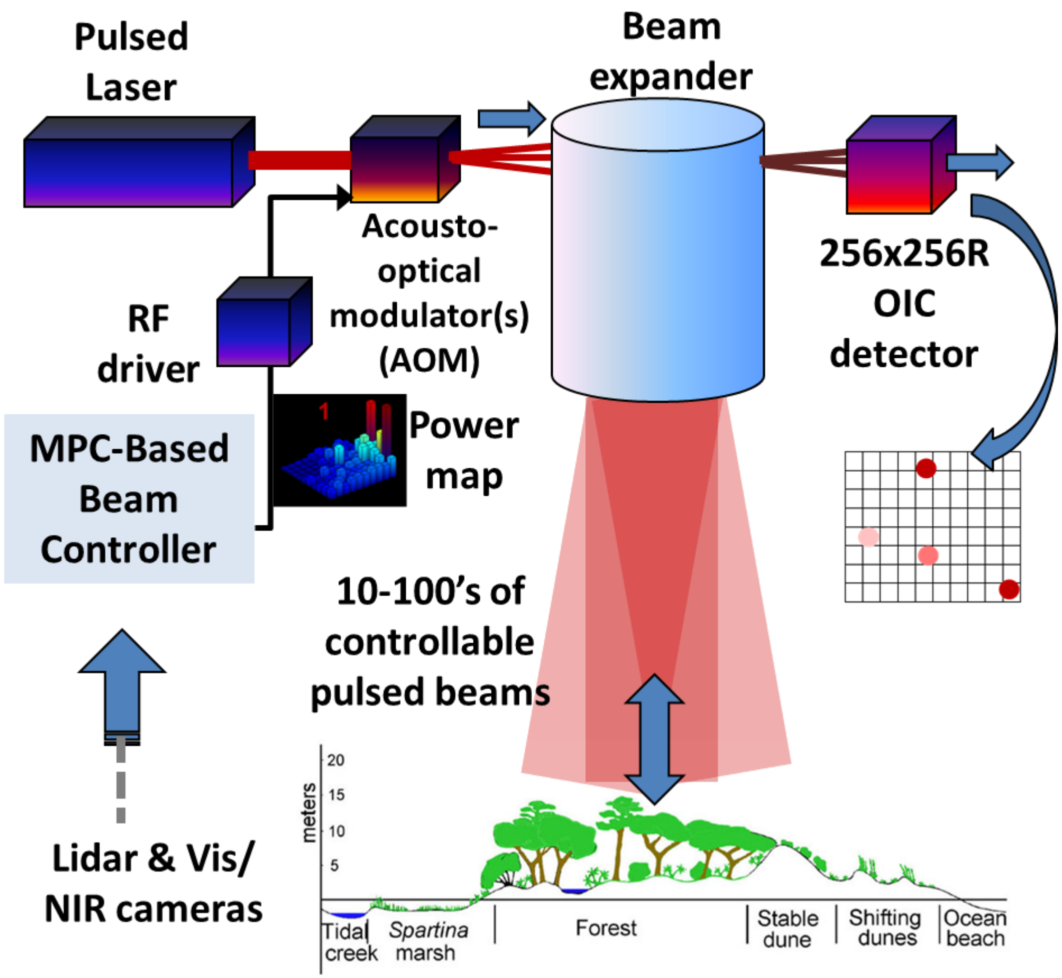
Desnoyer, Mark, "*Visual Utility : A Framework for Focusing Computer Vision Algorithms*", PHD thesis, CMU, Dec. 2015.

Why Use Model Predictive Control Architecture?

- By starting with MPC architecture, we can use a <u>top-down approach</u>. Therefore we can borrow from the large-scale development of other autonomous systems (cars, etc.).
- MPC automatically handles constraints and re-optimizes control at each time step.
- PCAES is a new development for space applications which will enable new types of sensor platforms and can take advantage of recent developments in sparse signal processing, compressed sensing and deep learning algorithms.
- MPC architecture ban be basis for formation flying CubeSats/ Smallsats and other complex space-based mission.

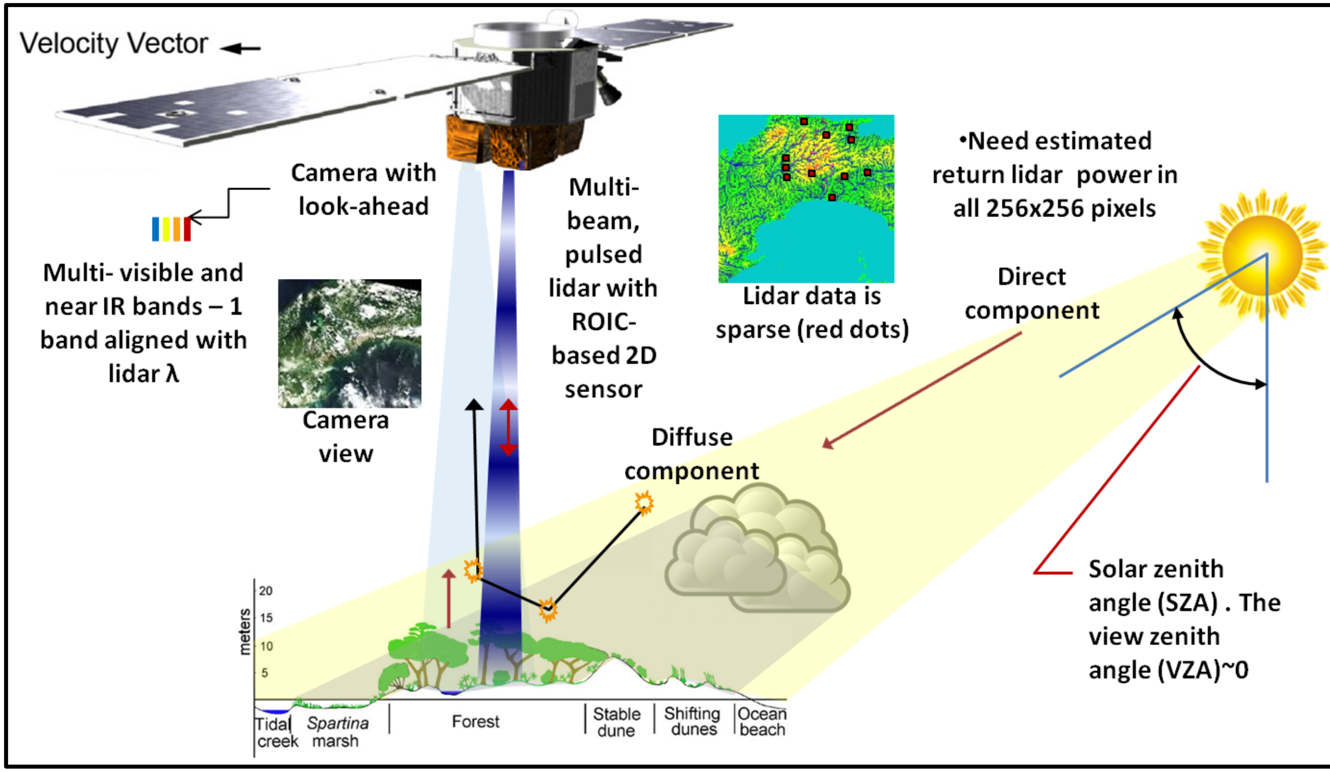
One Application - Multi-Beam Adaptive Lidar - ESFL

- We apply MPC architecture to an electronically steerable flash lidar (ESFL)
- AOM controls amplitude and angle (frequency) of each beamlet independently.
- 2D multi-beam steering
- Constraints:
  - Total power
  - SNR
  - Steering angle



Geometry of the Control Problem

- Lidar return data sparse – typically 1% of pixels. Need estimated return lidar power in all 256x256 pixels of ROIC receiver.
- Light flux measured by the lidar and camera is made up of two components – direct component (non-scattered) and diffuse component (scattered).
- Due to solar zenith angle, light seen by camera not same as lidar return signal. <u>Lidar return at hotspot</u> (typically 3˚ FWHM)

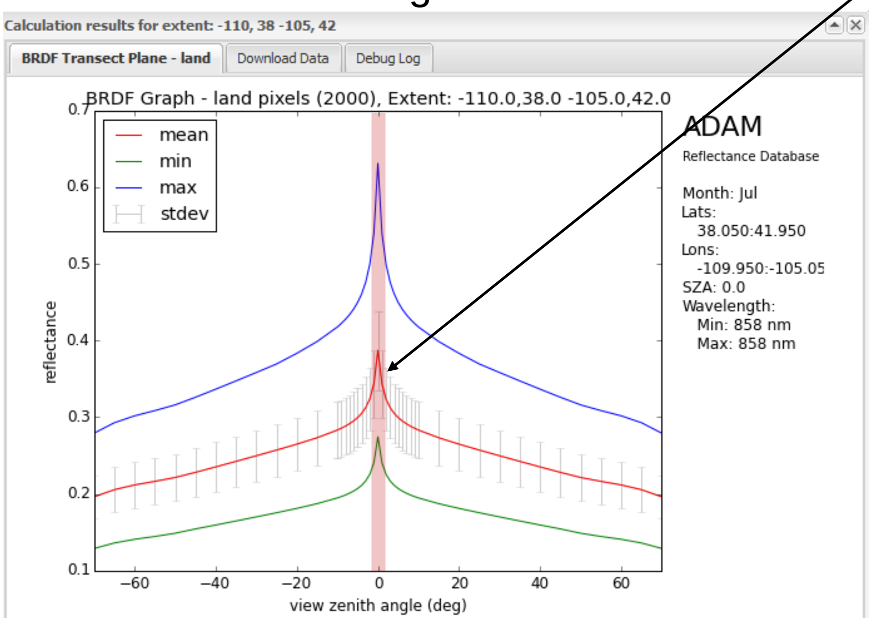


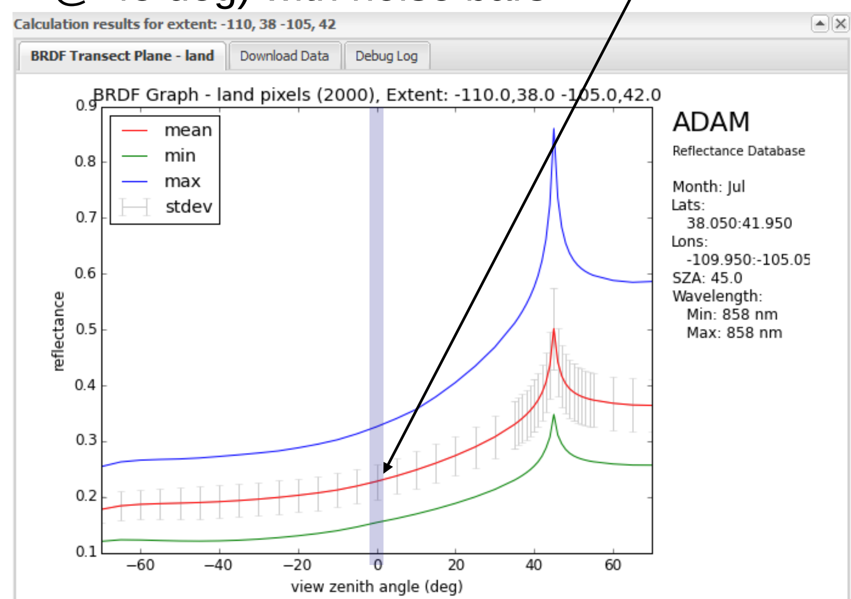
Multi-Spectral Camera Receives Different Flux Than What Lidar Sensor Sees

- The difference between the camera measured signal and the lidar return can be significant and gets worse as the solar zenith angle increases.
- Below is shown mean reflectance – every ground pixel will have variability.

Normalized lidar return signal with noise bars

Camera measured signal (sun @ 45 deg) with noise bars



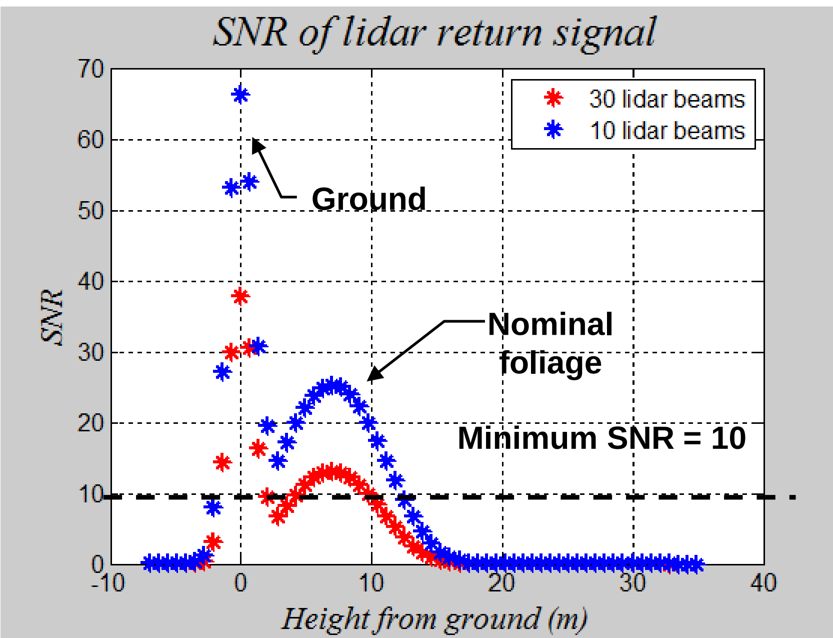


Ball Developed Lidar Radiometric Math Model Used for Mission Level Definition and Requirements

Parameter	Value	Units	Comments
Orbit altitude	440	km	
Spot size per beam	30	m	Landsat size – application driven
Across-track swath width	7.68/ 1.0	Km/ deg (instrument FOV)	
Solar background	0.0309	W/m^2 sr nm	
Background noise, Detector noise	1, 8	Photons/time bin/pixel	
Laser pulse energy/ Average power	1000/ 30	mJ/ W	Fibertek SQ laser – 1064 nm, eye-safe concern 1 beam
Maximum* SNR ground return [1 beam, 10 beams, 100 beams]	[243 66 15.7]	SNR	Maximum SNR of waveform return. 1 beam case not deflected.
Maximum* SNR foliage return [1 beam, 10 beams, 100 beams]	[96 25 3.3]	SNR	Maximum SNR of waveform return. 1 beam case not deflected.
Number pixels per footprint	1	-	Max SNR but poor resolution
iFOV	68	µrad	
Detector size	256 x 256	-	
Receiver telescope diameter	1	m	CALIPSO telescope design
Number of pixels across per degree FOV	256	-	
Range bins	61		
Resolution of lidar range	0.7	m	

Lidar Return SNR Depends Upon Surface and # of Beams

- Example output from Lidar Radiometric Model – ground and nominal foliage return signal.
- Radiometric calculations for 1064 nm, but Landsat/ MODIS data used in PCAES modeling is 850 nm band.



SNR = Signal photons in each bin/ Noise photons in each bin

Reflectance variation of surfaces

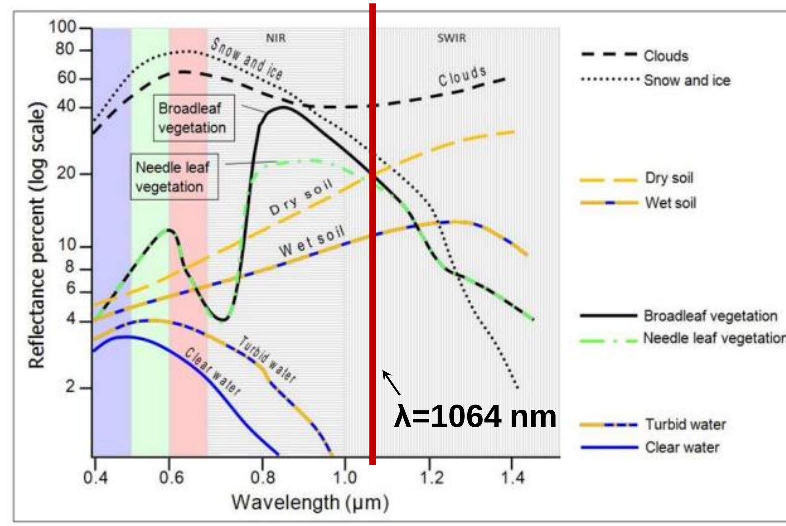
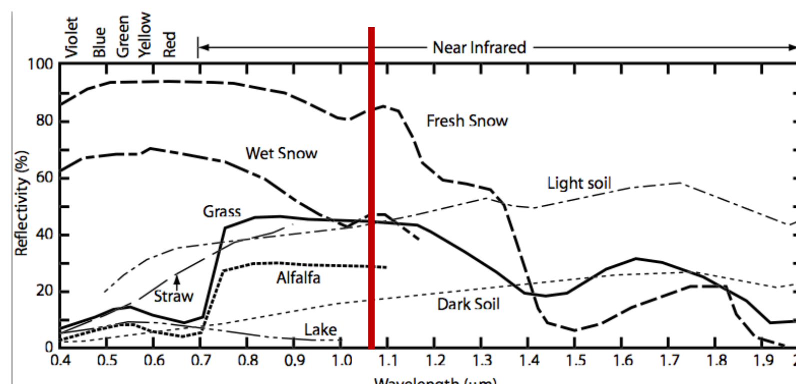


Figure 10. Spectral reflectance curves for the following paired landcover types (Aronoff, 2005):
- Clouds vs. Snow & ice
- Broadleaf vegetation vs. Needle leaf vegetation
- Dry soil vs. Wet soil
- Turbid water vs. Clear water

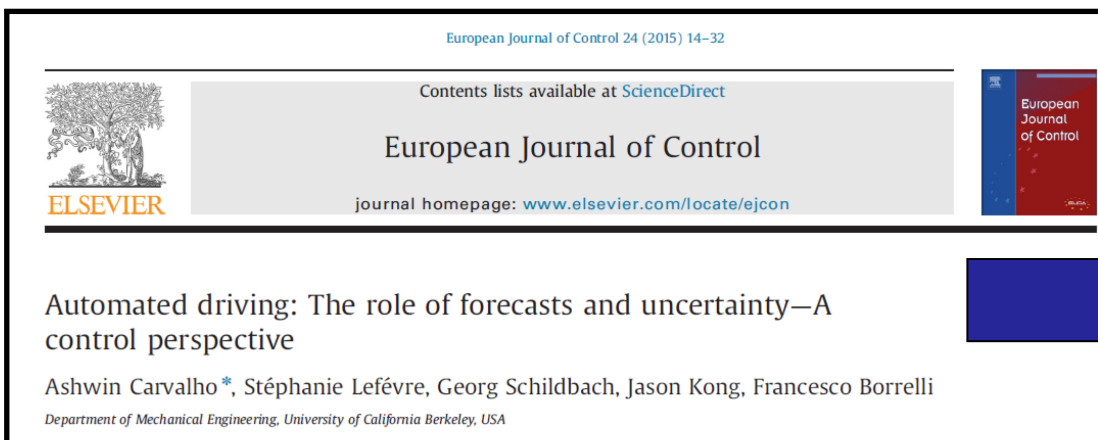


WHAT IS MPC TECHNOLOGY & WHY A DATA DRIVEN APPROACH FOR PCAES

Heuristic Explanation of MPC

- Works very much how one drives a car.
  - Continuous adjustment/ optimization of steering and speed using visual feedback of the operating environment while having an embedded model of car operating parameters (acceleration, turning sensitivity, braking) and considering constraints (lanes, other cars, max braking and acceleration). Predict ahead.
  - Multi-layered (the person with smart phone providing directions)

In fact – many approaches to autonomous cars use a version of MPC



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Automated driving: The role of forecasts and uncertainty—A control perspective

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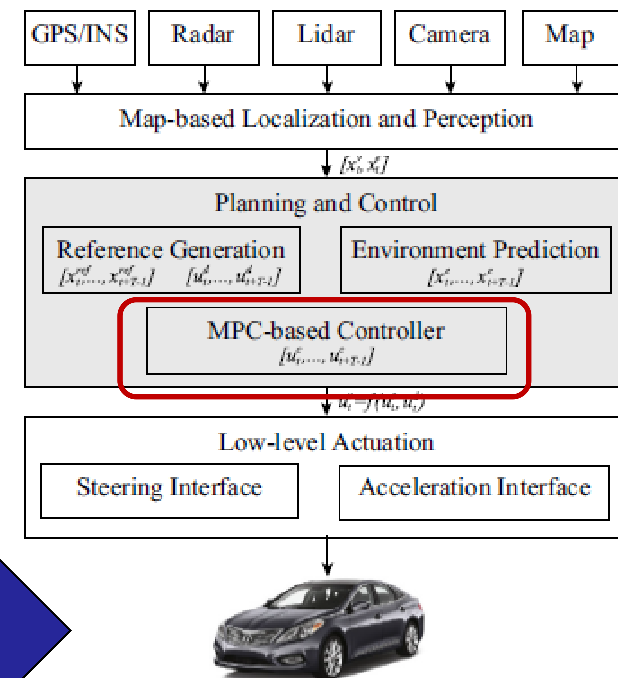
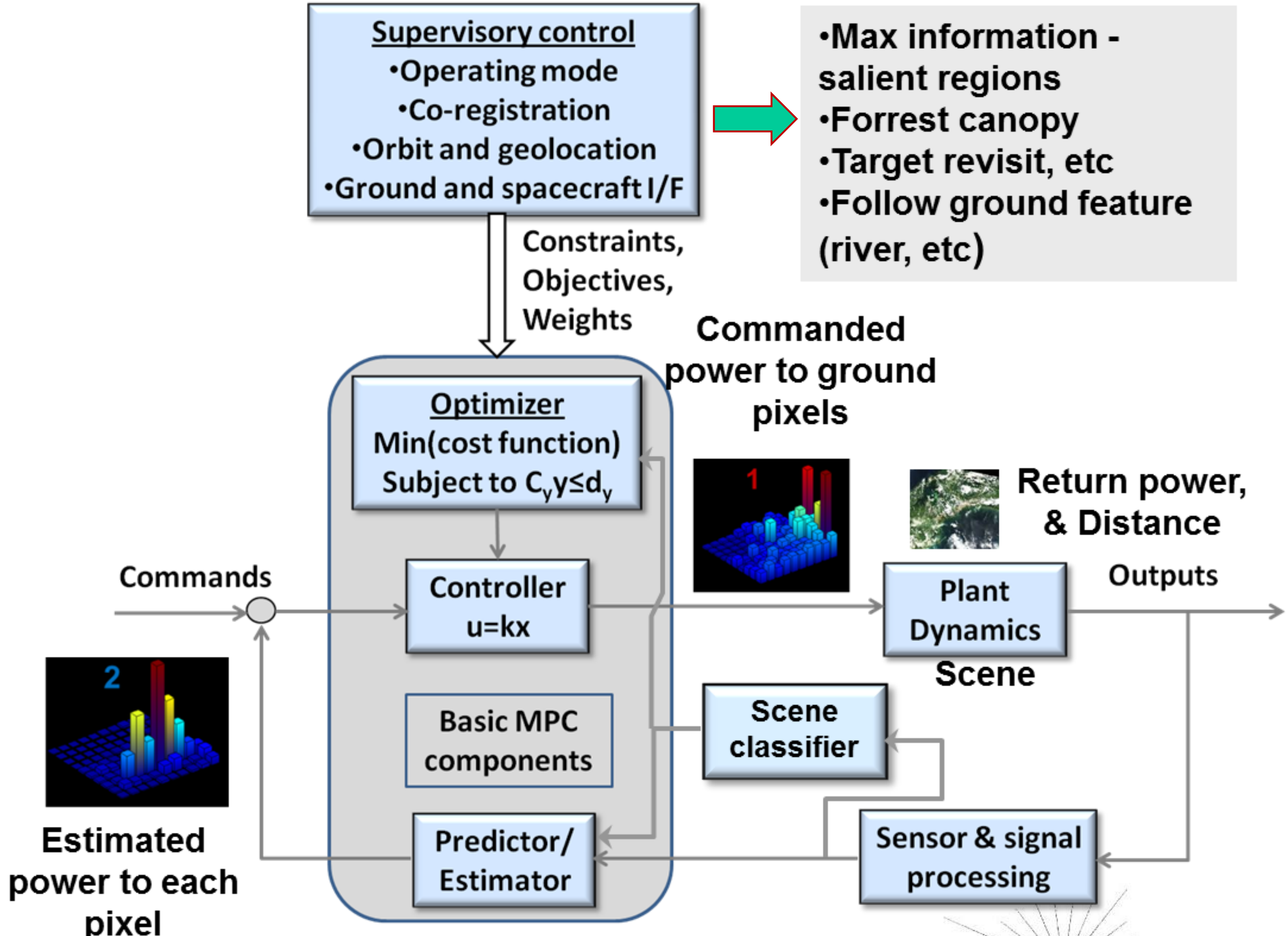


Fig. 1. Intelligent vehicle system overview.

What Does Simplified MPC Architecture Look Like?

- Two things are controlled – lidar power to ground pixels and dynamic range gate.
- Estimator predicts return power to ROIC receiver.
- Supervisory control passes down weights.
- Optimizer algorithm requires scene classification.



Unusual Characteristics of Our “Plant” Leads to Data Driven Approach

- We have to go to a data-driven control (DDC) approach because there is no conceivable mathematical model for the time-varying scene … well kind of true.
- Data driven approach uses the lidar return data as the model. We take it one step further by doing scene classification (system ID) – reduces model from 256x256 to perhaps 10-20 regions in the FOV.
- Our “actuators” are the lidar beamlets and the sun (daytime operation). We only control one and it only collects sparse returns over FOV (1% type numbers).

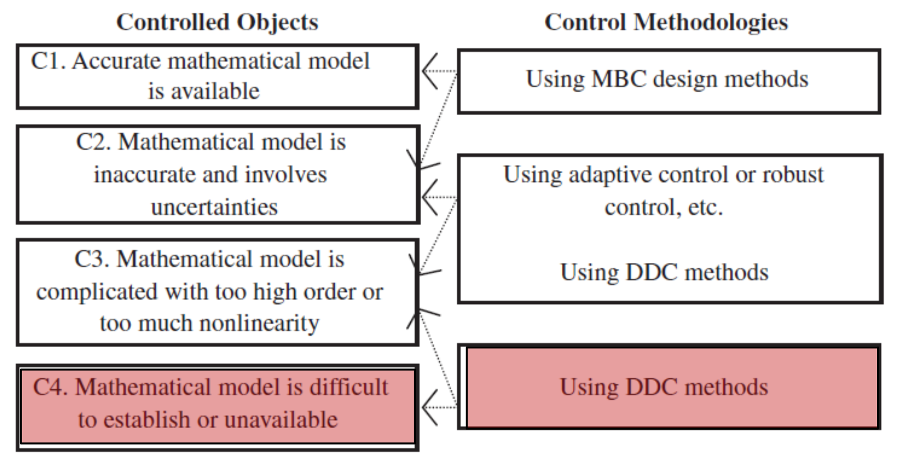


Fig. 3. Controlled objects of DDC.

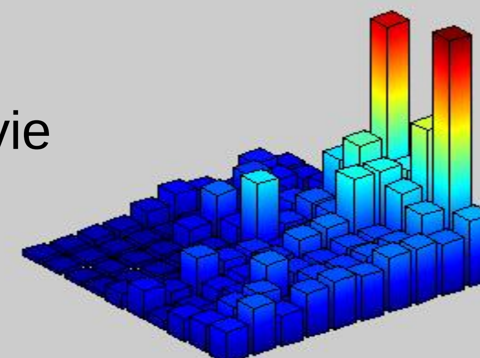
ESFL MPC in this category

Z.-S. Hou, “From model-based control to data-driven control: Survey, classification and perspective”, Inf. Sci., 235 (2013) 3-35.

Computational Speed Problem - Time Evolution of Power Map from Landscape and Clouds

- The example images are 10x10 –how power map changes as we go though a cloudy area. Simple weighting – clouds very penalized, water least penalized. Prior data collection not included.
- PCAES focuses on fastest, lower level computation.

Movie



Ground track and moving FOR over Panama canal

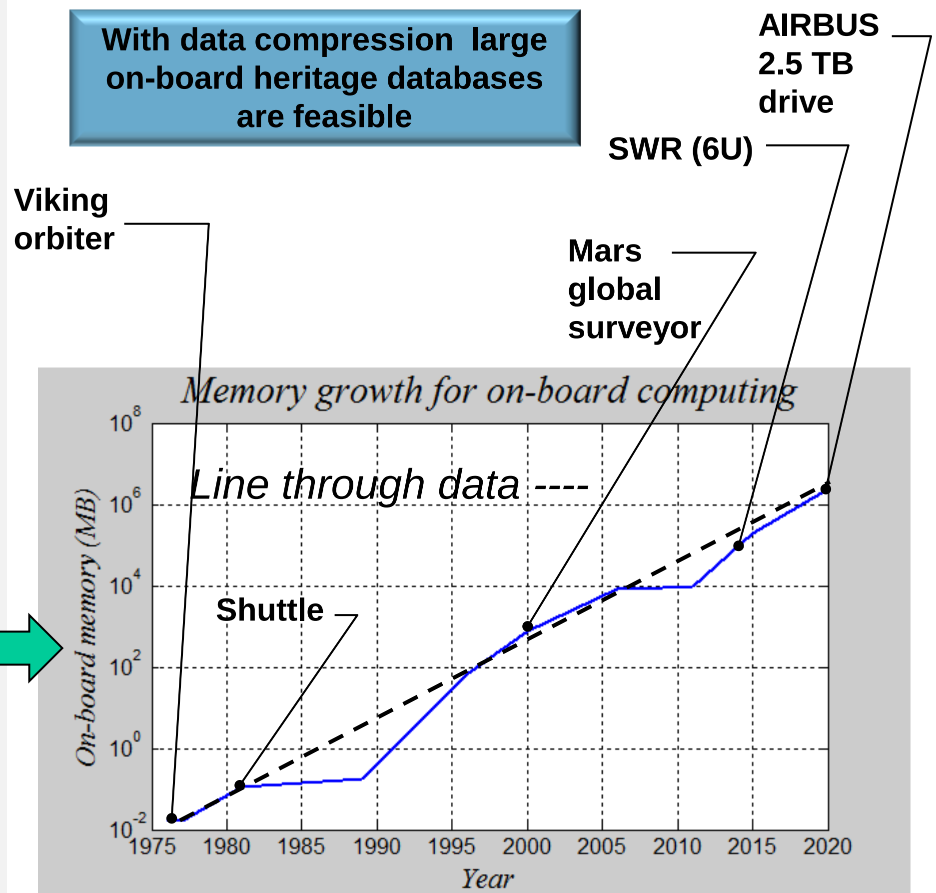
Instantaneous field-of-regard (FOR) of adaptive lidar

Power map before thresholding

Including Heritage Databases into Estimator – On-Board Memory

- Approximate on-board memory requirements (global land coverage – no compression) – 100 m/ 30 m pixels
  - BRDF heritage –90 GB/ 1.0 TB
  - DEM heritage – 75 GB/ 0.85 TB
  - Scene classification heritage - 22 GB/ 0.25 TB
  - *Total ~190 GB/ ~2.1 TB*
- Memory capabilities should be around 0.4 TB for 6U cubesats and 4 TB for full size spacecraft by 2020.
- ICESat-2 plans to carry multiple databases including global DEM.
  - 30 m to 1 km ground pixel size.

With data compression large on-board heritage databases are feasible



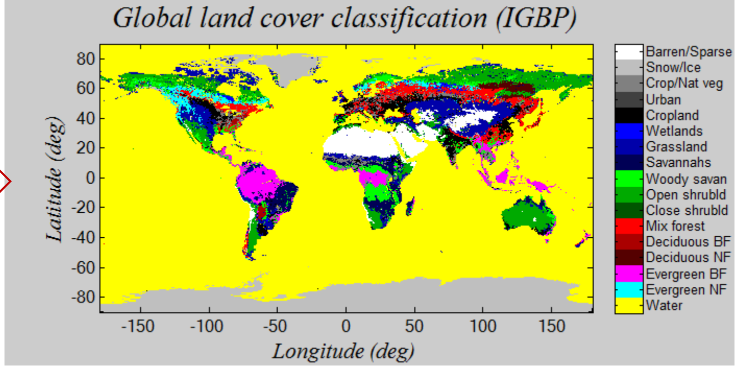
See http://www.cpushack.com/space-craft-cpu.html for years 1975 - 2011.
See SWRI and AIRBUS sites for 2015-2016 data.

SCENE GENERATION

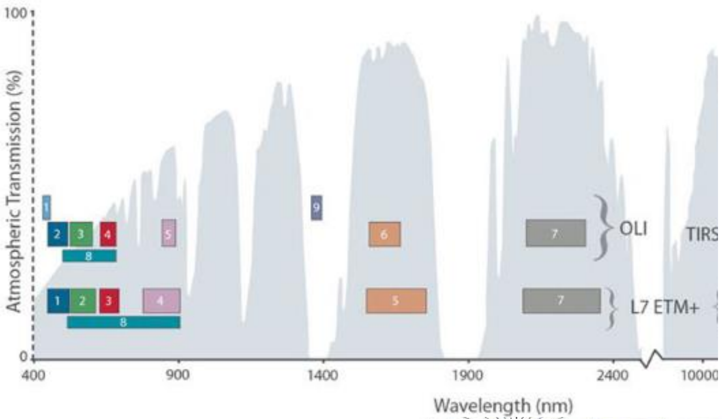
- MODEL AND LAB TESTING

Abundance of Real Satellite Scenery Provided Best Path Forward (1/2)

- MODIS data products:
  - Global BRDF and scene classification – 6.5 km pixels
    - Matlab SW extracts test strips and can pull 7 spectral bands
    - IGBP classification – 17 categories and we add in clouds.
  - US data base at 500 m and 1000 m pixels.
  - Downloaded from Earth Explorer.
    - Level 2 and 3 data – clouds removed and atmospheric corrected BRDF.
  - Also pulled in level 1b data that was not processed for clouds & aerosols.

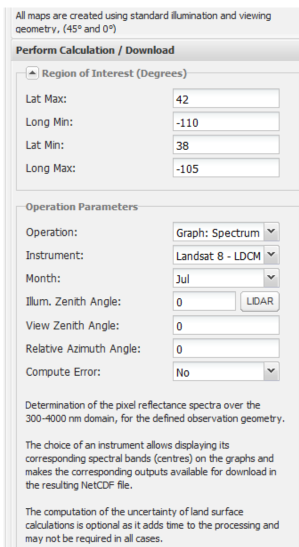


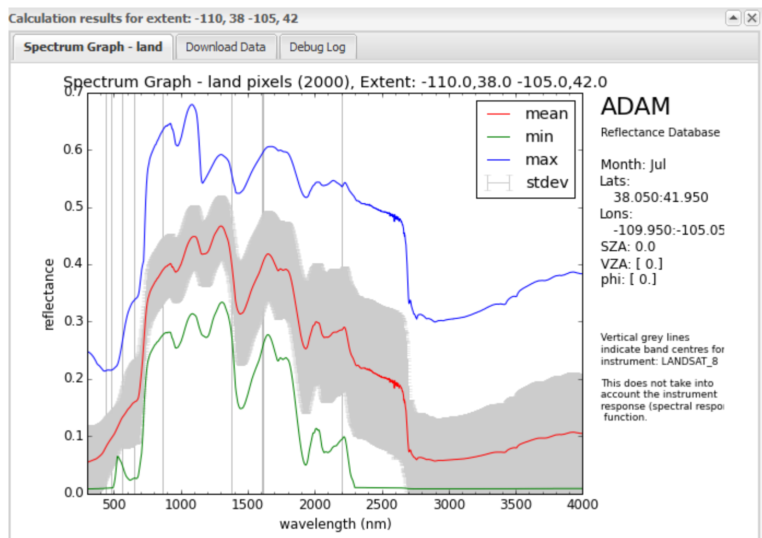
- Landsat data base:
  - 30 m pixel size data matches camera pixels
  - Variable amount of clouds.
  - Multiple spectral bands useful for classification



Abundance of Real Satellite Scenery Provided Best Path Forward (2/2)

- ADAM (A surface reflectance Database for ESA's earth observation Missions)
  - Provided reflectance (BRDF) data for global area but with 11 km pixels.
  - Generated variance and BRDF shape information
  - Allowed us to look at reflectance and sensitivity effects



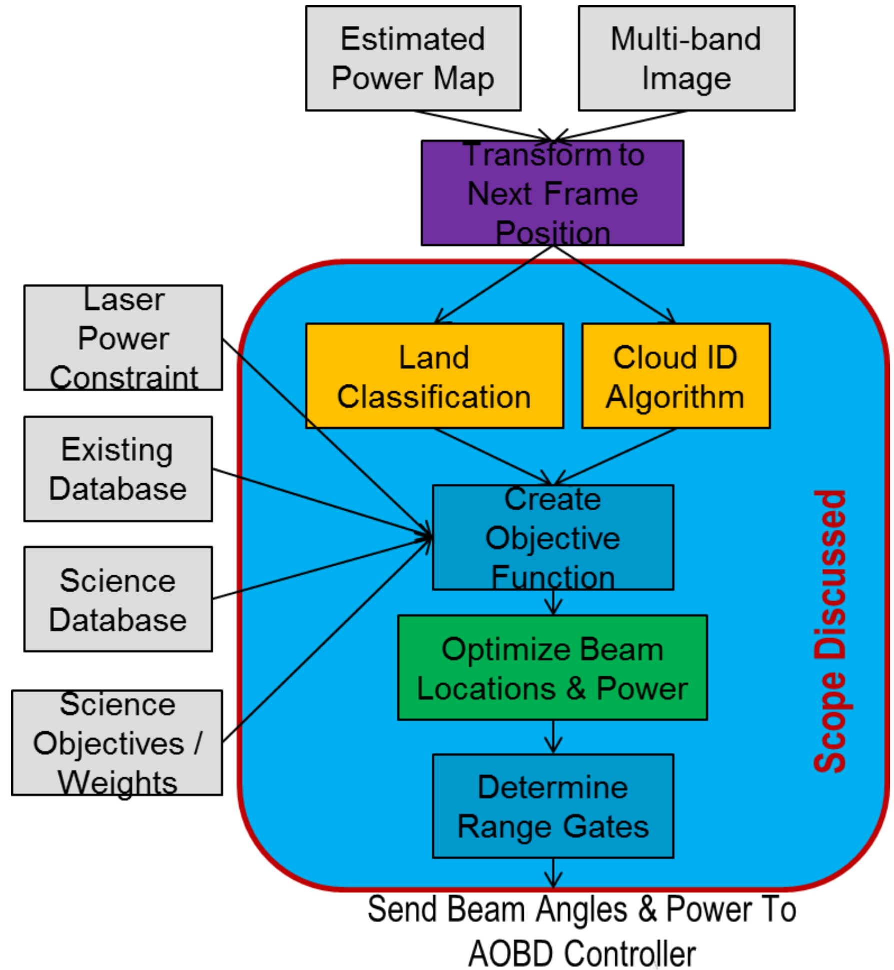


- Issues:
  - Data is not always compatible – different projections, pixel scales, units, file types, etc.

OPTIMIZATION & SCENE CLASSIFICATION

Overview Of Optimization & Classification

- Inputs:
  - Objective function
    - Weights
    - Science objectives
  - Cloud map (by pixel)
  - Desired pointing locations for each science objective
  - Map of where data has been collected already
  - Map of estimated power required for each pixel
  - Constraints
- Outputs:
  - Power map (by pixel) for next frame
  - Range gates

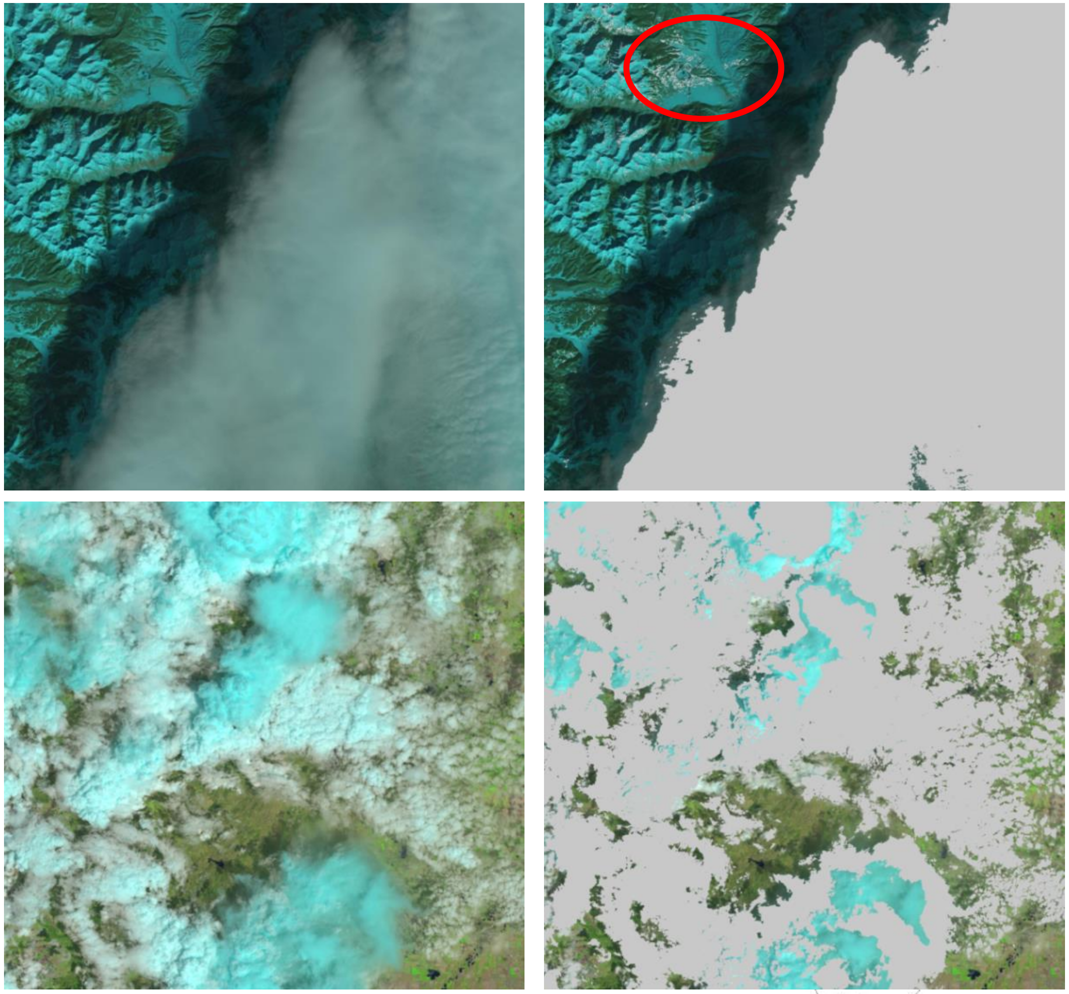


Scene Classification Overview

- Primary objective is to avoid clouds
  - Earth is 65% covered with clouds, so avoiding clouds is the biggest gain to be realized
- Secondary objective to identify difference in land type so science can be prioritized
- Attempt to limit the number of bands needed to avoid expensive instruments for the look-ahead camera
  - Current work uses 6 bands from Landsat-8
    - Green and SWIR1 for snow index
    - Blue and cirrus for cloud-vegetation differentiation
    - Red and NIR for vegetation index
  - Can be implemented with less precise instrument for rapid on-orbit classification

Cloud Identification

- Clouds are difficult to separate from snow and ice
  - Uses NDSI (snow index)
    - Green & SWIR1 bands*
  - Uses blue and cirrus bands
    - Ratio separates clouds from vegetation easily
- Upper images are a cloud bank over Colorado with snow on the mountains
  - Only small bits of snow are labeled as cloud
- Lower image is a mix of high and low altitude clouds over Colorado (no snow)
  - High altitude clouds are frozen, so look like snow if the correct bands are not available
  - Misses at transition from ice clouds to vapor clouds and in wispy icy clouds

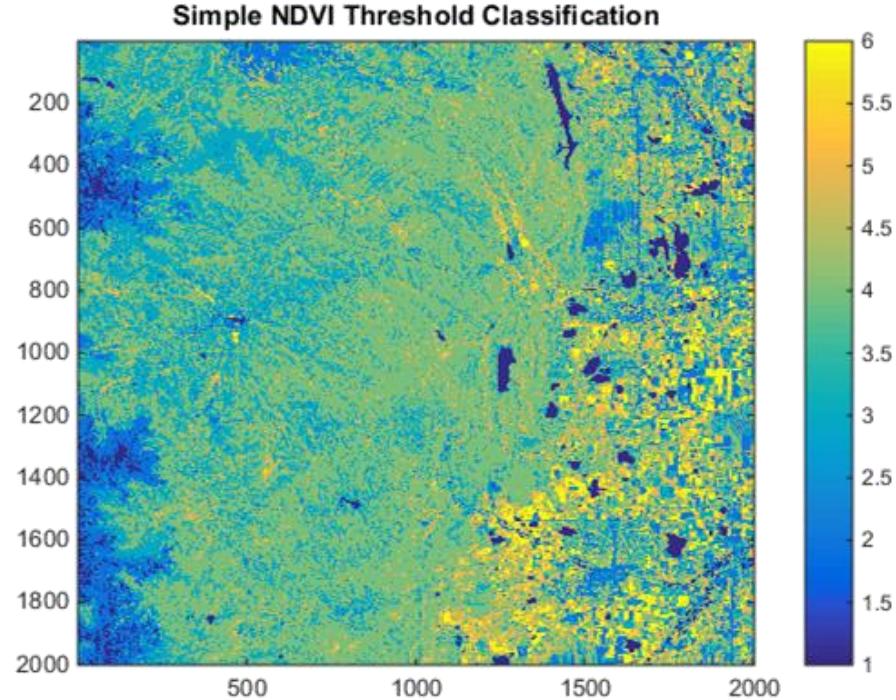


*Thompson, R., R. O. Green, D. Keymeulen, S. K. Lundeen, Y. Mouradi, D. C. Nunes, R. Castaño, and S. A. Chien "Rapid Spectral Cloud Screening Onboard Aircraft and Spacecraft", IEEE Trans. GRS, 52(11), Nov. 2014., 6779-6792.

Vegetation Classification - NDVI

- Early work used NDVI thresholds to determine the terrain type
  - Works, but is a bit crude
    - Requires tuning by region
  - Can't differentiate between scrubland and sparse forest
  - Different input images show that NDVI is more related to rain and subsequent growth rate
  - Computationally fast, and only requires two bands
    - Band 4 – Red
    - Band 5 – NIR
- NDVI = (NIR-red)/(NIR+red)
  - Data input in raw DN for my tests to simulate the raw data that would be available for on-orbit processing
- Many papers show improved methods, but rarely produce significantly better results

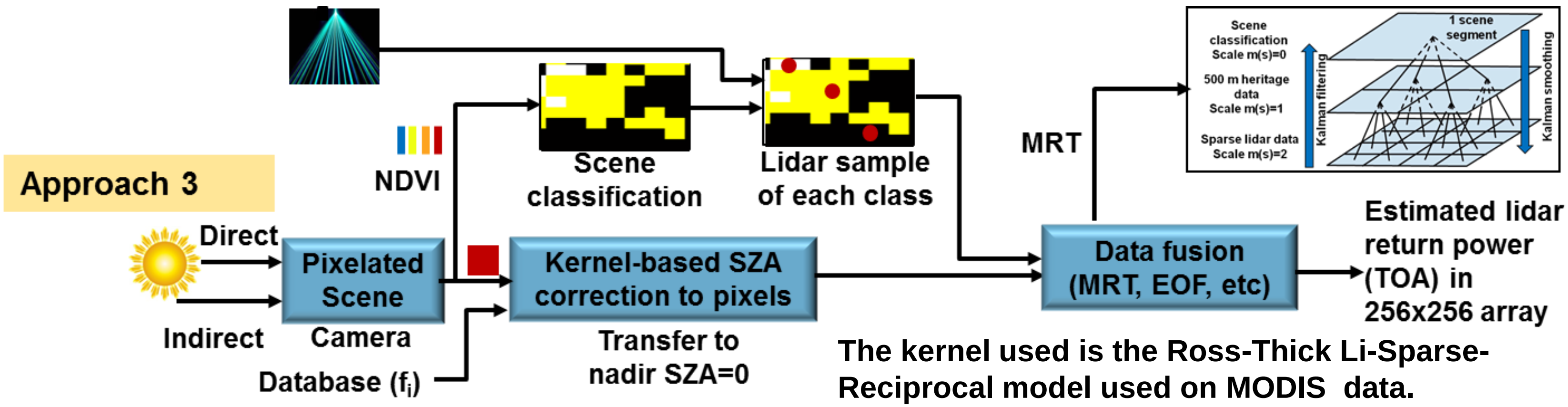
More actively growing vegetation



Less actively growing vegetation, water, and concrete/asphalt

LIDAR RETURN POWER ESTIMATION

Approaches to Power Estimation (3/4)



ID	Description	Attributes	Issues
3	Heritage derived kernel coeff. to transform camera power to SZA=0. Uses data fusion from classification, lidar sampling of each IGBP class in the current lidar FOV, heritage data, transformed camera data to arrive at optimal estimate of lidar return power for entire array.	Algorithms combine multiple data sources to arrive at a optimal power estimate for all pixels. Can provide feedback to correct scene classification if it appears misclassified. Has been demonstrated in multiple papers to provide better estimate of albedo (MRT approach). Multiple approaches available to fusion data of different resolutions and noise properties.	Large computational framework needs to be studied to see if it fits within FPGA computational speed. Requires additional global on-board heritage data bases. Kernel equation only valid where clouds non-existent and may be limited unless aerosol effects can be added back in using camera data. Need to understand if limitations at large SZA. MRT more efficient than most other data fusion approaches. Kernel can include hotspot.

Computing Predicted Power Output Using BRDF – Kernel Based Approach (3)

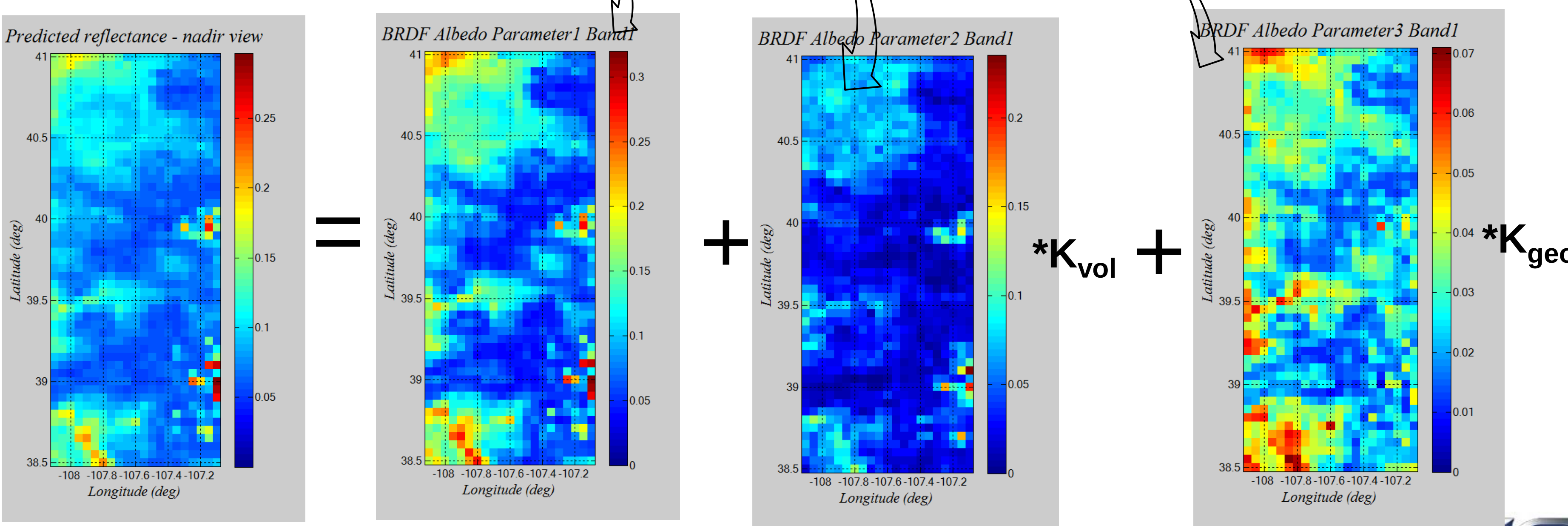
- The equation below computes the BRF from three terms:

We have assumed kernel functions are constant (scalars) over small FOV.

$$R(\theta,\vartheta,\phi,\Lambda)=f_{iso}(\Lambda)+f_{vol}(\Lambda)K_{vol}(\Lambda)+f_{geo}(\Lambda)K_{geo}(\Lambda) \quad \textit{where}$$

K_{vol}, K_{geo}, *and* K_{fwd} *are the scattering kernels and the* f_i *terms are the coefficients.*

- The kernel functions can be pre-computed knowing the solar zenith angle, the view zenith angle and the relative azimuth angle. Below is a plot of selected sub-region with 3 coefficients for 645 nm band.

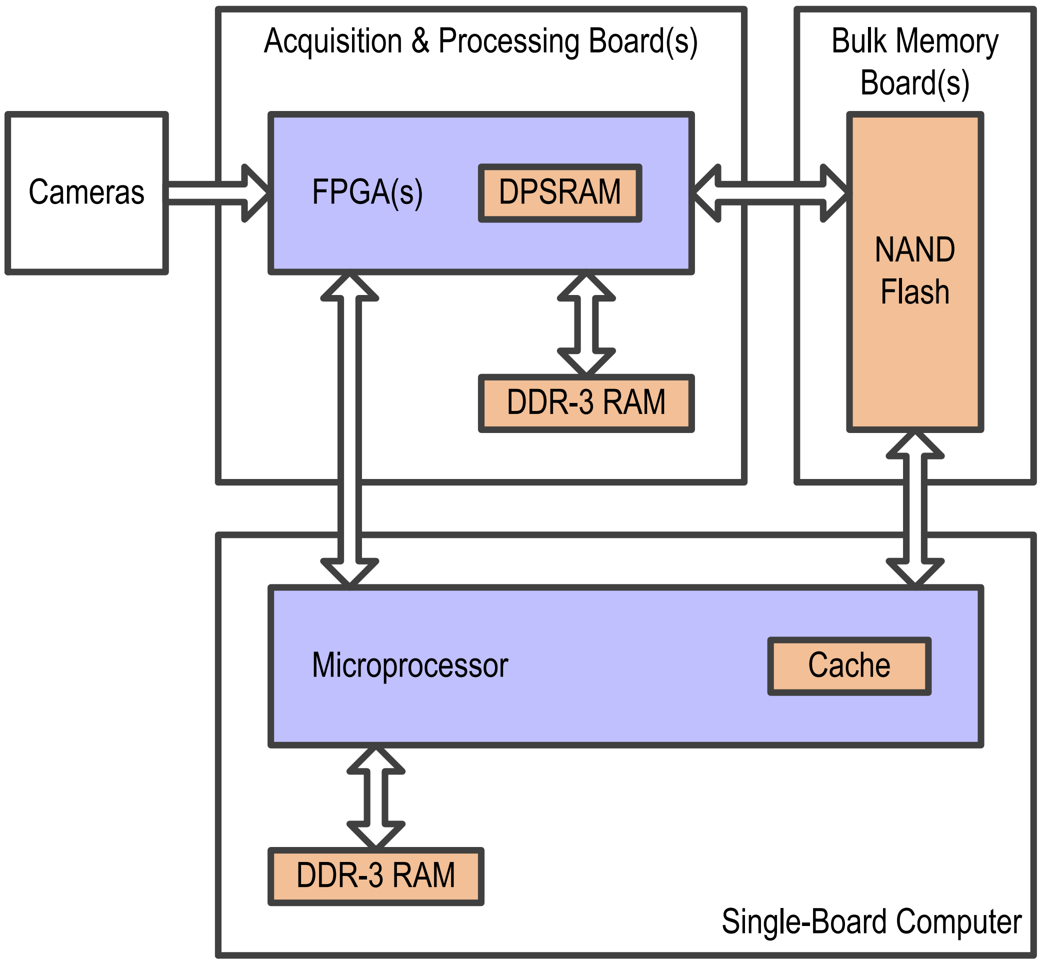


FPGA IMPLEMENTATION

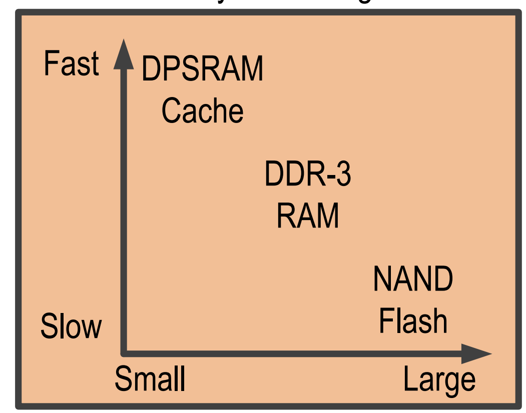
MIKE ADKINS

Processing Hardware Architecture

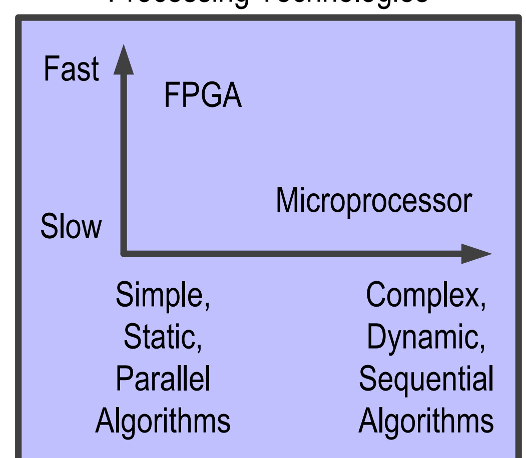
Hardware Architecture



Memory Technologies



Processing Technologies



Assessing Algorithms for Computational Requirements

- Assess algorithms relative to:
  - FPGA hardware resources (DSP slices, LUT-FF Pairs, DPSRAM)
    - Notionally Xilinx Virtex-5QV
  - Memory interface throughput
  - Processing time
    - Nominal goal – 30 Hz update rate (33 ms)
  - Not considering microprocessor (yet)

- We assumed the simplest algorithms that still provide value. Future work would increase sophistication and resolution of these algorithms.

Algorithm		DSP Slices	LUT-FF Pairs	DPSRAM	DDR-3 Transfer Time [ms]	Flash Transfer Time [ms]	Processing Time [ms]
Classification		9%	4%	0%	0.0	N/A	2.1
Optimizer		0%	small	0%	3.1	N/A	3.1
DEM Data Handling		TBD	TBD	TBD	TBD	TBD	TBD
Power Estimation/ Prediction	Approach 1	1%	Small	0%	0.4	N/A	0.5
	Approach 2	1%	Small	0%	0.4		1.1
	Approach 3	2%	small	0%	1.2		1.1
Powermap Conversion		TBD	TBD	TBD	TBD	TBD	TBD**

** Comparative estimate in Matlab about same time as classification.

LAB IMPLEMENTATION - HW AND SW

Lab Demonstration Captures Key SW Functionality – with Some Limitations

Compare with features of "real" system:

- Embedded controller directs beam deflections in real time
  - *Demo implemented on lab PC - envisioned FPGA , hybrid computing platform not practical here*
  - *No synchronization involved due to low-power CW laser used*
- PCAES algorithms determine number, angles of beams and intensity.
  - *First two are verified but extensive processing would be required to mimic beam intensities accurately using lab SLM*
- Multi-band camera is key input for multispectral scene classification
  - *Feedback from any type of imaging camera impractical with a lab setup:*
    - — *Only have visible "band" in scene on screen created by RGB projector*
    - — *Wavelength of CW test laser interferes with image if standard RGB camera used*
- Lidar transceiver projects beams, collects return signal as feedback to algorithm
  - *No lidar system per se due to scaling relationships for beam projection*
    - — *Small diameter transmitted beam combined with angular expansion to match scale of scene on screen necessarily result in relatively larger beam spots and more significant diffraction and interference effects.*
  - *Range gating not useful within lab distances; "scene" is flat projection on screen only*
- Hardware aligned/calibrated for extremely accurate beam angles relative to scene
  - *Demonstration is rough aligned to a visual level only (see above about spot sizes)*

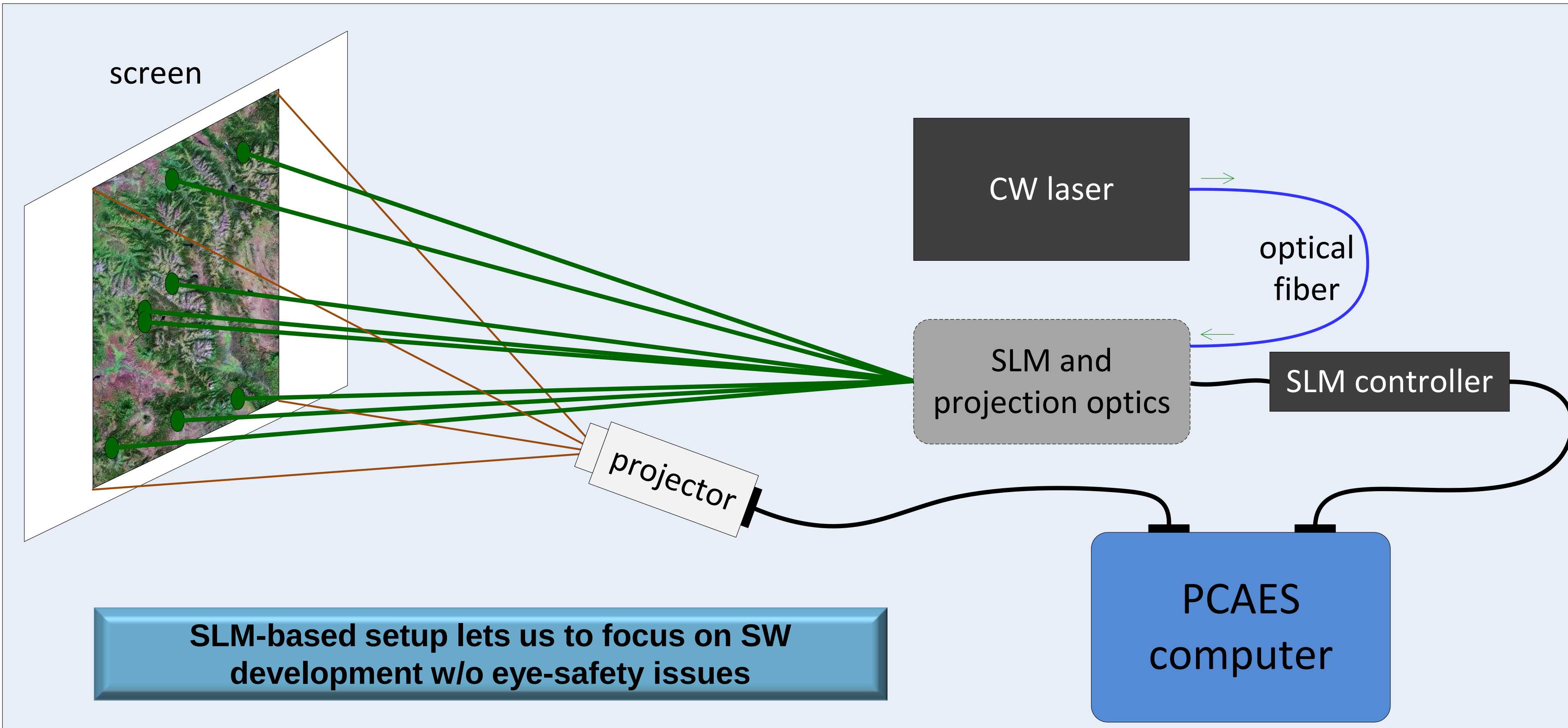
PCAES Laboratory Hardware

Jeff Applegate

Overall Configuration of Demo

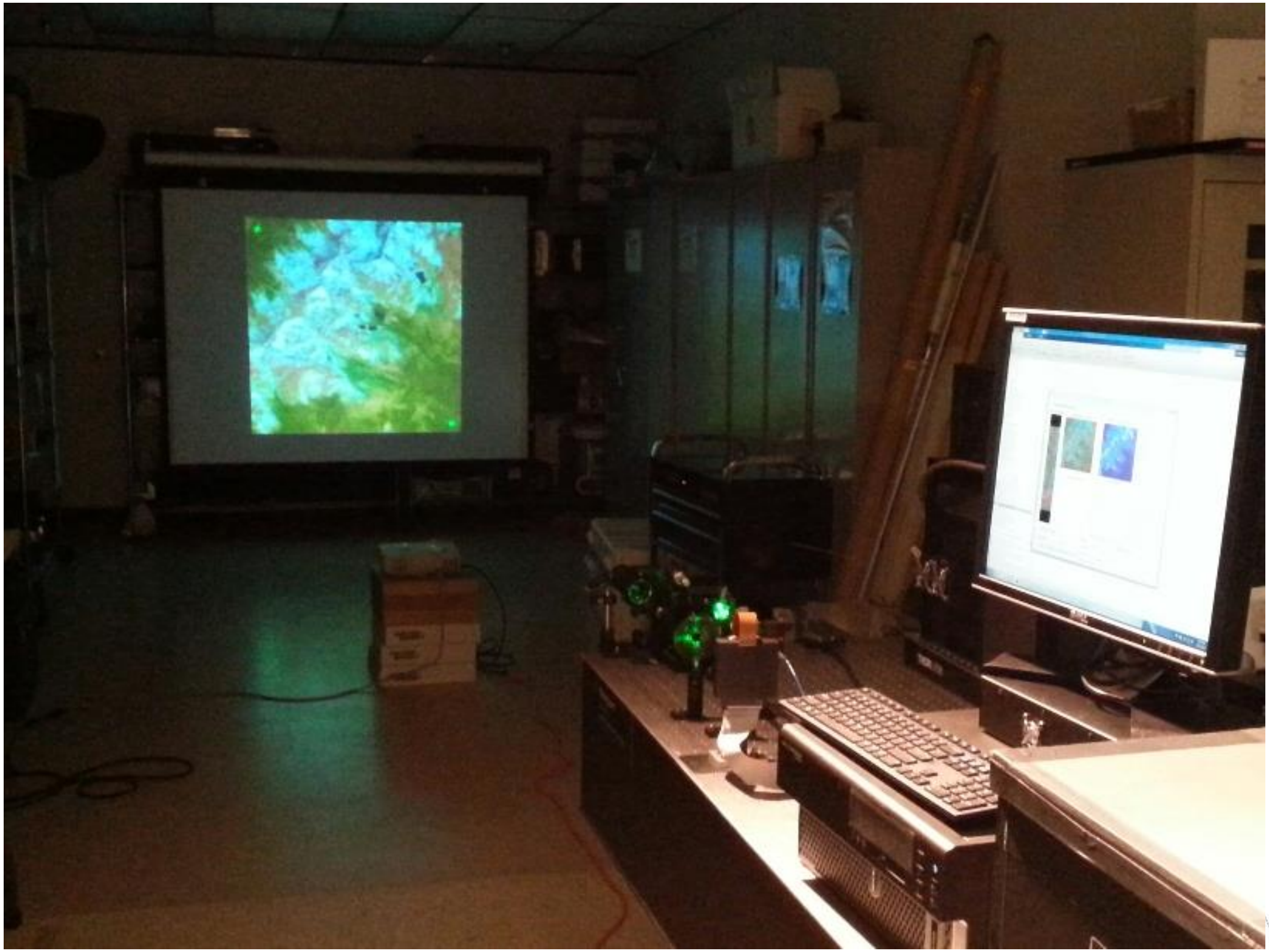
Schematic of Demo system showing hardware components

Spatial light modulator (SLM) substituted for AOBD.



SLM-based setup lets us to focus on SW development w/o eye-safety issues

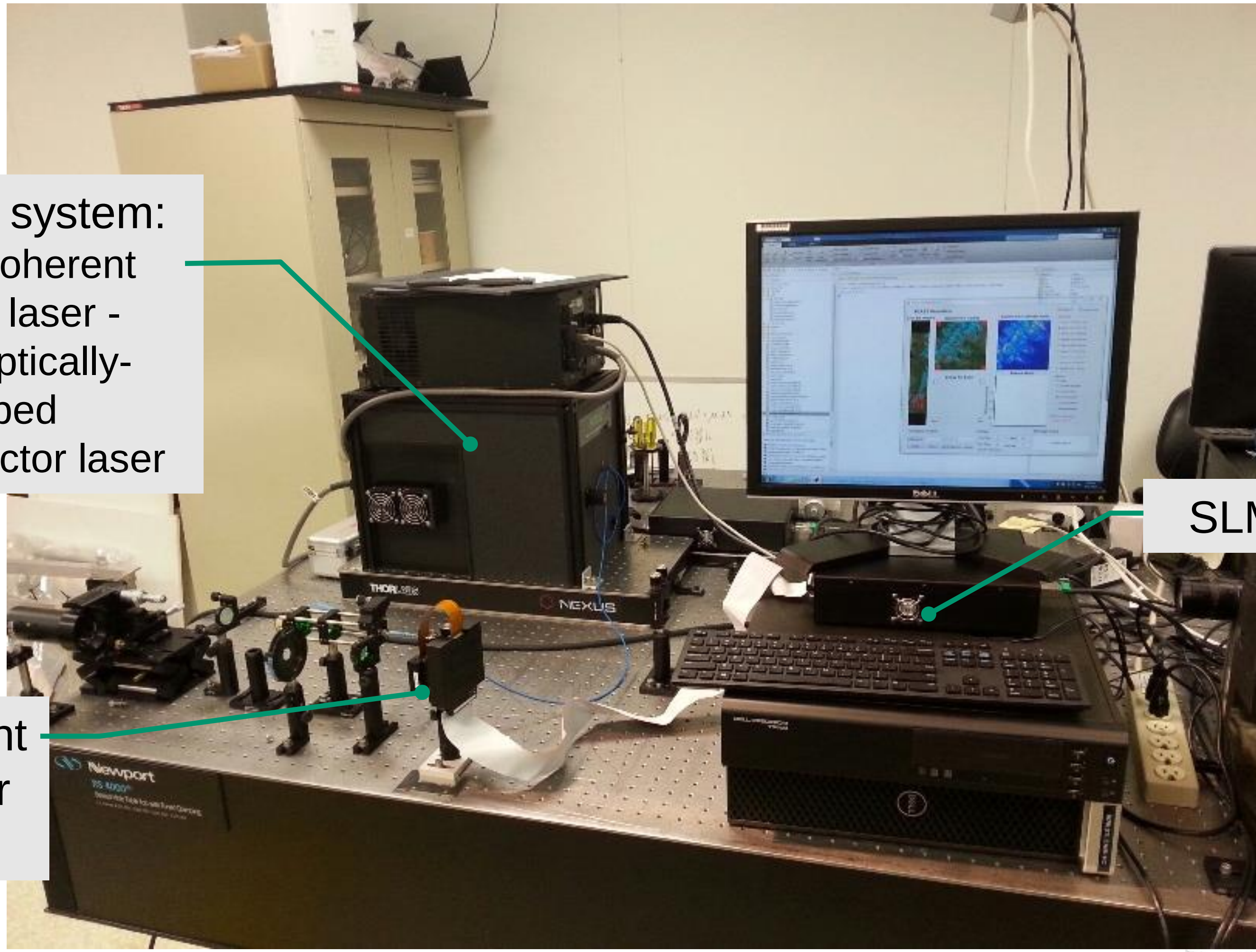
Image of Lab Demo During Use



Scene Projection - Calibration

Photo of projection screen during demonstration (shows beam test pattern)

Optical Setup, Computer on Bench

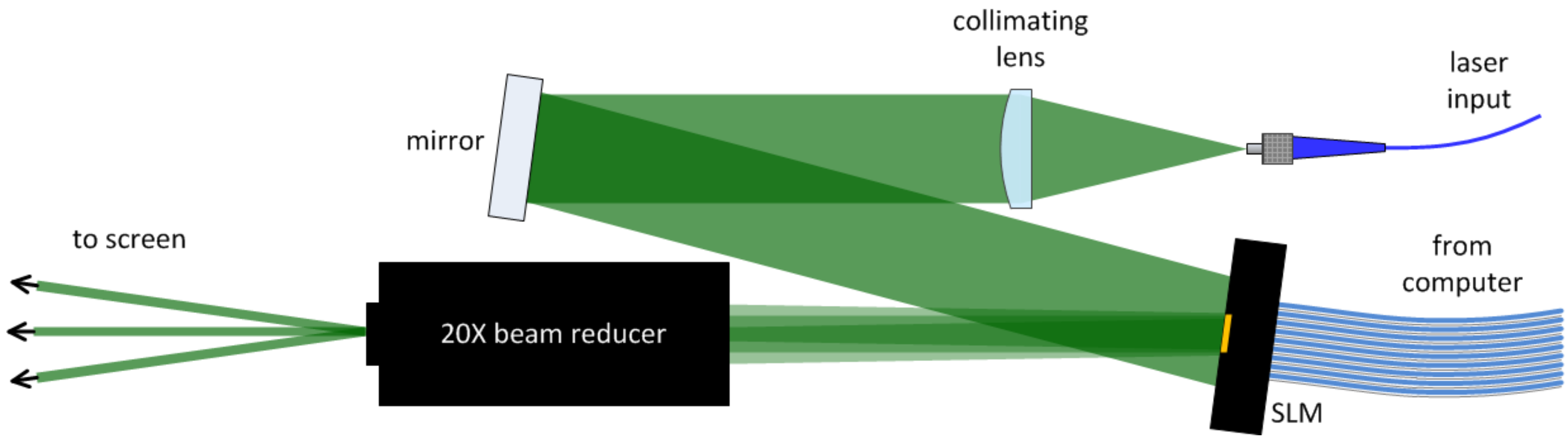


Test laser system: Uses a Coherent Genesis laser - 532nm optically-pumped semiconductor laser

SLM controller

Spatial light modulator (SLM)

Optical Layout of Beam Projector

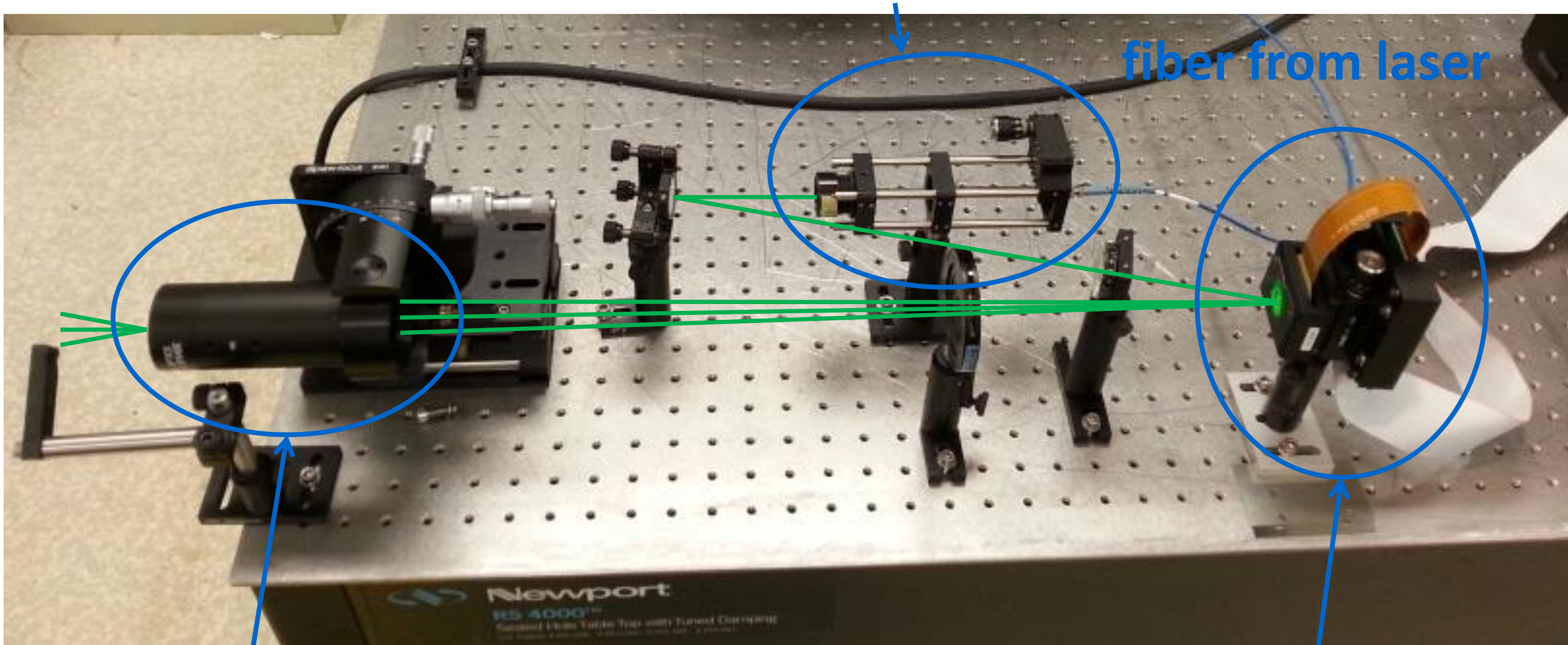


Component details:

Laser	Coherent Genesis MX SLM-532: eye-safe fiber-coupled 532nm CW
Fiber	Polarization-maintaining single-mode patch cable
SLM	Meadowlark Optics P512 – 0532; XY nematic reflective series (512x512)
Beam reducer	20X refractive

Image of Optical Path

collimator



20X beam reducer

SLM

Earth Science Technology Office

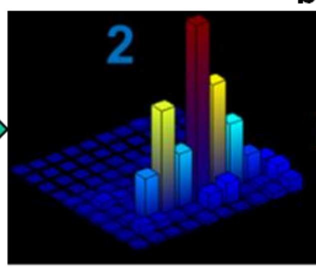
PCAES Laboratory Software

Nelson Kane

SLM Powermap Generation Code Development

- Bin packing SW poses challenge (problem is NP hard), but we only need approximate solution not optimal.
  - Constraints, (1) pack sub-grating images into 512x512 array, (2) minimum patch is ≥ 64x64 pixels and close to square aspect, no left-over pixels (or undefined pixels)

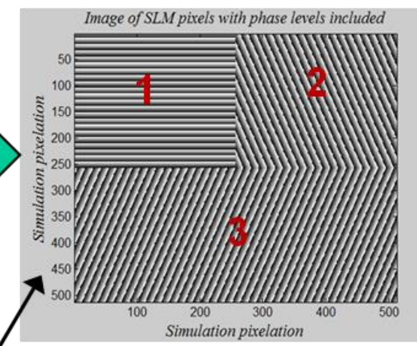
Output of optimization SW, $t_k = 2$



Select 3 largest beamlets

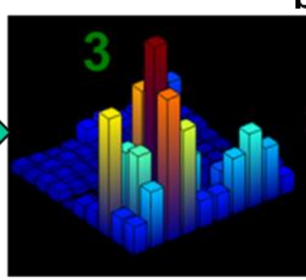
Transform powermap magnitudes & xy locations to grating patterns

Bin packing SW - Tree structure

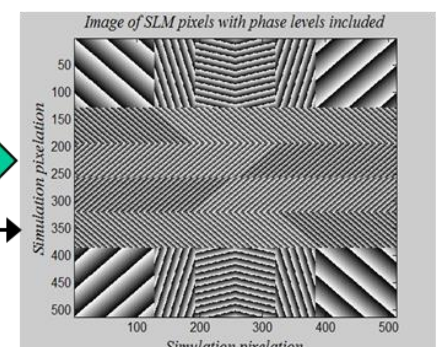


512x512 bmp grating pattern input to SLM with 3 sub-images

Output of optimization SW, $t_k = 3$



Select 16 largest beamlets



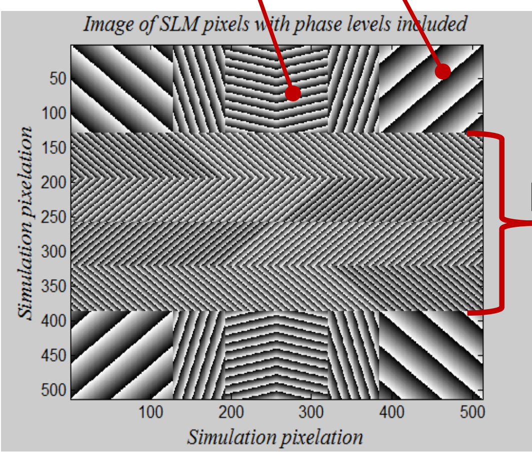
512x512 bmp grating pattern input to SLM with 16 sub-images

SLM Powermap Generation Code Development – Simulation and Testing Validation

- Lab measurements correlate with simulation results except for extra zero-order term (which can be minimized).

Inner ring (4)

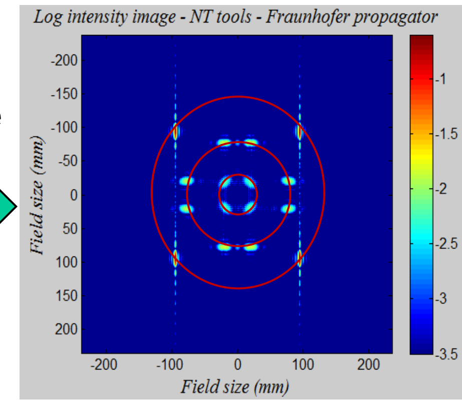
Middle ring (8)



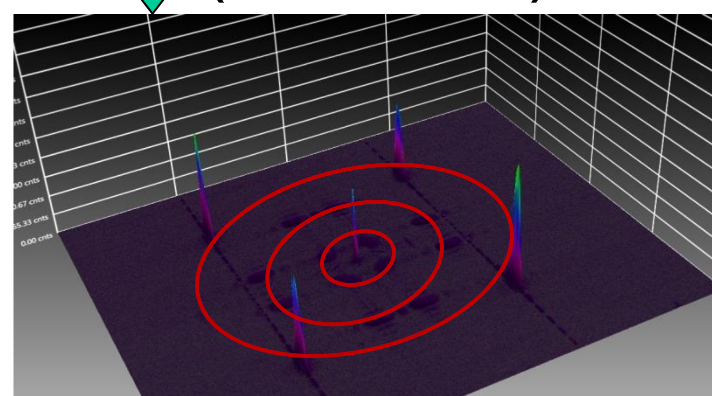
Outer ring (4)

Load into SLM

Far field image (simulated)



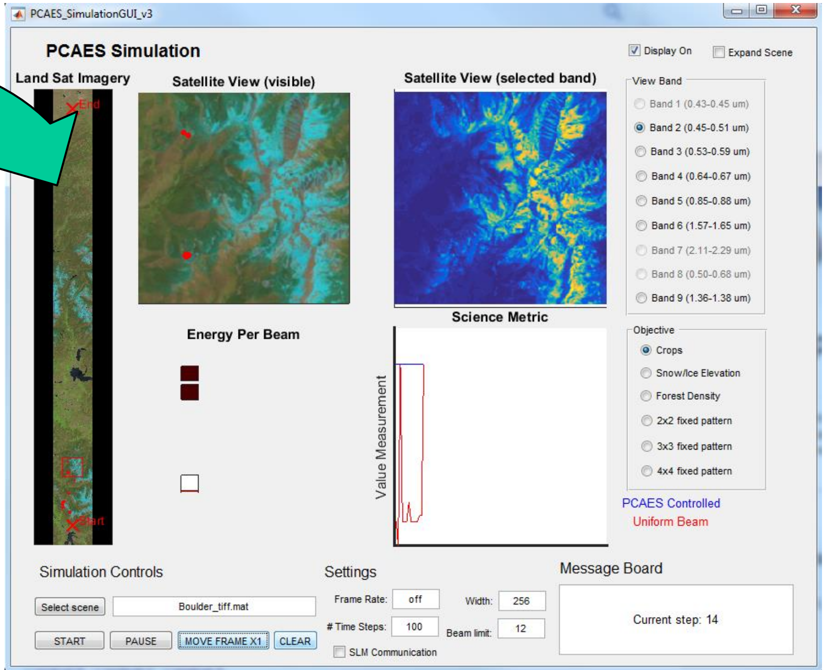
Far field image (lab measurement)



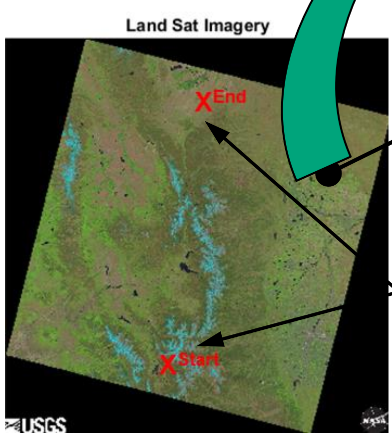
SW Graphical User Interface (GUI) & RT Control Interface (1/2)

- Lab SW interface to Laser HW and RT SW processing.
- User sets up ground track
- SW extracts sub-image at each time instant.
- Variable number of laser beams per time step.
- Matlab-based SW

GUI for Lab Validation & Demonstration of PCAES Technology



Strip extracted to show RT processing



User selected Landsat image - typical 7930x7800 pixels

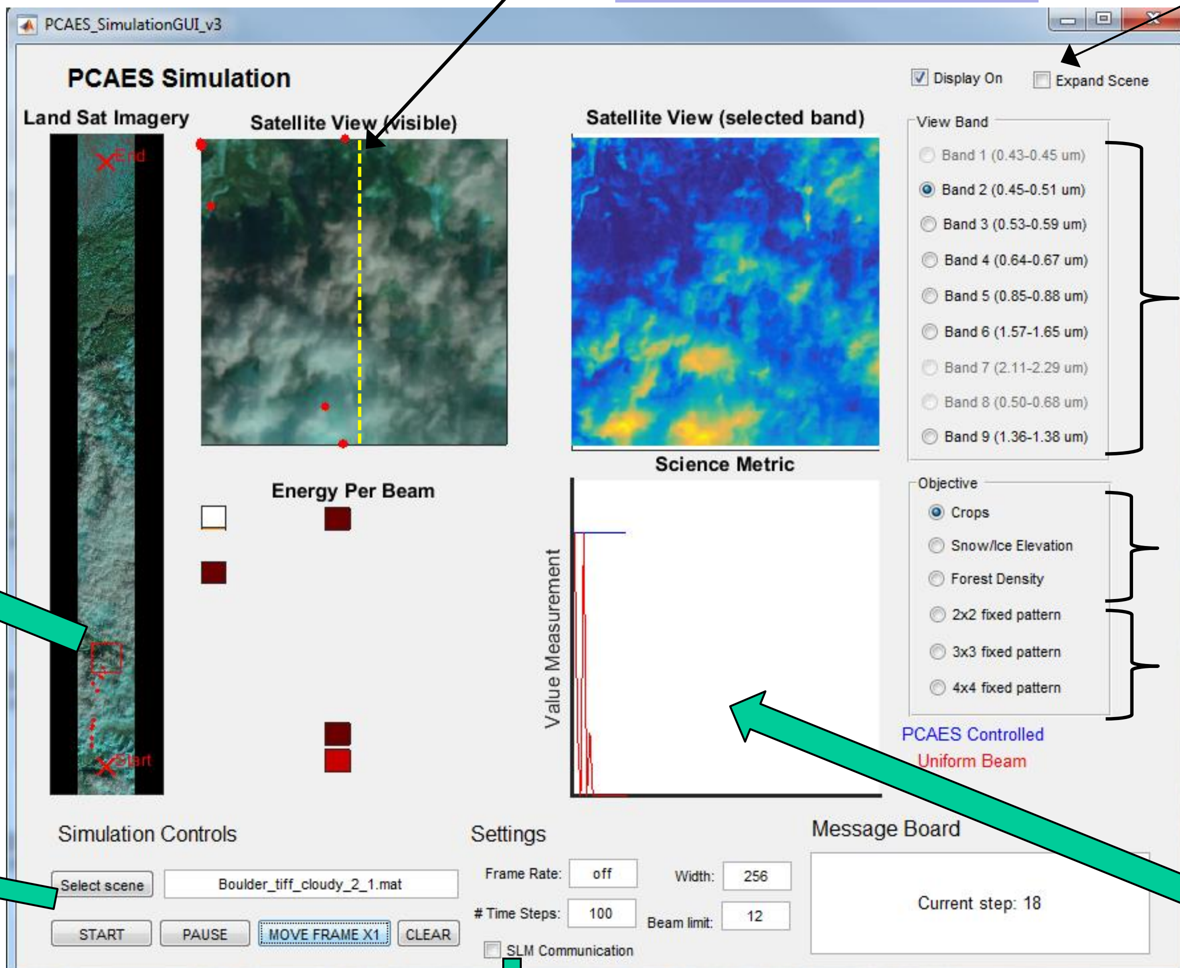
User select start/ stop orbital path

SW Graphical User Interface (GUI) & RT Control Interface (2/2)

Nominal ground track nadir pointing lidar

Output to projection system

Instantaneous FOV of multi-beam lidar



Landsat Vis/ IR bands (darkened bands are scene classification & cloud ID

Scene classes available

Test/ SW validation patterns for calibration

User selects scene from folder

Optimized data collection metric (see next chart)

Enables RT control of SLM

Science Collection Metric

- All science data collection compared to single beam lidar without adaptive beamlet control.
- The metric shown is the minimum achieved and does not take into account the added value of multiple beams which can increase the metric by 2 – 16 times more data as calculated in the lab SW.
- When we are over homogeneous areas, an algorithm using saliency ("the quality of being particularly noticeable or important") would be beneficial.
  - Area of tremendous amount of research
  - How important things are pulled out of a scene emulating human capability.

In conclusion, thank you to ESTO for funding this work!