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HOP Queue: Hyperspectral Onboard Processing Queue Demonstration

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ABSTRACT

The HOP Queue (Hyperspectral Onboard Processing Queue) demonstration leverages emerging COTS AI accelerators and GPUs to perform on-board processing of hyperspectral imagery data, with the aim of providing near-real time conservation-oriented data and metrics from Low Earth Orbit (LEO). These include forest health, fire detection, and coastal water health. Phase 1 of this project is currently underway, including a completed lab demonstration of this technology and ongoing flight testing. The data from this mission will support Northrop Grumman's enterprise "Technology for Conservation" campaign and will be provided to NASA's Surface Biology and Geology (SBG) organization, as well as other conservation efforts.

INTRODUCTION

Advances in low-SWAP, COTS processing power provide an opportunity to procure timely, space-based environmental monitoring data that can directly aid conservation-related challenges at relatively low cost. The HOP Queue (Hyperspectral Onboard Processing Queue) CubeSat mission will utilize a visible and short-wave hyperspectral (HSI) imager along with onboard processing (leveraging emerging COTS AI accelerators) to provide metrics of ecological health, with particular focus on forests and coastal waters. As part of Northrop Grumman's "Technology for Conservation" campaign[1], HOP Queue data will be provided to NASA's Surface Biology and Geology (SBG) organization, as well as other conservation efforts.

TECHNICAL APPROACH

Hyperspectral imaging (HSI) sensors collect simultaneous images in hundreds of narrow-wavelength-range bands across visible and infrared (IR) regions of the electromagnetic spectrum. By providing spectral information as well as spatial images, they have the flexibility to provide concurrent data suitable for informing multiple applications, such as determining the properties of water and of vegetation, as well as identifying events such as forest fires. However, the large size of the data files can cause challenges given typical bandwidth constraints. For this reason, we utilize onboard processing to enable data reduction via compression and image chipping around regions of interest. We further exploit advances in embedded sensor AI/ML in order to perform onboard image processing tasks.

This demonstration utilizes a hyperspectral sensor and processor hardware that would be capable of space flight in a CubeSat. The approach for this project mimics NASA SBG requirements[2,3], including GSD, signal to noise, and embedded algorithms designed to determine coastal water and forest health; however, the approach is applicable to other applications. The sensor is suitable for other missions requiring material identification. And, the algorithm methods and types can be extrapolated for not only other hyperspectral missions, but also other electro-optical (EO) sensors, including panchromatic and multispectral visible and infrared sensors.

Hyperspectral Sensor

HOP Queue is working in partnership with Spectral Sciences, Inc (SSI) to leverage a prototype HSI sensor. This miniaturized, lightweight turn-key hyperspectral sensor package incorporates a single, monolithic spectrograph, telescope and navigation system, which was built for airborne applications on small, Unmanned Aircraft Systems (UAS)[4]. The sensor uses components of Corning Inc.'s existing MicroHSI 410 Visible / Near Infrared (Vis/NIR) Selectable Hyperspectral Airborne

Remote sensing Kit (SHARK) that is currently used for airborne agricultural monitoring and climate research. It has 5 nm resolution, and measures only 46mm x 60mm x 76mm. Under DOE sponsorship, SSI and Corning developed a new monolithic spectrograph to cover the visible-to-extended-short-wave-infrared (Vis/SWIR) spectral range from 0.4-2.5 microns[4,5]. This new design is incorporated in a Vis/SWIR HSI sensor that is rugged enough to maintain alignment under harsh conditions of small UAS flight.

Note a version of the MicroHSI 425 was ruggedized for space flight in 2019 by Corning and Orbital Sidekick[6]. A ruggedization of the SSI/Corning sensor with the monolithic spectrograph for space flight would be advantageous for more robust alignment and a smaller size.

The Vis/SWIR HSI sensor package contains the spectrometer, camera, cooler, fore optics, and data acquisition electronics. The total system weight is < 2.4 kg (with foreoptics) and the dimensions are 9.4" x 4.9" x 4.7". Power usage during data collection is less then ~25 W. Sensor performance has been verified in test flights on a small UAS and manned aircraft.

Spectrometer Design

The Vis/SWIR sensor utilizes a solid monolithic block Offner spectrometer to enable a compact, high-performance HSI platform. The design has the advantage of significantly lighter weight and smaller size than conventional air-spaced HSI sensor designs. When light travels through a solid block of monolithic material with a higher index of refraction than air, the reflecting angles are smaller for the same numerical aperture (NA). This enables the spectrograph to be significantly more compact, with higher NA (f/1.5), leading to better signal to noise ratio (SNR).

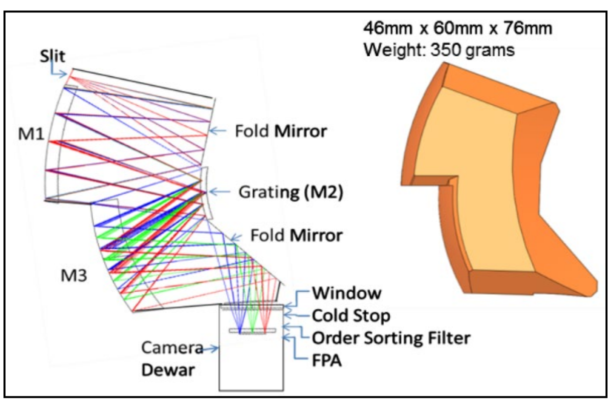

Figure 1: (left) Spectrograph cross-section with ray trace, (right) rendering of the spectrograph solid model

An Offner-based design also produces high image quality and low distortion. Manufacturing the spectrograph from a solid block, allows for tighter tolerances and higher mechanical and thermal stability, and provides lower cost manufacturing.

Camera

The spectrograph block is coupled to a back-thinned HgCdTe FPA covering the 0.4-2.5 micron spectral range. The camera has 640x512 pixels, with 15 µm pixel pitch. The camera's maximum frame rate is 120 Hz. An order sorting filter (OSF) is integrated in close proximity to the FPA, to maintain high performance throughout the wide wavelength range. The sensor has quantum efficiency greater than 0.85 throughout the spectral range, a large well depth of >1 Me-, and low read noise, leading to high SNR as shown in Figure 3.

Sensor Performance

Figure 2 compiles the performance metrics for the Vis/SWIR sensor. The Signal to Noise Ratio (SNR) of the sensor is quite good. The SNR shown in Figure 3 is based on the sensor metrics and a MODTRAN calculated scene with a 50% Lambertian reflector on ground, viewed from space, Solar Zenith Angle = 45 degrees, Rural aerosols, 20 km visibility, direct and diffuse transmission, and including aerosol scattering into the sensor.

MicroHSI™ 425	Values	UNIT
MCT FPA		
pixel width (spatial)	15	[um]
pixel width (spectral)	15	[um]
Spatial pixels	640	[px]
Spectral pixels	446	[px]
Spectral		
λ max	2450	[nm]
λ min	385	[nm]
Δλ	2065	[nm]
Slit length	9.6	[mm]
dispersion	4.6	[nm/px]
dispersion	300	[nm/mm]
spectrum width	6.8	[mm]

Figure 2: Sensor performance parameters

Figure 3 shows different curves relevant to the recent aircraft tests and a Low Earth Orbit (LEO) sensor, which may utilize either the f/1.5 or f/2 optics in a CubeSat. In either case the maximum frame rate is 120 Hz. For the aircraft tests, with f/1.5 optics, 120 Hz data collection will be appropriate to meet the NASA SBG[2,3] requirements for target detection and ID with SNR of order 200:1 in the extended SWIR. For an f/2 optic in LEO, the performance is somewhat lower but still within the SBG target range for sensors with 5 micron resolution. Higher SNR can be achieved at a lower frame rate of 60 Hz.

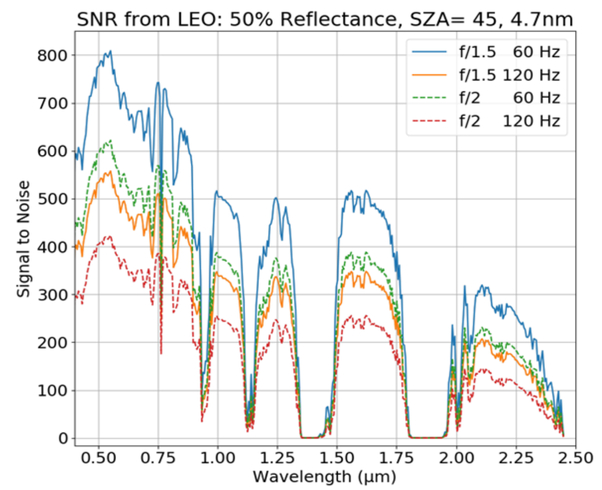

Figure 3: High SNR enables target detection and ID

Onboard Processing

To reduce data transmission requirements, the HOP Queue system concept is to process data onboard with low Size Weight and Power (SWaP) processors, perform data reduction, and transmit highly relevant data products. HOP Queue computes mission-relevant environmental health metrics per-pixel onboard the platform, identifies areas of interest based on these metrics, and sends these areas as chips of data.

The HOP Queue onboard processing architecture calibrates and registers raw sensor data, then corrects for atmospheric effects via an embedded C version of SSI's FLAASH algorithm[7] using a customized MODTRAN Look-Up-Table based on fight parameters like altitude and azimuth of the space vehicle.

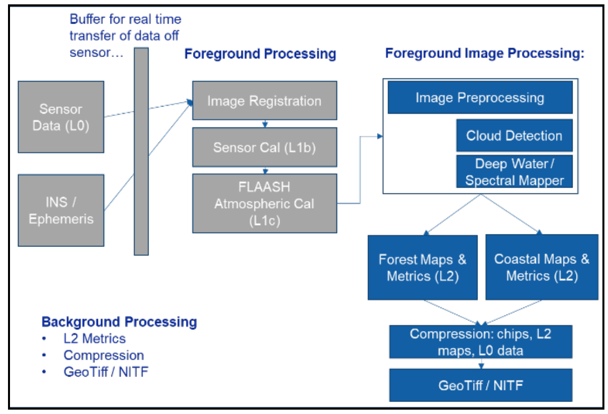

Figure 4: On-board processing flow

SSI Level 1 Processing Algorithms

The raw sensor data will be corrected and calibrated with SSI level 1 processing algorithms including bad pixels, scatter correction, radiometric non-uniformity correction (NUC), and crop and bin, as shown in Figure 5 and table 1.

The data are then processed through cloud detection and spectral mappers, such that only meaningful, calibrated data are sent on for use in calculating environmental health metrics. The HOP Queue runs a combination of algorithms that operate on the hyperspectral data cubes (e.g. spectral angle mapper) to produce multispectral products on-the-fly. Data are numerically losslessly compressed for downlink.

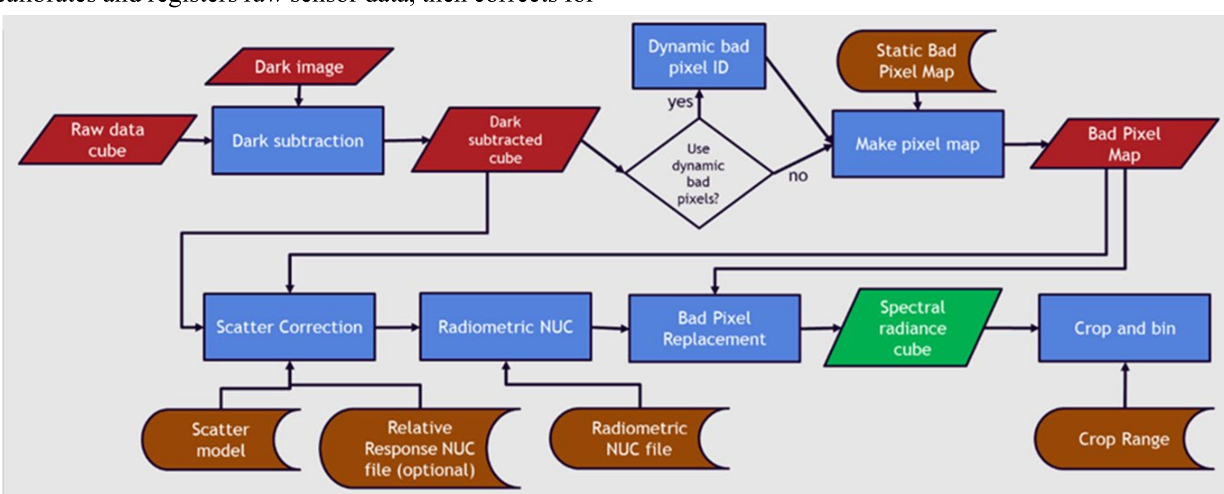

Figure 5: Level 1 processing algorithms enable accurate AI/ML target detection and ID.

Algorithm	Purpose
Bad Pixels	• Static map identified in calibration • Dynamic map identified from scene data • Replacement with 1D linear interpolation
Scatter Correction	• Subtract scattered light based on scene data • Scatter model is a set of coefficients for each type of scatter – updated for a new sensor build
Radiometric Non-Uniformity Correction (NUC)	Pixel gain coefficients measured in calibration
Crop and Bin	Based on static table

Table 1: SSI Level 1 processing algorithms correct and calibrate data, preparing it for target detection and identification

Environmental Health Metrics

After the raw data has been registered and atmospheric correction performed via FLAASH, environmental health metrics are calculated in order to provide insight into the condition of the observed region.

Coastal Water

Monitoring the health of coastal water ecosystems is a key aim of the HOP Queue mission. HOP Queue utilizes a variety of water clarity metrics and other quantities via algorithms provided by the University of South Florida Optical Oceanography Laboratory[8], as well as standard NASA ocean observation algorithms[9]. These include:

- Remote sensing reflectance (RSR): ratio of water-leaving radiance to downwelling irradiance just above the surface
- Photosynthetically active radiation (PAR): visible light available for photosynthesis
- Chlorophyll a (the amount of cholophyll-a present in the water)
- $K_{d,\ 490}$: diffuse attenuation coefficient at 490 nm
- Benthic available visible light (BA490):
- Secchi disk depth: water clarity measurement corresponding to the depth at which a Secchi disk is no longer viewable by an observer

These algorithms have been implemented and exercised with surrogate data during our lab demonstration. Further testing will occur during the airborne flight demonstrations, when we will also be able to calibrate algorithm output against in-situ measurements via “virtual buoy”[10] data.

Vegetation and Forest Health

HOP Queue has implemented a number of algorithms to monitor vegetation and forest health[11,12,13,14]. These include:

- Normalized Difference Vegetation Index (NDVI): detects green vegetation
- Red-Edge Normalized Difference Vegetation Index (RENDVI): sensitive to early stages of plant senescence
- Hyperspectral Fire Detection Index (HFDI): detects active fire
- Normalized Burn Ratio (NBR): detects burned areas
- Fuel Type Discrimination (e.g., grass, oak, pine)
- Fuel Moisture Content
- Fire Temperature and Sub-Pixel Fire Fraction

These algorithms were exercised on surrogate data from JPL’s AVIRIS imagery during lab tests and were verified during flight testing.

Compression and Image Chipping

CubeSat downlink time is limited by orbit trajectory and communication payload constraints due to SWaP. Maximal data throughput is achievable if compression is leveraged. Since onboard compression needs to be fast and have low computational overhead, a C++ platform was chosen. True sensor data is needed for validation of onboard algorithms, and so numerically lossless compression is key. The Consultative Committee for Space Data Systems (CCSDS 123.0-B-1) industry standard compression algorithm was evaluated against the Northrop Grumman proprietary 1-D Differential Pulse Code Modulation (DPCM) algorithm. CCSDS is 3-dimensional entropy encoding, has a parameterized block or sample, and is implemented in both firmware and software. DPCM is 1-dimensional entropy encoding, provides numerically lossless, visually lossless, and lossy compression modes, and is a highly parameterized implementation using table look-ups. Previous hardware implementations have been performed on rad-hard, space qualified components and in space flight.

Table 2 compares the two compression approaches as tested on a common set of AVIRIS images. Tests were run on the same computer to evaluate performance in terms of run time and compression ratio. Image segments were selected to probe a variety of scene content, texture, and dynamic range. Both the NG DPCM algorithm and the CCSDS standard demonstrated adequate performance to warrant further consideration for use in the HOP Queue mission.

Table 2: Comparison of Compression methods.

Margin	CCSDS 123.0-B-1	NGSC DPCM
Runtime	2.8 ± 0.9 s	0.60 ± 0.03 s
Compression Ratio	1.14 ± 0.08	1.68 ± 0.6

Downlink use will vary based on the platform and mission, the sensor duty cycle, and the downlink budget. Typical scenarios for space vehicles collecting large data sets include: 1) Low collection duty cycle / high downlink budget: the current state of the art, which includes downlinking all data for ground processing; and 2) high collection duty cycle / low downlink budget. The collection duty cycle is limited by data storage on the space vehicle, which will fill quickly between downlinks unless it is ported off-vehicle through a mesh network. The baseline approach on HOP Queue includes downlinking only data of interest. This baseline approach can include downlinking only select spectral bands or image regions cued by onboard algorithms (e.g., detection of ground cover type), or commanded (e.g., specific geographical area). This low downlink CONOPS can also include processing to downlink image chips containing pixels within a bounded geographic area. For example: the processor can always process Hyperspectral Fire Detection Index (HFDI), and store chips for downlink on fire detection.

LABORATORY DEMONSTRATION OF PROTOTYPE PROCESSING CHAIN

The laboratory demonstration took place in December 2021 and included an execution of embedded processing algorithms on both a commodity server with Intel processor and an Nvidia GPU, and a Xilinx Versal VCK190 development board representative of onboard processing hardware. This demonstration used NASA AVIRIS airborne hyperspectral data as the input.

The demonstration highlighted the ability of the onboard processing to calculate relevant metrics before sending data to the ground, and to use those metrics to make efficient use of downlink bandwidth by extracting and transmitting only the most relevant data. This was highlighted by using the HFDI index to identify image chips containing active fires to be packaged for downlink. Please see Figure 6.

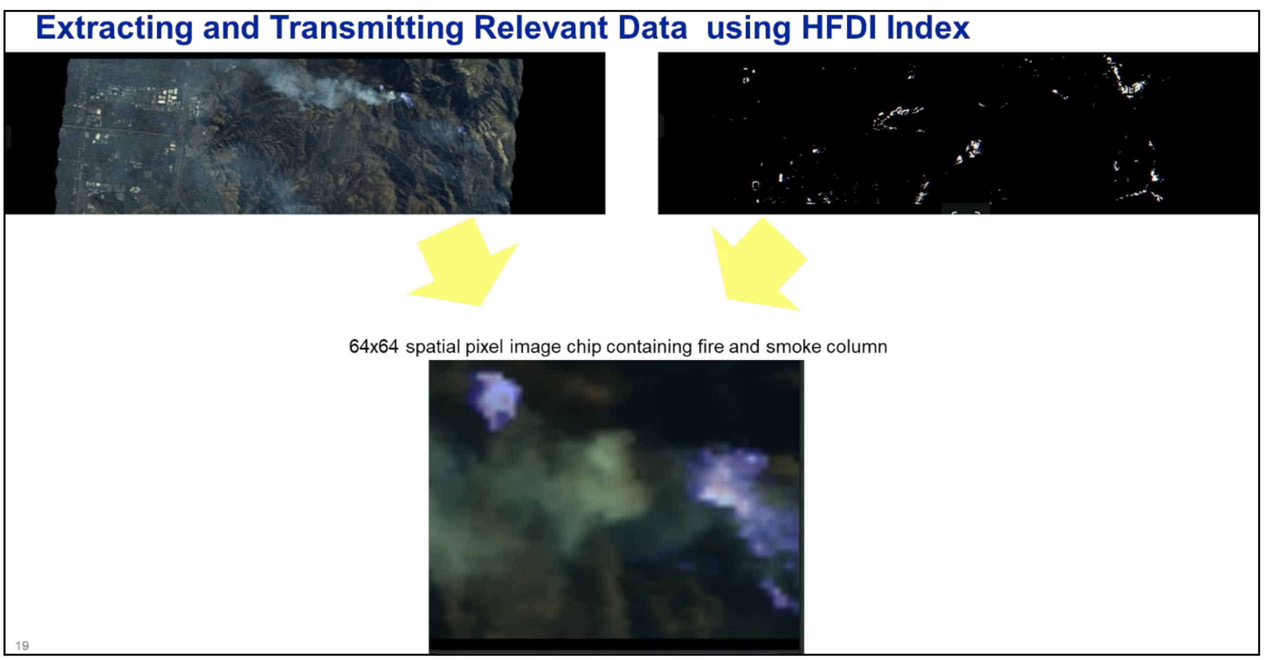

Figure 6: embedded processing is made efficient with the use of extracting and transmitting only the relevant data through the processing chain.

Processor Hardware

We have tested the HOP Queue processing concept on representative low-SWAP hardware by implementing a the processing chain on a surrogate embedded processor and demonstrated the generation of computing metrics for forest and maritime environments. A XILINX Versal VCK 190 development board which served as a surrogate embedded processor. In addition, we also prototyped key aspects of an eventual system and ensured that they could execute in relevant timeframes on a processor. Benchmarking in terms of execution ability, speed, and accuracy has been performed using generic algorithms (e.g., Gaussian blur, Hough transform) as part of the laboratory demonstration. This work will be extended in the near future to include HOP Queue-specific Deep Learning (DL) models, and algorithms will be evaluated.

One key element of the prototyping effort was to the assess potential for applying XILINX's DPU accelerator to onboard deep learning inference on multispectral and hyperspectral data. To validate the applicability of the DPU, we used DeepWaterMap[16], an existing TensorFlow-based image segmentation model that segments land from water using six-band multispectral data. DeepWaterMap's publicly available annotated training set allowed us to use it as an exemplar to walk through the process of modifying and retraining a multispectral image segmentation model to conform to the requirements of the XILINX DPU. After executing the existing model using an Nvidia GPU, we adapted it to create a model targeting the DPU's feature set (8-bit quantization, using only TensorFlow layer types supported by XILINX's Vitis tooling), and trained that DeepWaterMap-derived model from the original DeepWaterMap training set. We executed it within XILINX's VITIS framework to verify that it performed as acceptably on representative test images.

In this prototype, the XILINX tools enabled a fairly rapid rehosting process from a TensorFlow-based model on commodity GPUs to the VCK190 board. This rapid rehosting shows promise for bringing additional onboard deep learning-based multispectral image segmentation and object classification capabilities to this platform in the future.

FLIGHT TESTING

A flight campaign will be conducted in order to simulate data collection from a LEO platform and provide realistic data to test the processing chain. The SSI Vis/SWIR sensor will be flown in a jet aircraft at altitudes of up to 10.6km, and the data will be binned to simulate the 30m GSD of a LEO sensor. Please see Figure 7 for our overall approach. The airplane demonstration data collection will include flying over coastal water and forested areas. For the coastal water collection, we are collecting data across the Chesapeake Bay. Smart buoys will be deployed to collect truth data, while NASA assets concurrently collect multispectral data overhead for comparison to hyperspectral capabilities. A similar setup will be used for forest data collections in Virginia, where USGS forest truth data will be used.

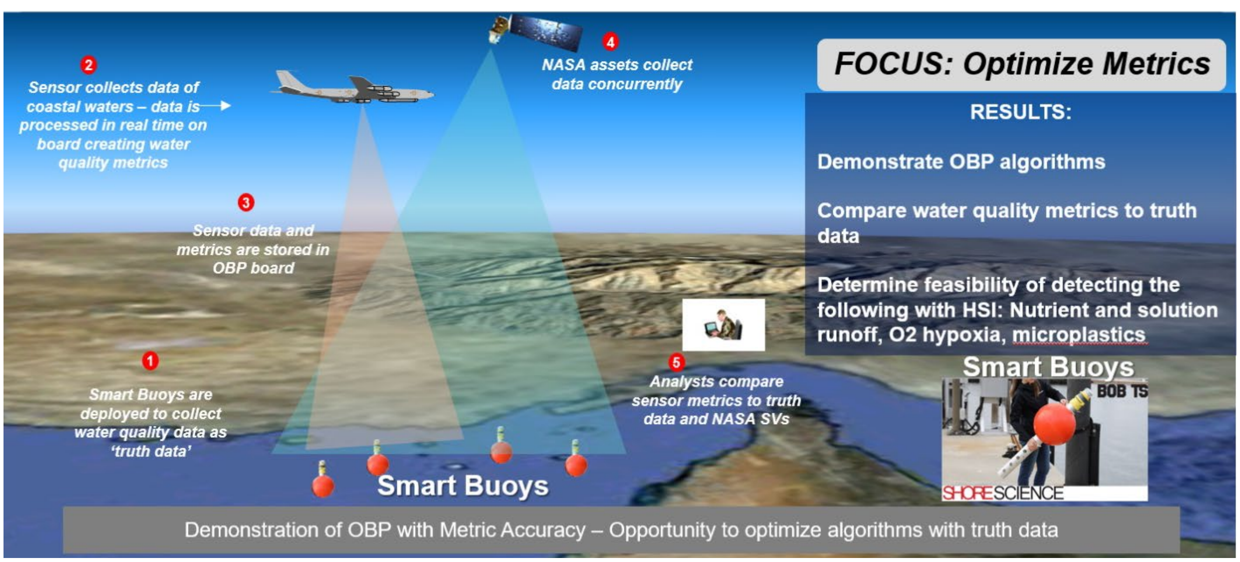

Figure 7: Airplane demo

The airplane demonstration utilizes an SSI HSI prototype to capture data to validate an onboard processing chain that includes sensor calibration and correction, FLAASH atmospheric correction, cloud detection and deep learning, coastal and forest health metric calculations, compression, and NITF generation of the chipped target images over coastal waters and forested areas.

After the data collection flight, a lab-based testbed will be used to play back hyperspectral data cubes along with navigation data. This testbed will impose the timing constraints of an onboard processor by presenting data via a socket at the speed it was collected during the flight test.

While the initial lab demonstration used AVIRIS data with atmospheric correction already applied, the only pre-processing performed on our upcoming data collection will be operations to make the collected data better match what would be expected on a CubeSat. These corrections include applying a scatter correction to bring the collected data into line with what is expected from future production sensors, as well as combining spatially adjacent pixels to achieve a GSD representative of the CubeSat system concept.

FUTURE WORK

By leveraging lab-based demonstrations and airborne data collections, HOP Queue's prototypes have validated key aspects of next generation imaging and processing subsystems for an HSI CubeSat.

Meaningful metrics have been extracted from post-atmospheric correction of exploited data onboard without launching a CubeSat. The collected data, and the lab-based onboard processing prototype will provide a testbed to evaluate additional candidate processors with the same code base, and prototype additional applications of onboard HSI processing, such as additional forest health assessment algorithms, material identification, and image segmentation by deep learning.

Acknowledgments

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