NASA/TM-20230013571

2023 Advanced Information Systems Technology (AIST) Novel Observing Strategies (NOS) Grouped Annual Reviews

Jacqueline J. Le Moigne, Editor

October 2023

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Jacqueline J. Le Moigne, Editor
NASA Goddard Space Flight Center, Greenbelt, MD

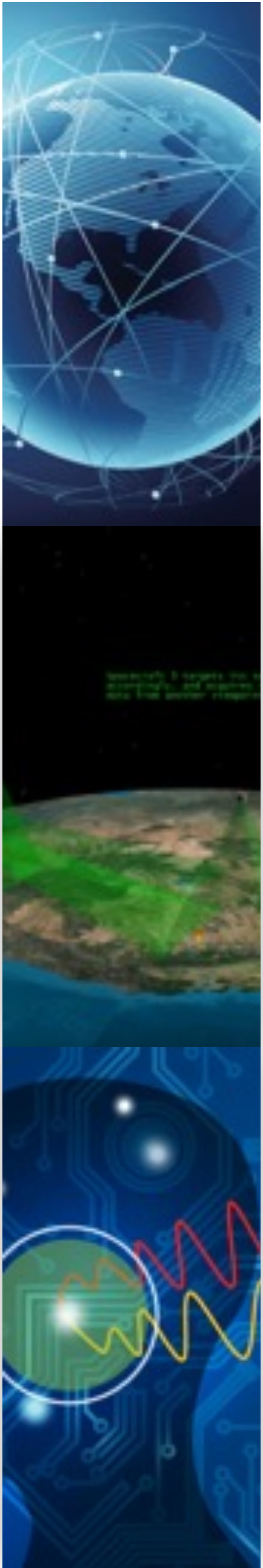
National Aeronautics and
Space Administration

Goddard Space Flight Center
Greenbelt, Maryland 20771

October 2023

Level of Review: This material has been technically reviewed by technical management.

This report is available in electronic form at https://www.sti.nasa.gov/ and https://ntrs.nasa.gov/



Advanced Information Systems Technology (AIST)

2023 Annual Reviews

Novel Observing Strategies (NOS)

July 12, 2023

Earth Science Technology Office

AIST Grouped Annual Reviews
NOS Focus Area
Wednesday July 12, 2023

NASA Headquarters
MIC 3 Conference Room
300 E Street S.W.
Washington, D.C.

Time	End	Duration	Project #	Short Title	PI
8:30 AM	8:45 AM	0:15	**Introduction**		
8:45 AM	9:10 AM	0:25	AIST-21-0043	Edge Intelligence for Hyperspectral Applications	Carr
9:10 AM	9:35 AM	0:25	AIST-QRS-23-0001	Dynamic Tasking	Chien
9:35 AM	10:00 AM	0:25	AIST-21-0059	Geometric Deep Learning for onboard detectino	Gel
10:00 AM	10:25 AM	0:25	AIST-21-0098	Intelligent Long Duration Observing System	Chandarana
10:25 AM	10:45 AM	0:20	**BREAK**		
10:45 AM	11:10 AM	0:25	AIST-21-0049	River surface flow velocities	Legleiter
11:10 AM	11:35 AM	0:25	NOAA	TAT-C/ParOSSE trade space capability for mission design	Grogan, Posselt
11:35 AM	12:00 PM	0:25	SERC NOS-T	NOS Testbed	Grogan
12:00 PM	1:25 PM	125	**LUNCH**		
1:25 PM	1:50 PM	0:25	AIST-21-0102	Quantum-computing assisted Acquisition tasking and processing	Grabbe
1:50 PM	2:15 PM	0:25	AIST-QRS-23-0003	Blockchain Distributed Ledger for Space Resource Access Control	Yesha
2:15 PM	2:40 PM	0:25	AIST-21-0055	New Snow Observing Strategy	Vuyovich
2:40 PM	3:00 PM	0:20	**BREAK**		
3:00 PM	3:25 PM	0:25	AIST-21-0072	Multi-path Fusion Machine Learning for NOS Design and Operations	MacKinnon
3:25 PM	3:50 PM	0:25	AIST-21-0089	3D-CHESS	Selva
3:50 PM	4:00 PM	0:10	**Wrap up**		

NASA ESTO
Advanced Information Systems Technology (AIST)

ESTO AIST

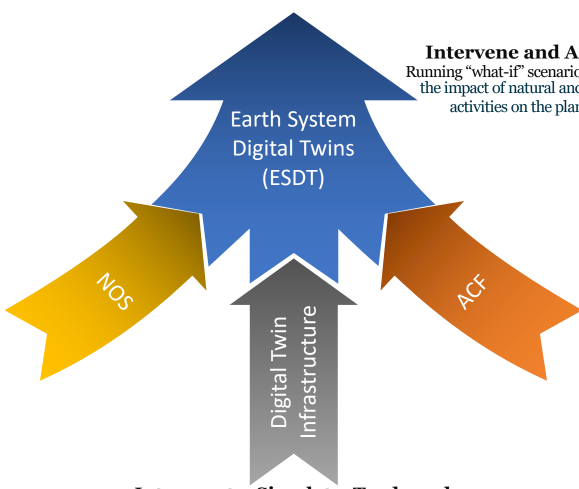
Novel Observing Strategies (NOS)
Annual Grouped Technical Reviews

Jacqueline Le Moigne
July 12, 2023

Three AIST Thrusts

ESTO AIST

Intervene and Assess
Running "what-if" scenarios to assess the impact of natural and human activities on the planet.



Observe, Target and Coordinate
Edge and on-the-ground intelligent planning, evaluating, coordinating and operating collections of diverse and distributed observing assets

Fuse, Analyze, Share and Collaborate
Simplify access to diverse and large amounts of data, analytics & modeling tools and advanced computational resources for collaborative science

Interrogate, Simulate, Trade and Visualize
Robust tools for interrogating, assessing uncertainties & causality, and for visualization, leveraging diverse data, models and products

NOS = Novel Observing Strategies

ACF = Analytic Collaborative Frameworks

Novel Observing Strategies (NOS)
... or How to create an Internet-of-EarthThings (IoET)

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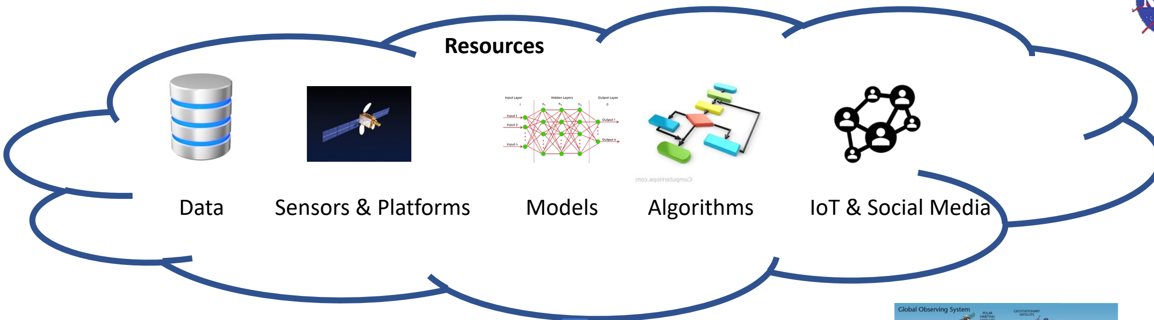
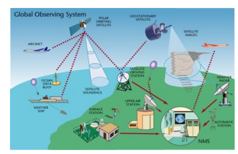


An Observation System is a configuration of resources to answer science questions in order to advance knowledge and benefit society.



Observation System

Novel Observing Strategies (NOS)
... or How to create an Internet-of-EarthThings (IoET)

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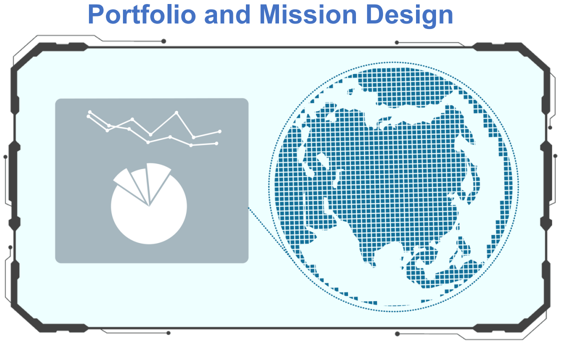
OBJECTIVES:

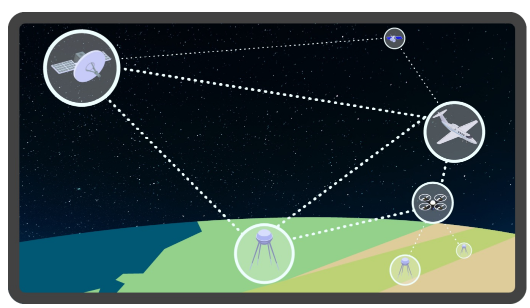
1. **Design and develop New Observing Concepts:**
   - From Decadal Survey or Model; **Various size spacecraft;** Systems of systems (***Internet-of-Space***); **Various organizations**
   - **Perform trades** on sensor number/type, spacecraft, orbits; resolutions; onboard vs. on-the-ground computing; inter-sensor communications, etc.
   - System being **designed in advance** as a mission or observing system **or incrementally and dynamically over time**
2. **Respond to various science and applied science events of interest:** Various overall observation timeframes; Various area coverages; Dynamic/Timely; Scheduling, re-targeting/re-pointing assets, as possible

System-of-Systems NOS-Testbed for technologies & concepts validation, demonstration, comparison and socialization

Optimize current & future Mission Portfolio and Mission Design



Drive Coordinated, Event-Driven Observations



Novel Observing Strategies (NOS)
... or How to create an Internet-of-EarthThings (IoET)

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Earth Observatory Optimization

"Hello NOS, I am the 2027 Earth Science Decadal Survey: I have received many science wishes for new science measurements. With a limited budget, how could I optimize the number and cost of satellites we will need to launch and yet maximize the number of measurements that will satisfy these science requirements?"

Coordinated Observations

"Hello NOS, I am the LIS Model: there was a fire in San Bernardino, CA, last month, and with all the rain lately, I am almost sure that there is going to be a flood in that area: can you ask Capella to retask their sensor so I can improve my prediction of which areas will be flooded next week?"

NOS Demonstrations Roadmap

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NOS-T Historical Flood Demonstration

Early Spring 2021:
- NOS-T Node Coordination
- Simulated Trigger Generation
- Integration of *Historical* Data **On Demand**
- GSaaS *Simulation* Demonstration

NOS-T Live Flood Demonstration (If/When Live Event Happens)

Late Spring 2021:
- NOS-T Node Coordination
- **Live** Trigger Generation *(not necessarily autonomous)*
- Integration of **Live** Data **On Demand**
- GSaaS **Live** Demonstration

NOS + NOS-T Live (NOS-L) Live Science Demonstration

2022:
- NOS-T Node Coordination for **Science Application**
- **Actual** Autonomous Trigger Generation
- Integration of **Live** Data **On Demand**
- GSaaS **Live** Demonstration

Future Potential NOS Science Demonstration, e.g., Ocean Science (with PACE)

TBD:
- NOS **Science Scenario** in coordination with upcoming mission
- "Virtual Field Campaign"
- Potential coordination with prototype ESDT

Grouped Reviews Objectives

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- Respond to **Annual ESTO AIST Reporting Requirements**
  - Technical Annual Reviews Grouped by Focus Areas
  - Individual Programmatic Reporting
- Establish **Relationship between Awardees**
  - Assess complementarity of various approaches and technologies in same AIST thrust
  - Investigate potential collaboration/coordination opportunities (potentially share algorithms, codes or ideas)
  - Investigate 3rd Optional Year teaming arrangements:
    - If proposed, optional 3rd Years – will be *selected* 18 Months after project start
    - For one of three purposes:
      1. Transition AIST technology to another Program or project
      2. Develop NOS-Testbed Concept and/or Demonstration
      3. ESDT Prototype
    - Not all proposed 3rd Years might be funded
    - Can be different than original proposal but no budget increase
    - Collaborative AIST Projects will be prioritized/encouraged (i.e., several AIST projects in a system-of-systems approach
- Introduce AIST Projects and PIs to **Broader Community**
  - Present AIST projects to NASA ESD Program Managers/Scientists and partner organizations
  - Facilitate technology infusions and knowledge transfer of AIST projects upon completion.
- **Review Needs** in terms of:
  - SMCE (NASA Science Managed Cloud Environment): AWS system access
  - ESIP: Project analysis to improve infusion and transition opportunities

ESIP Evaluation

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Between 12 and 18 months in your project, you can request an **<u>Assessment of Maturity by ESIP</u>** ("Earth Science Information Partners")

- **No cost to the PIs**

- **Process:**
  1. ***Objectives Set up and Facilitation:***
     - ESIP provides access to the Earth Science community & feedback on your technology/product/tool
     - ESIP will work with PIs to set specific objectives, taking into consideration TRL
     - ESIP will facilitate evaluator calls, development of evaluation plan, communication with PIs
  2. ***Technical Exchange Meeting:***
     - PI team meets evaluators.
     - Big picture to backend… evaluators should have a solid understanding of the purpose and goals of technology
  3. ***Evaluation Period:***
     - ESIP coordinates evaluation process.
     - Evaluators meet regularly, requesting information from PIs when necessary.
  4. ***Final Report:***
     - ESIP works with evaluators to create final report to be shared with PIs & AIST.
     - Reports can be public upon PI request.

AIST

Edge Intelligence for Hyperspectral Applications in Earth Science for New Observing Systems

Jim Carr (PI, Carr Astronautics)
Chris Wilson, Joanna Joiner (Co-Is, NASA/GSFC)
Virginia Kalb (Collaborator, NASA/GSFC)

AIST-21-0043 Annual Review
12 July 2023

NASA/GSFC: Justin Goodwill, Zachary Fasnacht
Carr Astro: Houria Madani, Jason Welsh, Subhatra Sivam

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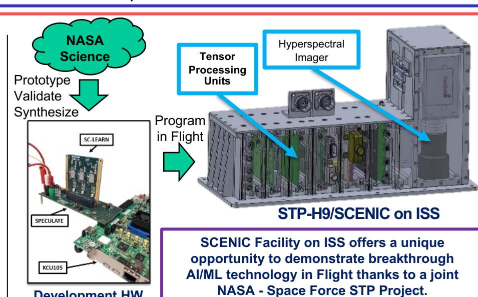
Edge Intelligence for Hyperspectral Applications in Earth Science for New Observing Strategies

PI: James Carr, Carr Astronautics Corporation

Objective

- Demonstrate & Mature breakthrough space AI/ML technology relevant to high-priority Decadal Survey science.
- Enable NOS Future, Diverse CubeSat/SmallSat Science:
  - Demonstrate onboard Edge Intelligence on an AI/ML-enabled CubeSat-type flight processor by fully developing two Earth Science Use Cases.
  - Diffuse know-how across the broader Earth Science Community to benefit a large class of AI/ML applications.
- Demonstrate Science Use Cases in Flight on ISS for rapid TRL advancement made possible with synergy with the Space Technology Program

AET/NOS



SCENIC Facility on ISS offers a unique opportunity to demonstrate breakthrough AI/ML technology in Flight thanks to a joint NASA - Space Force STP Project.

Approach

- Prototype Earth Science Use Cases in Common Framework
  - Reflectance/clouds/chlorophyll retrievals
  - Mapping types of nightlights (LED, Hg, etc.) in use
- Validate Science Prototypes with Proxy Hyperspectral Data
- Synthesize, Load, and Test in AI/ML-enabled Development HW
- Build as Flight App on NASA's core Flight Software (cFS)
- Program STP-H9/SCENIC with Flight App for ISS Demonstration
- Exercise Development HW with TEMPO EV-I Datasets
- Exercise Flight App on SCENIC on ISS
- Iterate Application for Flight Build #2
- Exercise Flight Build #2
- Share with Earth Science Community

Co-Is/Partners: Christopher Wilson, Joanna Joiner, Virginia Kalb GSFC; Space Test Program U.S. Space Force; TEMPO EV-I

Key Milestones

- **Two Earth Science Use Cases Prototyped** — **01/23**
  - Cloud/Aerosol Penetration
  - Nightlights Spectroscopic Classification
- **Applications on SpaceCube/SPECULATE in Lab** — **07/23**
  - cFS AI Applications on Development Hardware
- **Flight Build 1 on ISS for Science Test** — **08/23**
  - Program SC-LEARN in SCENIC & Operate
- **Flight Build 2 on ISS to Refine Applications** — **01/24**
  - Update Application and Continue Science Testing

TRL_{in} = 4 (Daytime Apps) **TRL_{out} = 8 (Both)**
TRL_{in} = 3 (Nightlights), Now 4

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Presentation Contents

- Background and Objectives
- Technical and Science Advancements
  - AI Hardware for Space
  - Science Cases for SCENIC Hyperspectral Imager
- Summary of Accomplishments and Future Plans
  - AI Application Development
  - SCENIC Challenges and Commissioning
  - Plans for Year 2
- Actual or Potential Infusions and Collaborations
- Publications – List of Acronyms

Background and Objectives

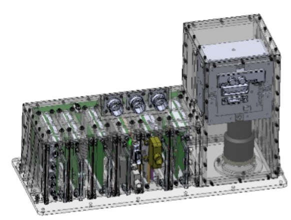
- Vision
  - Advance capabilities for AI application development on AI-enabled space processors
  - Develop Two AI/ML-Enabled Science Cases
    - Daylight
    - Nighttime
- Project End State
  - Deploy and Test Science Cases on STP-H9/SCENIC
  - Infuse Technology into TEMPO (EVI-1) and demonstrate

AI Hardware for Space

SCENIC Experiment Summary
(SpaceCube Edge Node Intelligent Collaboration)

ISS-based testbed to evaluate and validate AI/machine learning technology on FPGA and custom AI microchip platforms in space

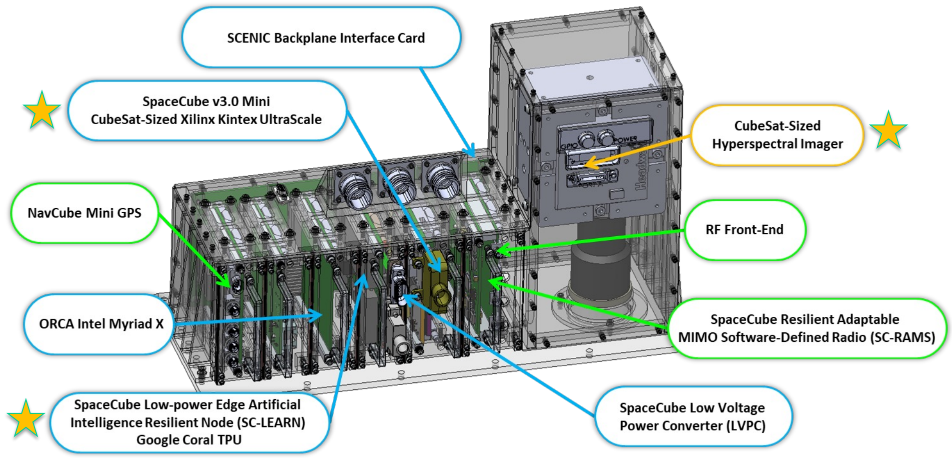
- Goals
  - Demonstrate **cutting-edge AI applications** on multiple space-based platforms for next-generation on-board intelligence, and monitor device availability due to radiation effects (i.e., Intel Myriad X, Google Coral TPU, AMD-Xilinx DPU)
- Motivations
  - Custom AI devices have vast potential for accelerating applications in the artificial intelligence domain, however, many have not been evaluated for flight
  - Collaboration between Goddard, AFRL/RV, and The Aerospace Corp. to explore onboard AI



- Challenges
  - Rapid development for fast-turn launch schedule
  - Developing software framework to train machine-learning (ML) frameworks, upload, and reprogram devices
  - Entire mission on very small **IRAD-enabled budgets**

SCENIC Hardware Configuration

ISS-based testbed consists of modified ~4U (40×10×10 cm) SmallSat chassis with 8× cards, plus attached CubeSat hyperspectral imager



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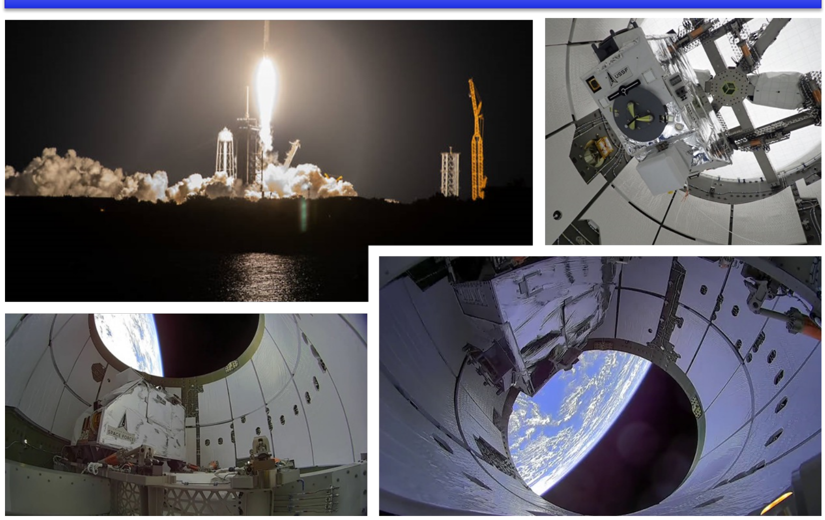
Launch Photos

CRS-27 Launch and STP-H9 with Limb-of-the-Earth Views



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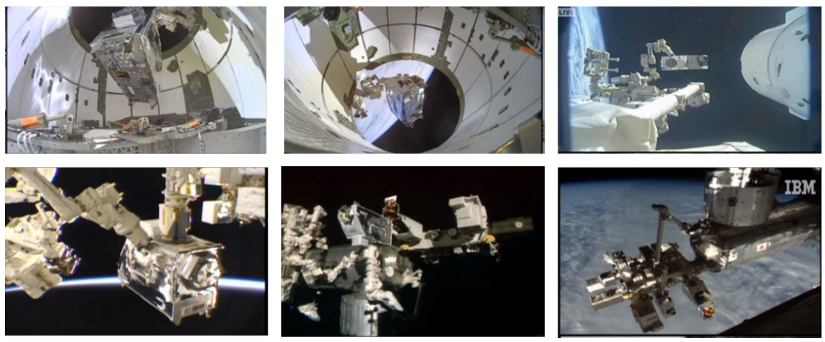
Installation Sequence

Installed into JEM-EF location (March 2023)



SCENIC is being Commissioned Now

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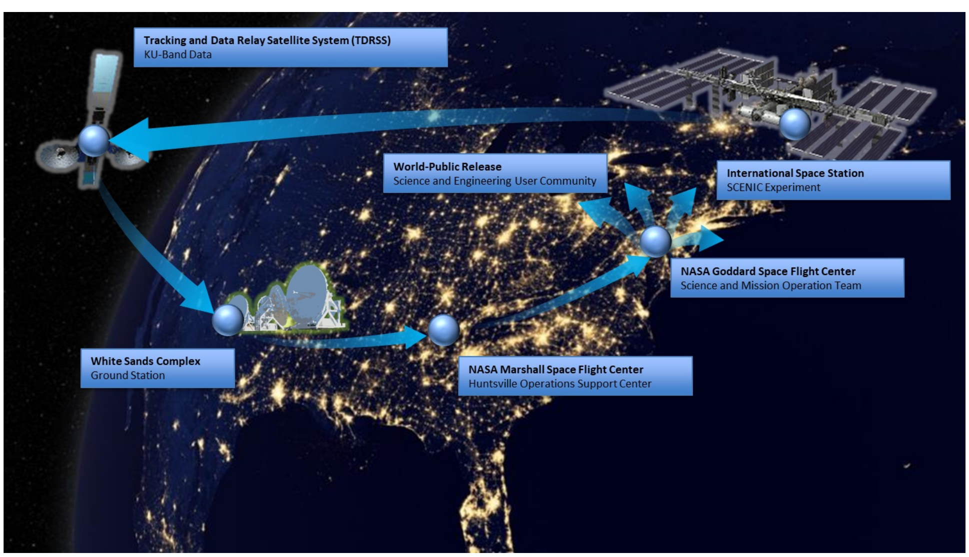
Datapath Pipeline



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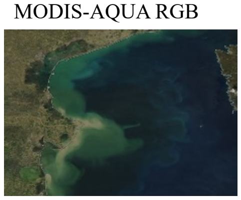
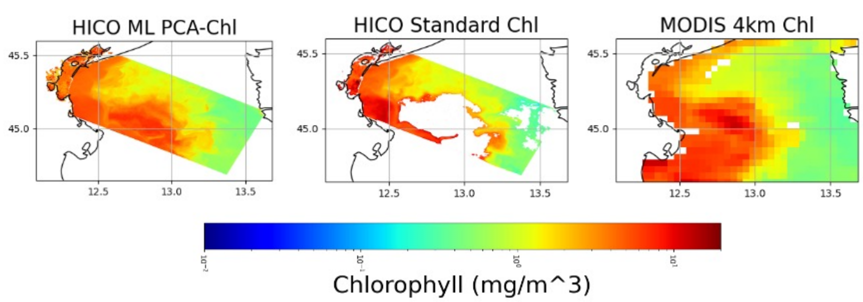
Science Cases: Day & Night

Neural Network Retrievals: Chlorophyll

MODIS-AQUA RGB



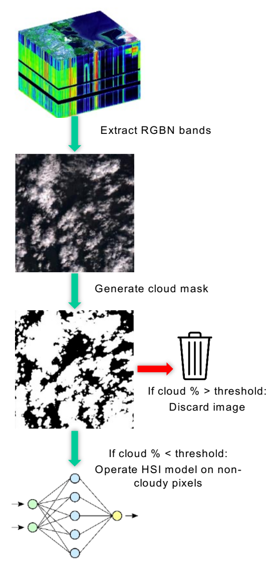
- Here we show an example of NN+PCA approach applied to HICO for March 7, 2014 in northern Adriatic Sea
- AI/ML estimated chlorophyll (bottom left) compares well with chlorophyll from traditional HICO Ocean Color algorithm (bottom middle) and with the MODIS 4km chlorophyll product (bottom right)
- The NN-based approach seems to fill the gaps of the HICO retrieval where the physically based algorithm does not work



Cloud Masking AI Model

- Cloud-masking can **help quickly identify useful images/pixels** to operate HSI models
  - HSI models typically operate per pixel, which can lead to long inference times
- Cloud-Masking AI Model
  - Original Cloud-Net FCN model **too large to fit on Edge TPU**
  - Some operations would need to run on host processor instead of on Edge TPU, which would severely bottleneck inferencing performance
- Implemented **UNet-MobileNetV2** model designed for image segmentation that is small enough to fit on Edge TPU
- Trained on 38-Cloud dataset, which uses RGBN bands of LandSat 8 L1T data products (within spectral range of SCENIC)
- Performance **metrics on par with state-of-the-art**

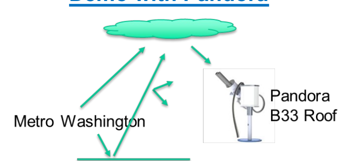
Method	Jaccard	Precision	Recall	Specificity	Overall Accuracy
Fmask [8]	75.16	77.71	97.22	93.96	94.89
Cloud-Net	78.50	91.23	84.85	98.67	96.48
UNet-MobileNetV2	76.990	87.683	82.551	97.912	95.716



Neural Network Nightlights Classifier

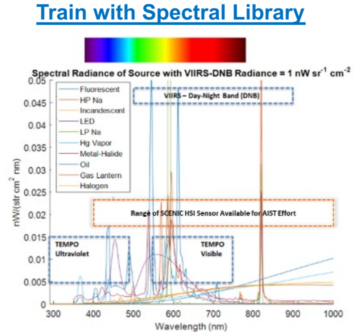
- Inventory artificial lighting in use
- Black Marble Program
  - Human Health
  - Ecology
  - Energy Infrastructure
  - Dark Skies

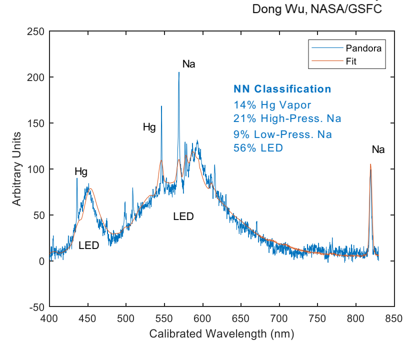
Demo with Pandora



Pandora Data Courtesy: Dong Wu, NASA/GSFC

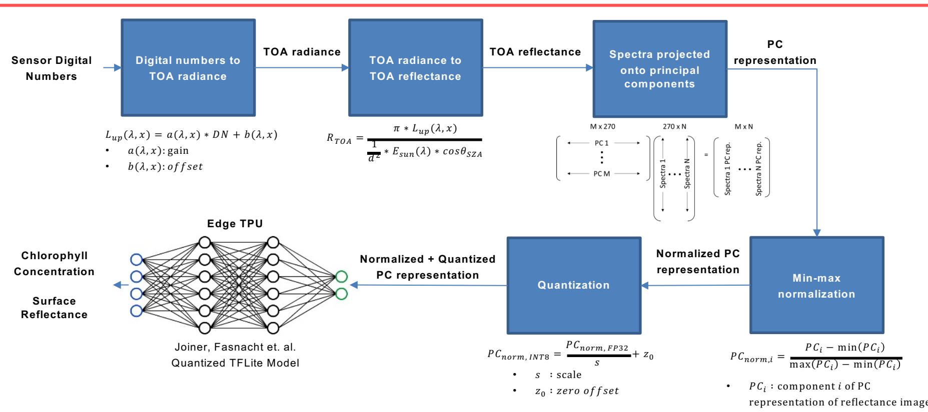
Train with Spectral Library





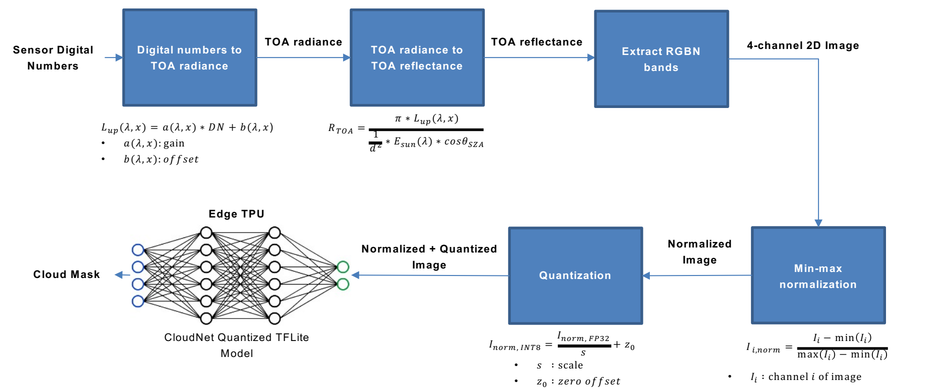
AI Application Development

Onboard Preprocessing Pipeline: Daytime



- Preprocessing Stages:
  - Spectra are radiometrically corrected
  - Spectra are decomposed onto principal components for dimensionality reduction purposes
  - Principal component representations are normalized and quantized

Onboard Preprocessing Pipeline: Cloud Masking



- Cloud masking pipeline **can leverage many preprocessing stages** already developed for HSI models
- Only need to develop stage for extracting RGBN bands from HSI image

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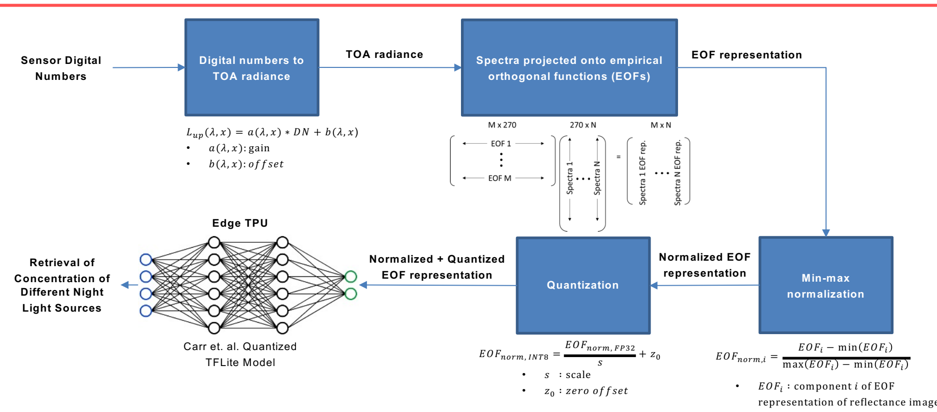
Onboard Preprocessing Pipeline: Nighttime



- Identical preprocessing stages as daytime application, with few exceptions:
  - Not necessary to calculate reflectance
  - Spectral library with K-means clustering to pick canonical lighting types from which to derive Empirical Orthogonal Functions (EOFs) for the "feature engineering" in place of training with other remote sensing data

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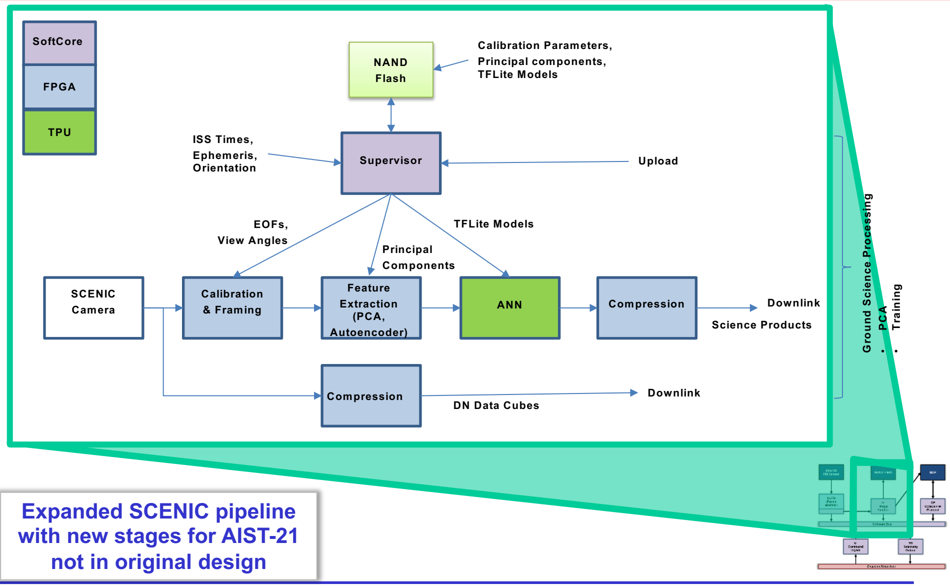
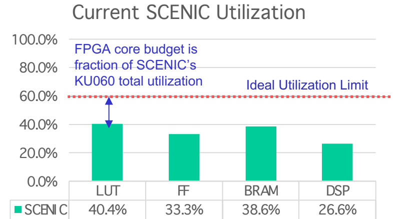
SCENIC AIST-21 Pipeline



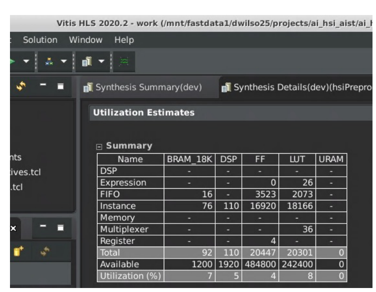
Expanded SCENIC pipeline with new stages for AIST-21 not in original design

SCENIC Resource Utilization

- AIST targets SCENIC for initial deployment of FPGA core
  - SCENIC has available FPGA resources to implement FPGA core
  - However, integration should keep total resource costs within ideal utilization limit
  - At high utilizations (60+%), FPGA tools commonly face **"timing closure" issues**
  - Kintex FPGA is **3-5 × larger than previous generation** Virtex-5 FPGA, a single SpaceCube v3.0 is roughly as powerful as two SpaceCube v2.0 processor cards (each with two Virtex-5s)
- Using rapid prototyping of HLS, co-developed FPGA core with HSI preprocessing developers
  - Use early resource estimations to inform SW devs of impact to resource budgets
  - Rapidly implement FPGA design as algorithm changes, unlike traditional approaches where algorithm must be relatively fixed



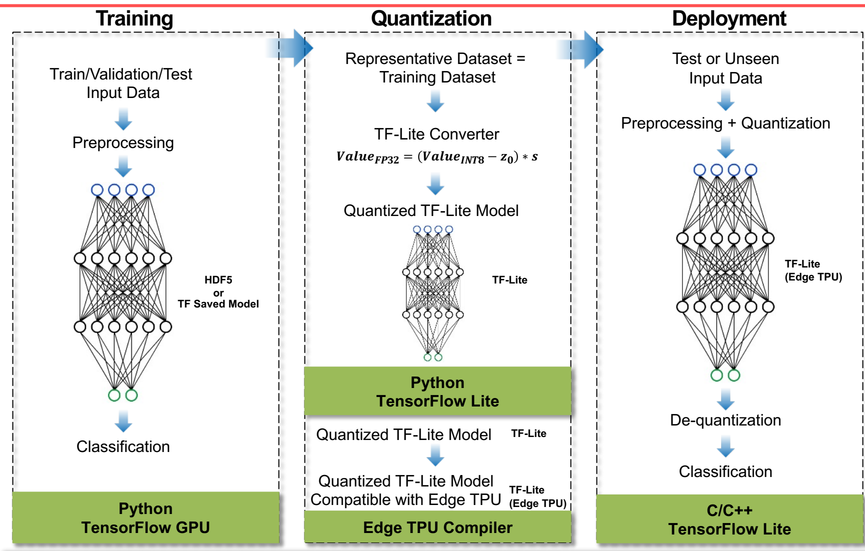
	LUT	FF	BRAM	DSP
SCENIC	40.4%	33.3%	38.6%	26.6%



Name	BRAM_18K	DSP	FF	LUT	URAM
DSP	-	-	-	-	-
Expression	-	-	0	26	-
FIFO	16	-	3523	2073	-
Instance	76	110	16920	18166	-
Memory	-	-	-	-	-
Multiplexer	-	-	-	36	-
Register	-	-	4	-	-
Total	92	110	20447	20301	0
Available	1200	1920	484800	242400	0
Utilization (%)	7	5	4	8	0

As preprocessing pipeline changes, use HLS tools to generate utilization estimates

SC-LEARN Model Development Flow



This flow shows the Training, Quantization, and Deployment steps required to run models on the SC-LEARN.

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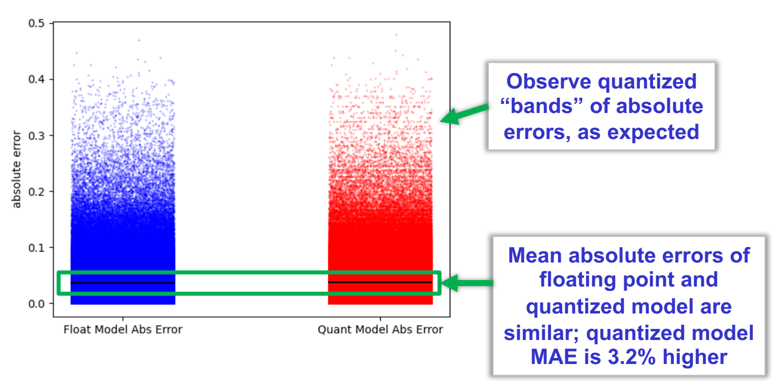
Daytime HICO Chlorophyll Model Quantization

- Performed post-training quantization on daytime HICO chlorophyll model using TensorFlow Lite converter (HICO chlorophyll training dataset was used as representative dataset)
- Compared absolute error of floating point vs. quantized model chlorophyll retrieval on test dataset



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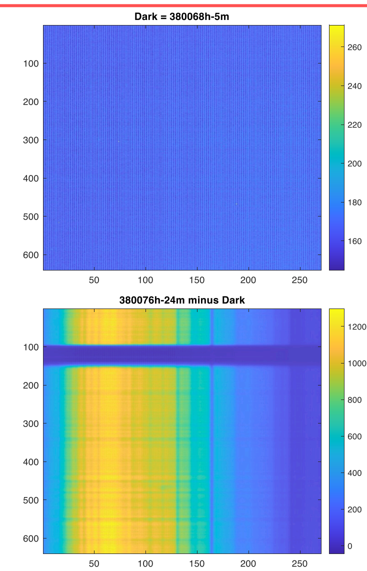
SCENIC Challenges & Commissioning

SCENIC Challenges

- Delays establishing reliable communications for file transfers of large HSI files
  - Up to 50% of frames missing
  - Ideal download procedure not established until mid Jun
- Several maintenance patches on SCENIC are required due to CONOPS
- Possible partial slit blockage reduces useable swath
- Currently calibrating and identifying settings for sensor day & night (not complete)
- Need good geolocation for training (currently working an STK solution)

Calibration

- Calibration starts with lab data
- Calibration targets
  - Dark frames (over ocean/night) for radiance zero levels
  - Atmospheric absorption features are good for spectral calibration
  - Bright scenes (day over thick clouds) provide gain in radiance equation and relative calibration to equalize responses (fix spatial streaks)
- SCENIC will not be calibrated to the same standards as a NASA Observatory-Class instrument
  - Technology project
  - With some Science too



Conclusions

- AIST-21 Edge Computing...
  - Will establish much needed precedent and trailblaze path-forward for onboard applications deploying AI models
  - Will advance research and TRL of realistically deploying applications onboard flight systems
  - Will create templates and reference documentation for allowing science and engineering community to propose and create their own models and applications
  - Will inform ongoing center efforts for DSM
  - Has demonstrated significant use-case examples for very, FPGA specific issues (not covered here) in simulation and co-simulation development scenarios which will be included as dedicated section in upcoming paper and referenced for future missions
  - Has shown extensive development cycles are possible, notably, each iteration process was full end-to-end development and tested at each step, including hardware execution and full software driver integration
- Future Work
  - Perform additional camera testing and characterization with engineering test unit and referenced flight data
  - Update applications for initial Flight Build #1
  - Apply AI (on ground to TEMPO)
  - Author manuscripts and lessons learned

Infusions and Collaborations

- EVI-1 TEMPO Program
  - Co-I Joanna Joiner and PI Jim Carr belong to TEMPO Science Team
  - Presentations at Science Team meetings
  - Plans to do Nightlights Spectroscopy as a “Green Paper” activity (on ground AI processing)
- NASA Black Marble Program
  - Collaborator Virginia Kalb belongs to Black Marble Science Team
  - Black Marble team briefed on SCENIC/TEMPO

Publications & Acronyms

SEE/MAPLD Conference

- Invited workshop talk due to increased interest in onboard AI approaches
- Discussed need for onboard AI and modeling and computing challenges associated developing onboard AI models
  - Amount of labeled data is critical for performance of deep-learning models
  - Knowledge of complexity of preprocessing steps is critical as they must be executed onboard
    - Illustrated complexity of SCENIC preprocessing pipeline
  - Continuous model validation in deployment
    - How much data do you need to send back to validate your model performance?
  - Computing Limitations
- Radiation performance of new devices amenable for onboard AI
  - HPSC
  - Xilinx Versal ACAP
  - Google Edge TPU and Myriad X
  - Qualcomm Snapdragon

Acronyms

List of Acronyms

Acronym	Definition
3D	Three Dimensional
ADT	Application Development Testbed
AET	Advanced and Emerging Technology
AFRL	Air Force Research Lab
AGU	American Geophysical Union
AI	Artificial Intelligence
AIST	Advanced Information Systems Technology
ANN	Artificial Neural Network
ANSI	American National Standards Institute
API	Application Programming Interface
ASIC	Application Specific Integrated Circuit
CCSDS	Consultative Committee for Space Data Systems
CF	Core Flight
CFDP	CCSDS File Delivery Protocol
cFS	Core Flight System
CLFG	Camera Link Frame Grabber
CNN	Convolutional Neural Networks
Co-I	Co-Investigator
COSMOS	C# Open Source Managed Operating System
CPU	Central Processing Unit
CS^2	CubeSat Card Specification
DDR	Double Data Rate (Type of RAM)
DNB	Day-Night Band
DoD	Department of Defense
DSB	Data Storage Board
EO-1	Earth Observing-1
ESA	European Space Agency
ESTO	Earth Science Technology Office
EVI	Earth Venture Instrument
FPGA	Field Programmable Gate Array
FTDP	File Transfer Data Protocol
GFSC	Goddard Space Flight Center
GOME-2	Global Ozone Monitoring Experiment-2
GPU	Graphics Processing Unit
HICO	Hyperspectral Imager for the Coastal Oceans
HLS	High-Level Synthesis
HSI	Hyperspectral Imaging
HW	Hardware
HYTI	Hyperspectral Thermal Imager
IH	Image Handler
IMPS	Intelligent Multi-Purpose System
IP	Intellectual Property
IPEX	Intelligent Payload Experiment
IRAD	Internal Research & Development
ISS	International Space Station
LED	Light-Emitting Diode
LVPC	Low Voltage Power Converter
MAE	Mean Absolute Error
MetOp	Meteorological Operational
ML	Machine Learning
NAND	Not-And (Logic Gate)
NASA	National Aeronautics and Space Administration
NGDC	National Geophysical Data Center
NIR	Near Infrared
NIST	National Institute of Standards and Technology
NN	Neural Neteork
NOS	New Observing Strategies
O1	Objective 1
OLI	Optical Line Imager

OMI	Ozone Monitoring Instrument
PCA	Principal Components Analysis
PCB	Printed Circuit Board
PCs	Principal Components
PI	Principal Investigator
REAG	Radiation Effects and Analysis Group
RISC-V	Reduced Instruction Set Computer-V
ROSES	Research Opportunities in Space and Earth Science
SBG	Surface Biology and Geology
SCENIC	SpaceCube Edge-Node Intelligent Collaboration
SC-LEARN	SpaceCube Low-power Edge Artificial Intelligence Resilient Node
SfM	Structure from Motion
SmallSat	Small Satellite
SPECULATE	SPacE CUbe LeArn TEst
SSDR	Solid State Data Recorder
STK	Satellite Tool Kit
STP	Space Test Program
SW	Software
TCL	Tool Command Language
TDRSS	Tracking and Data Relay Satellite System
TEMPO	Tropospheric Emissions: Monitoring Pollution
TID	Total Ionizing Dose
TOA	Top of Atmosphere
TPUs	Tensor Processing Units
TRL	Technology Readiness Level
TROPOMI	Tropospheric Monitoring Instrument
UIO	User-space Input/Output
USB	Universal Serial Bus
VIIRS	Visible Infrared Imaging Radiometer Suite
VNIR	Visible-Near-InfraRed
VPU	Vision Processing Unit
WBS	Work Breakdown Structure

Backups

SCENIC Experiment Summary

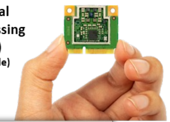
Mission Objectives

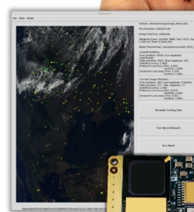
SCENIC will accomplish multiple primary and secondary objectives

- Primary Experiment Objectives
  - Demonstrate and evaluate commercial AI microchip technology (i.e., Intel Movidius X, Google Coral TPU) for radiation characterization in relevant space environment
  - Collect extensive image archive of terrestrial scenes required to train data-driven deep neural networks and perform real-time generation of data products for downlink to information subscribers
  - Demonstrate and evaluate NASA's next-generation CubeSat-sized, rad-tolerant, high-performance computer known as SpaceCube v3.0 Mini including fault-tolerant computer architecture design and Xilinx DPU

- Secondary Experiment Objectives
  - Upload new mass-less payload experiments for additional selected science/defense applications (i.e., semantic segmentation)
  - TRL advancement for new software framework applications supporting the open source Core Flight System (cFS)
  - Validate new CubeSat form-factor guidance and navigation cards

Google Coral Tensor Processing Unit (TPU) (courtesy Google)





Fire Detection ML Training GUI

SpaceCube v3.0 Mini CubeSat-Sized Processor Card

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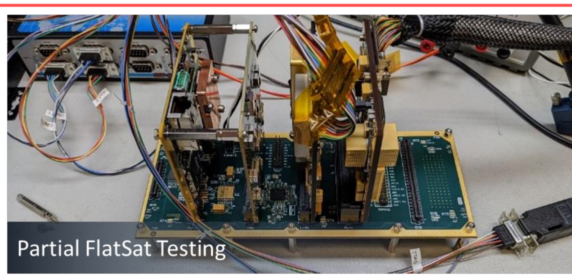
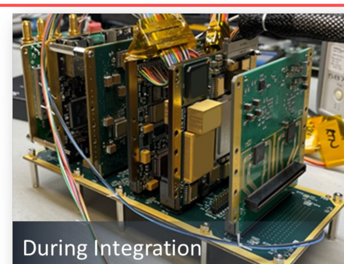
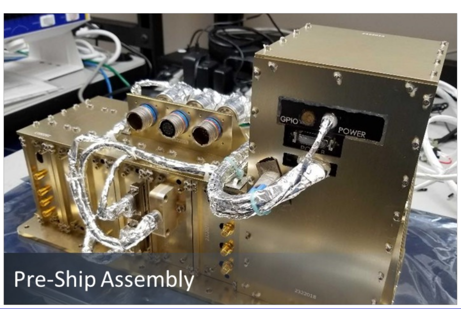
SCENIC Assembly



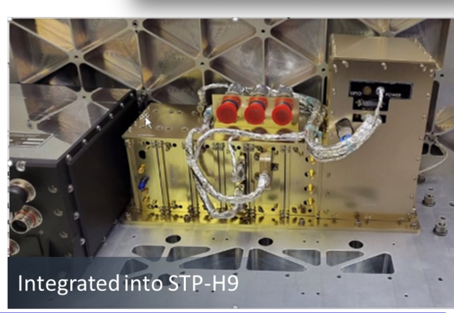
Partial FlatSat Testing



During Integration



Pre-Ship Assembly



Integrated into STP-H9

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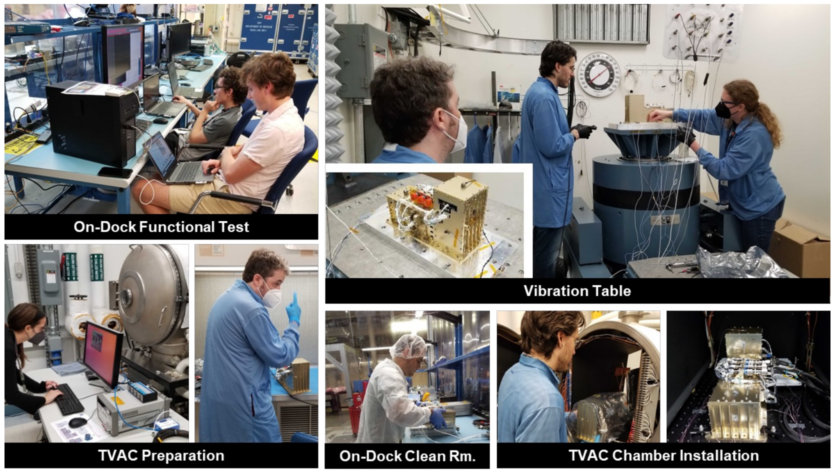
Environmental Testing

Conducted rigorous TRL-6 environmental testing prior to launch



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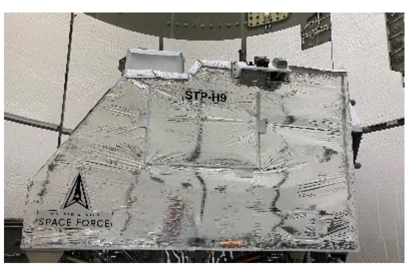
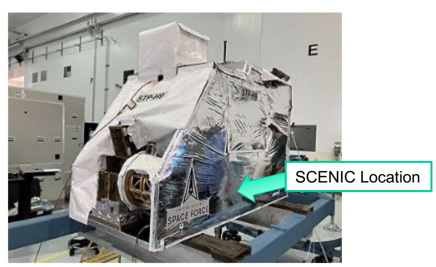
STP-H9
Space Test Program – Houston 9

- STP-Houston provides opportunities for DoD and civilian space agencies to perform on-orbit research and technology demonstrations from International Space Station (ISS)
- STP-H9-SCENIC is one of eight experiments on STP-H9 payload, which operates on International Space Station Japanese Experiment Module - Exposed Facility (JEM-EF)

STP-H9 Payload in Dragon Trunk and Space Station Processing Facility





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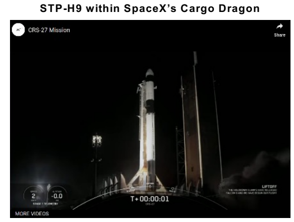
SCENIC Launch Timeline

- Launch Details
  - Rocket: Falcon 9 (B1073.7)
  - Payload: Cargo Dragon (CRS-27)
  - Launch Site: LC-39A,
    Kennedy Space Center, Florida
  - Launch Date: March 14, 2023
  - Launch Time: 8:30:42 p.m. EDT
- Onboard Activation
  - Removed from Dragon Trunk:
    19 March, 17:25 Central
  - Installed on JEM-EF:
    19 March, 23:15 Central
  - Power Applied:
    19 March, 23:15 Central
  - Activation Completed:
    20 March, 01:03 Central
  - All 8 experiments activated nominally

STP-H9 within SpaceX's Cargo Dragon



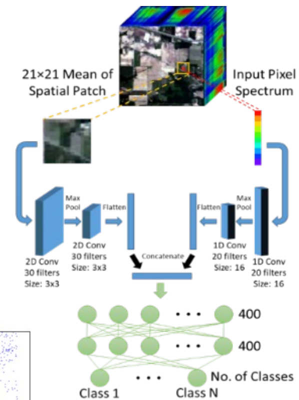
SpaceX's Cargo Dragon spacecraft on top of a Falcon 9 rocket, awaiting liftoff Tuesday from pad 39A

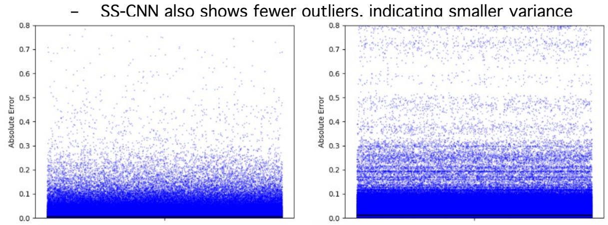
SCENIC and AIST-21 Edge Intelligence

- Overview
  - SCENIC data pipeline is configurable and fully supports uploading of AIST-21 applications
  - SCENIC's onboard processor is softcore MicroBlaze which is comparable to GR712 LEON3FT
    - New missions pair SpaceCube v3.0 Mini and SpaceCube Mini-Z which has dual-core ARM Cortex-A9s
    - While running nominal flight software applications MicroBlaze will struggle with many preprocessing (or general processing workloads)
  - Fortunately, many vision processing algorithms are amenable to rapid hardware acceleration in FPGA fabric
  - Unplanned AIST-21 Preprocessing stages can be rapidly designed and tested using FPGA High-Level Synthesis (HLS)
  - Highly iterative and evolving design changes for AIST highlighted in upcoming slides
- Challenges
  - While SCENIC launched in March, commissioning proceeded slower than anticipated due to operations team pulled to other projects to resolve critical issues
  - Significant delays due to GSFC IT preventing usage of other ground-station operating machines and file transfer server for large HSI files
  - Ideal download procedure not established until mid Jun
  - Several maintenance patches on SCENIC are required due to con-ops
  - Currently calibrating and identifying settings for sensor (not complete)

Spectral-Spatial Convolution Neural Network (SS-CNN)

- Experimented with SS-CNN AI model for HICO (Hyperspectral Imager for the Coastal Ocean) chlorophyll retrieval
  - Leverages both spectral and spatial features
  - Uses 2D CNN on mean of spatial patch surrounding pixel of interest
  - Uses 1D CNN on spectrum at particular pixel
  - Concatenates spatial and spectral features into combined feature vector, which is fed through fully connected network for final chlorophyll retrieval
- Compared absolute error distribution of SS-CNN model to spectral-only MLP on test set
  - SS-CNN MAE is 2-3 × smaller than spectral-only Baseline MLP
  - SS-CNN also shows fewer outliers, indicating smaller variance

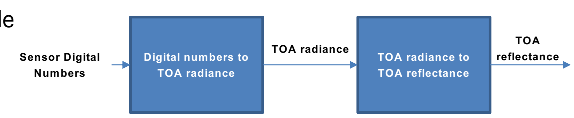




SS-CNN MAE: 0.00450 **Spectral-Only MLP MAE: 0.01170**

Generating Proxy SCENIC Data from HICO

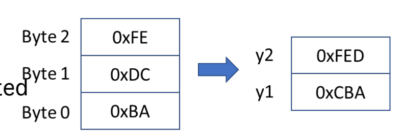
- To validate HLS input processing pipeline, representative SCENIC DN HSI Cube was required
  - Used HICO TOA reflectance since it covers similar spectral range as SCENIC and was deployed on ISS
  - Upsampled HICO from 87 HICO wavelength bands to 270 SCENIC bands via linear interpolation
- Estimated parameters for reflectance-to-DN inverse calculation
  - $E_{sun,\lambda}$ - solar spectral irradiance
  - θ_{SZA} - solar zenith angle
  - d - distance between sun and earth in AU
  - a_λ - gain
  - b_λ - offset
- Implemented packing of two 12-bit values into three 8-bit representation that SCENIC instrument employs
- All preprocessing stages implemented in both Python and C/C++



$L_{up}(\lambda,x) = a(\lambda,x) * DN + b(\lambda,x)$

- $a(\lambda,x)$: gain
- $b(\lambda,x)$: $offset$

$$R_{TOA} = \frac{\pi * L_{up}(\lambda,x)}{\frac{1}{d^2} * E_{sun}(\lambda) * \cos\theta_{SZA}}$$



Chlorophyll: Current State and Future Plans

- Goal:
  Develop an ML model for SCENIC instrument to retrieve ocean color properties
- Current state:
  Technique has been applied to HICO as proof of concept and shown to provide comparable ocean color retrievals with MODIS/HICO. Software tool for developing and training SCENIC NN model has been delivered to be ready when possible.
- Future plans:
  Applying technique with delivered software to the SCENIC instrument once geo-location information from SCENIC is available (geo-location of field of view is important for compiling training dataset using MODIS ocean color products).

  Possible research to develop techniques for detecting Sargassum (seaweed) from SCENIC instrument. Already developed test for TROPOMI instrument and appears promising.

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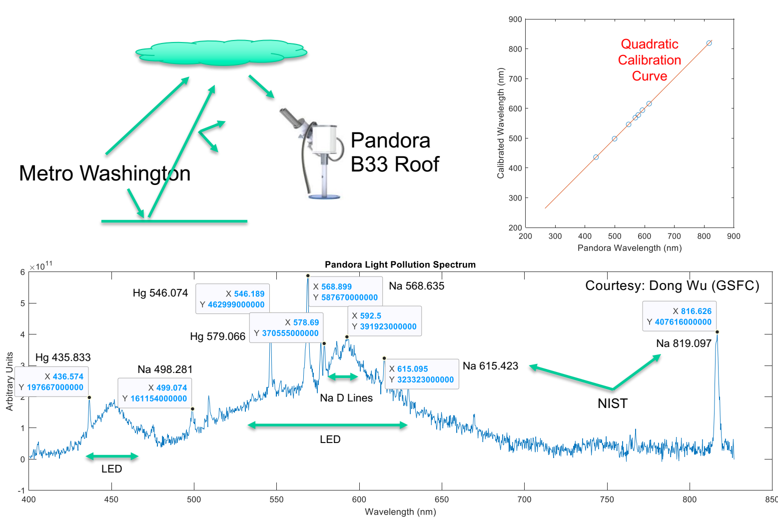
Pandora Spectral Calibration



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Analysis of Pandora Data

- From Pandora spectrum identified 4 categories of lights.
- Using a light library with 81 lights in 4 categories:
  - Mercury vapor
  - High pressure sodium
  - Low pressure sodium
  - LED
- Percentage of each light is randomly generated.
- These percentages (or fractions) are the targets for the NN training.

Steps for Processing Spectral Data

- Convolved with the spectral line spread function of the SCENIC instrument.
- Modeled the SRF as a Gaussian function with FWHM = 2.4 nm.

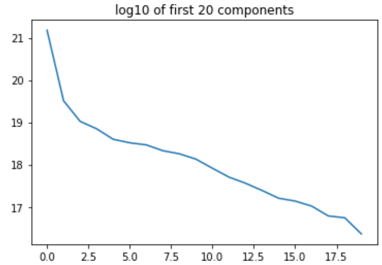
$$SRF(\Delta\lambda)=exp(-(4\ ln2)\ (\Delta\lambda/FWHM)^{\wedge}2\ )$$

- Sampling at the Pandora wavelengths.
- Converted counts to radiance and applied spectral calibration.
- Used the finest wavelength step (0.25 nm) and the range 264 nm to 850 nm.
- Scaled to the DNB response of 1 nW/(cm^2 sr).
- Converted radiance from nW/(str cm^2 nm) units into photons/(s str cm^2 nm)
- J_per_photon = (6.62606957e-34*2.99792458e8)/ (lambdas*1e-9)
- radiance = (1e-9*radiance0.T)/J_per_photon

Applying Single Value Decomposition (SVD)

- Construct Empirical Orthogonal Functions (EOFs) from library
- Reduce spectral dimension of each spatial pixel with EOFs (a dot-product operation) and normalize

log10 of first 20 components



Singular Value Decomposition

covariance-like matrix

$$cov(s) = ss^T$$

$$[V^T, D, V] = SVD(cov)$$

Variances
Var % = 99.98

used 16 leading EOFs

Neural Network
Adam as optimizer

```
num_of_nodes = 128
model = Sequential([
    Dense(units = num_of_nodes,
    kernel_initializer=GlorotUniform(),
    input_shape=(num_eofs,),activation='relu'),
    Dense(units = num_of_nodes/2, activation = 'relu'),
    Dense(units = num_of_nodes/4, activation = 'relu'),
    Dense(units = 4,activation='softmax')
    ])

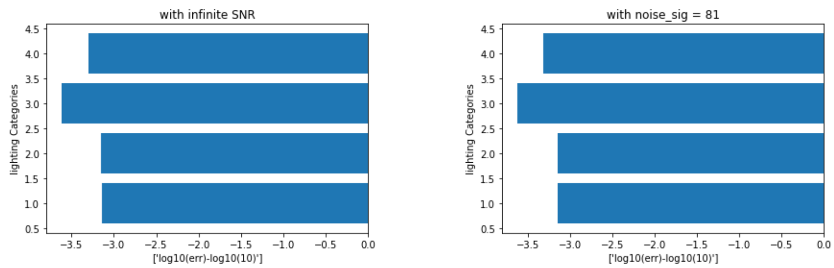
model.compile(optimizer=Adam(learning_rate=0.001),
          loss='mean_squared_error',metrics=['mse'])

batch_size = 64
 epochs = 500
```

4096 samples
spectra have 2000 wavelengths.

Run Time:
1.138 minutes

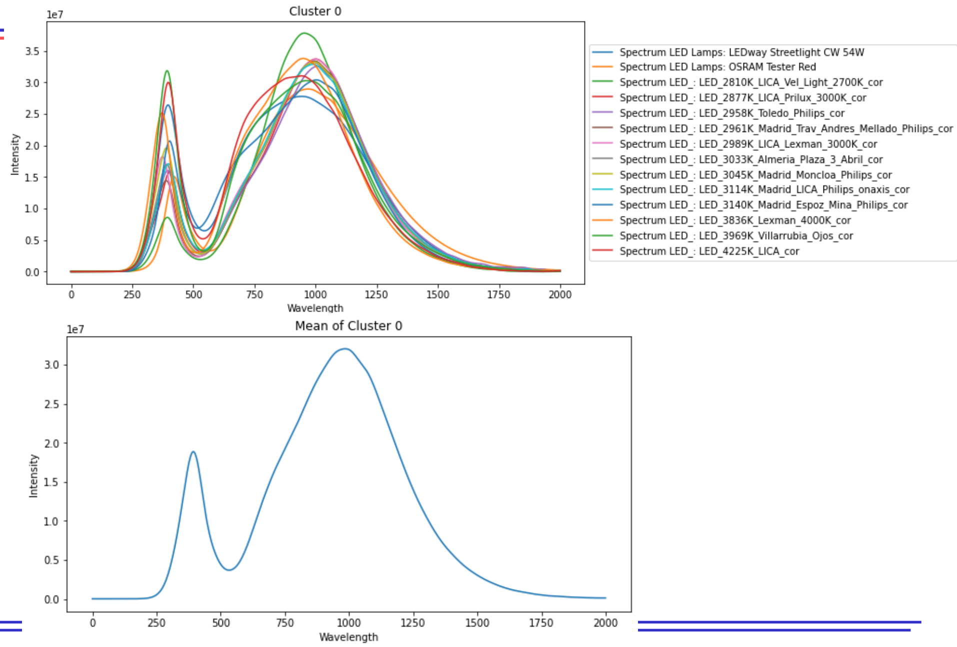
NN Performance



K-means clustering

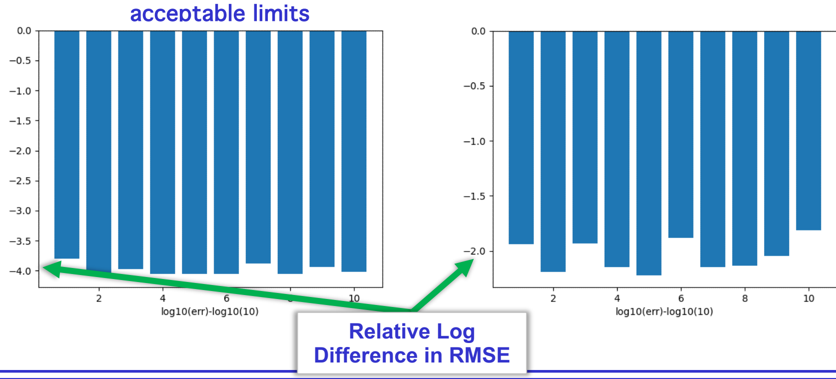
- To reduce several spectra of the same category of light (example LED) to fewer lights we can use clustering techniques such as K-means clustering.
- With K-means clustering we can partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean.
- We can then use the mean of each cluster or a representative of the cluster by selecting the spectrum that is closest to the centroid of the cluster.
- We used k-means clustering to reduce the number of LED lights from 62 to 16 and the number of High-Pressure Sodium Lights from 12 to 4.

Example of a cluster of LED Lights

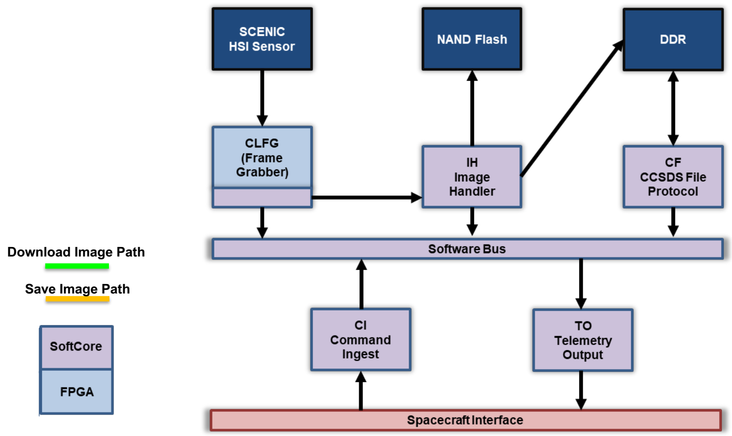


Nighttime Model Quantization

- Likewise, performed post-training quantization on night-light retrieval model using TensorFlow Lite converter
  - Training dataset was used as representative dataset
- Compared **RMSE** of floating point vs. quantized model on retrievals for 11 classes of night lights
  - While non-negligible quantization error was observed, RMSE of **quantized model retrievals were deemed to be well within acceptable limits**



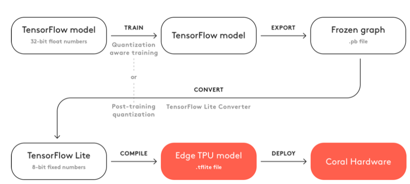
SCENIC Internal Capture App Flow



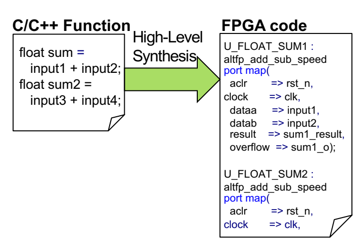
*Simplified architecture for clarity for applications involved in camera capture does not depict all cFS applications within flight hardware system

HSI Preprocessing FPGA Core

- One major AIST task is developing FPGA core to accelerate HSI preprocessing
- Edge AI models require data in specific formats before performing inferencing
  - Commonly, Edge device compilers support a specific set of operations and architectures
  - However, software-only execution would be prohibitive on target MicroBlaze
  - Target SCENIC platform has available FPGA resources to implement FPGA-based acceleration
- Previous AIST-18 StereoBit findings showed FPGA High-level Synthesis (HLS) could grant highly-productive FPGA development
  - High-level synthesis uses high-level C/C++ code to generate low-level FPGA code
  - Enables more rapid prototyping and hardware acceleration compared to lengthy traditional approaches on order of months



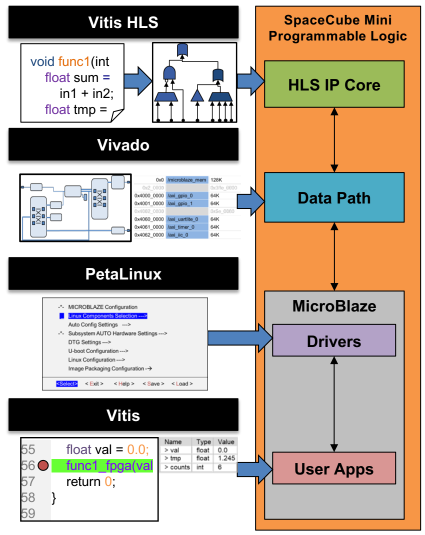
Quantization is common preprocessing step required, with Coral Edge TPU models expecting 8-bit fixed numbers[1]



[1]https://coral.ai/docs/edgetpu/models-intro/

FPGA HLS Development Flow

- FPGA HLS Development Flow significantly leverages lessons learned from AIST-18 StereoBit
  - Use **Vitis HLS** to rapidly generate acceleration IP cores from FPGA-amenable science code
  - Use **Vivado** to integrate HLS IP into data path of SpaceCube FPGA reference designs
  - Use **PetaLinux** to integrate Vitis HLS-generated drivers into customizable embedded Linux distro for MicroBlaze
  - Use **Vitis** to develop user-level apps that use drivers to call FPGA-accelerated science functions
- Development flow uses extensive scripted build flows to rapidly integrate new HLS kernels



Reflectance Kernel

- Initial HLS development started with reflectance computation for daytime app
- Reflectance code amenable to FPGA-based HW acceleration
  - Dataflow-oriented (i.e., data flows from one function to another)
  - Large for-loop with constant bound suitable for parallelization
  - No inter-iteration dependencies that limit parallelization
- Use HLS pipelines to infer systolic array to calculate several reflectance values concurrently
  - "Assembly line" structure where data passes from one stage to another
  - Accelerates a for-loop by processing multiple iterations at different stages concurrently

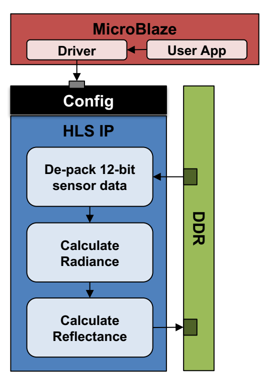


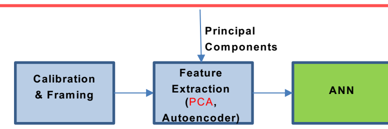
Illustration of HLS IP flow chart in KCU105 reference design

Main process loop in reflectance code

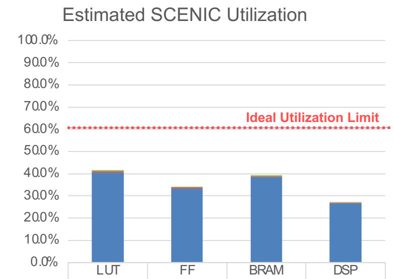
```
for (int p = 0; p < NUM_PIX; p++) {
#pragma HLS PIPELINE
  img_t val = imgStrm.read();
  float radiance = alpha * val + beta;
  float reflect = gamma * radiance;
  resultStrm.write(reflect);
```

PCA Stage Kernel

- Developed HLS core for PCA stage
  - In PCA stage, spectra is “projected” onto principal components (PCs)
  - Computation is largely floating-point matrix multiplication with configurable batch number (N)
- Matrix multiplication is a commonly accelerated kernel on FPGAs
  - Dataflow-oriented, but also memory-intensive
  - Use HLS pipelines with PC values buffered in Block RAM for computation
- Initial PCA kernel and reflectance kernel well within resource budget



PCA is one of the several feature extraction preprocessing steps for proposed pipeline



	LUT	FF	BRAM	DSP
PCA Stage	0.6%	0.4%	0.6%	0.3%
Reflect	0.6%	0.4%	0.3%	0.3%
SCENIC	40.4%	33.3%	38.6%	26.6%

SCENIC Reflect PCA Stage

Update to Reflectance Kernel

- To support nighttime use case, updated HLS code to conditionally output radiance values
- Output selection is relatively straightforward design change for FPGA
  - FPGA logic already includes fixed logic to compute both values so output is selected from fixed logic
  - In contrast, a software design may return early after computing radiance if radiance is selected
- HLS pipeline code can adapt to configurable output through additional “selection” stage
  - Pipeline still calculates radiance and reflectance in their respective stages
  - Pipeline uses additional stage to “select” between registered radiance/reflectance values

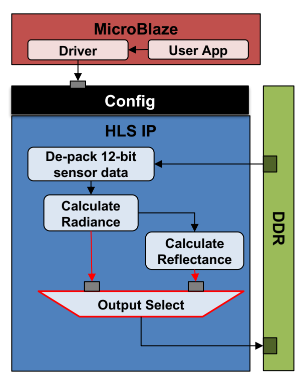


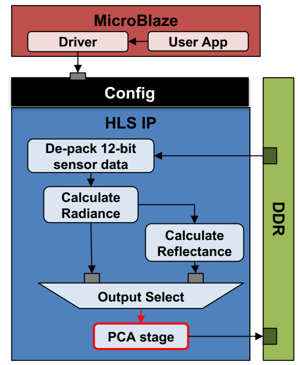
Illustration of HLS IP flow chart in KCU105 reference design

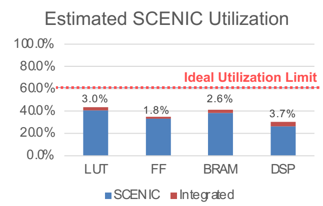
```
for (int p = 0; p < NUM_PIX; p++) {
#pragma HLS PIPELINE
  img_t val = imgStrm.read();
  float rad = alpha * val + beta;
  float reflect = gamma * rad;
  float result = (sel) ? rad : reflect;
  resultStrm.write(result);
```

Main process loop in updated code

Integrated HLS Core

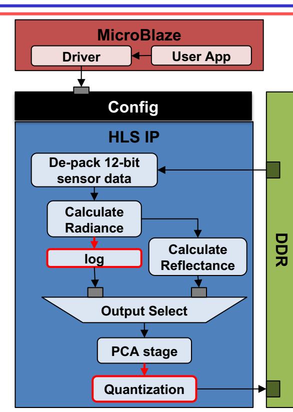
- Developed integrated HLS core combining reflectance and PCA cores
  - Reflectance logic now directly feeds data to PCA stage instead of writing output to DDR
- However, PCA logic must be updated to support data organization from reflectance logic
  - Previously, matrix data expected row-major order data format (i.e., mat[channel][height*width])
  - From the reflectance logic, PCA logic was adapted to match HSI data cube ordering (i.e., mat[height][channel][width])
- Since vector data would arrive non-contiguously, HLS code modified to store several partial sums
  - Added several block RAM (BRAM) buffers to store partial sums until all vector data has arrived

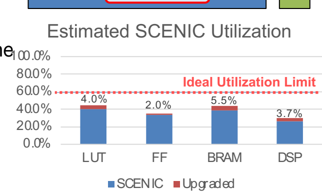




Updated Integrated HLS Core

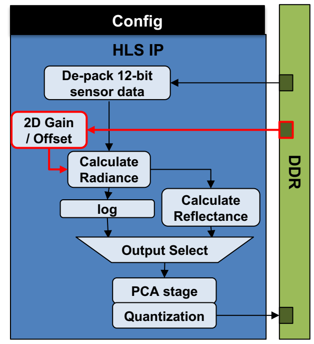
- Updated integrated HLS core to incorporate additional identified preprocessing stages
  - Quantization is common preprocessing step **required for Edge AI models**
  - Specifically, Edge TPU models expect quantized 8-bit fixed-point input data
- Like output selection, new stages implemented as additional pipeline stages
  - Quantize data streamed from output select stage and write data to DDR
  - Control quantization stage with runtime-configured quantization parameters (i.e., min/max, scale, etc…)
- HLS code modified to add quantization as new dataflow function
  - HLS dataflow functions are implemented as independent compute units that read/write data from channels (e.g., FIFOs) between dataflow functions
  - Read data from output select FIFO and use HLS pipeline to perform several quantization computations in parallel

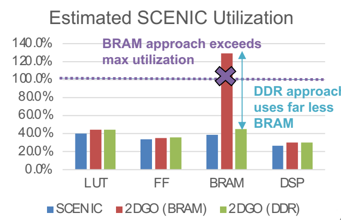




2D Array Gain/Offset

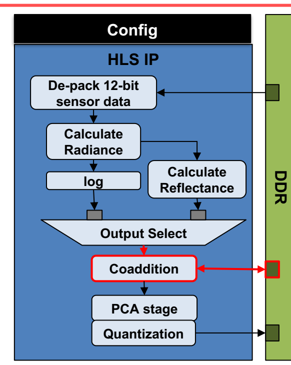
- For daytime use case, investigated HLS core that used 2D array of gain/offsets
  - Previously, 1D array of gain/offsets were reused between spectral channels (i.e., 640 elements)
  - 2D array of gain/offsets has separate gain/offsets across spectral channels (i.e., 270 × 640 elements)
- Previous approach relied on buffering 1D array of gain/offsets in on-chip BRAM
  - However, extending BRAM approach to 2D array requires prohibitive BRAM utilization (i.e., 130%)
  - Must store 2D array of gain/offsets in larger DDR storage at cost of longer access times
- New approach uses DDR with small BRAM cache to buffer gain/offsets
  - HLS core now re-reads 2D array of gain/offsets from DDR for each frame in the HSI data cube
  - Simultaneously, HLS core computes radiance using gain/offsets currently buffered in BRAM cache

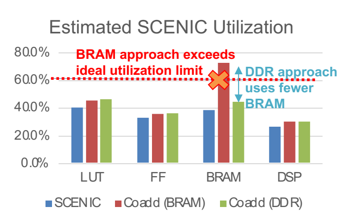




Coaddition

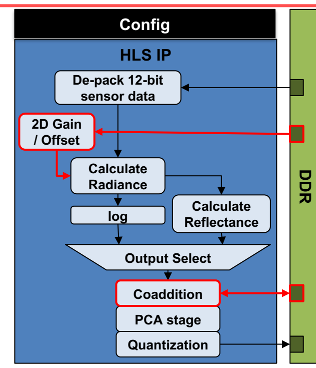
- Concurrently, developed a coaddition processing stage as feature for both use cases
  - In both cross-track and along-track with configurable reduction factors
- Coaddition presents non-trivial changes in underlying FPGA design and HLS code
  - Configurable reduction factors generate variable amounts of data that must be handled correctly by the PCA stage and other downstream stages
  - Along-track coaddition requires storing partial sums across entire frames of data in BRAM/DDR
- New design also uses DDR-based approach to store partial sums between frames of data
  - Preliminary design used only BRAM and yielded resource estimates exceeding ideal utilization limit
  - Like 2D array gain/offsets, usage of DDR storage with small BRAM cache reduced overall BRAM cost

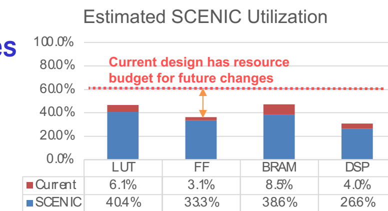




Current Integrated Design

- Updated Integrated design to include both coaddition and 2D gain and offset
- Integration of both features required close examination of DDR access
  - Both features relied on DDR access through individual master AXI ports
  - To save FPGA resources, FPGA core was rewritten logic to infer logic that time shared master AXI ports for DDR accesses
- Current design **still has resource budget for future processing stages**
- For initial AIST experiments, current design is now **ready to port to SCENIC** FPGA design





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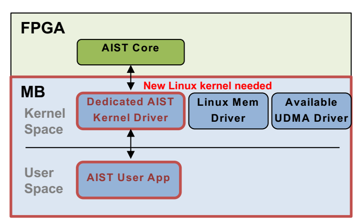
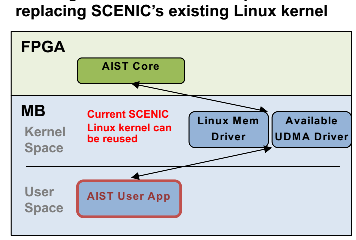
User Space HLS Driver

- To control and configure FPGA core, SCENIC's MicroBlaze needs **software drivers for FPGA core**
  - For each code iteration, used HLS-generated drivers in self-checking benchmarks to validate correctness
  - Responsible for setting runtime settings, such as coadd reduction factors (e.g., along-track (AT), cross-track (XT))
- However, existing driver software cannot be used on SCENIC's current Linux kernel image
  - Existing drivers rely on device tree nodes to load drivers
  - Current SCENIC kernel **does not support runtime configuration of device tree**
- One alternative is developing drivers that reuse existing kernel resources
  - Although not appropriate for all FPGA cores, suitable for simple control interface to HLS core
  - Preliminary results show that **new driver software approach yields slower, but not prohibitive**, performance

Daytime Use Case on flight-representative dev board KCU105	AT XT	Dedicated Driver Execution (s)	New Driver Approach Execution (s)	Difference
HICO Test Data (400x640x87) x 10	1 16	8.506426	14.94324	6.436811
	10 16	8.319302	15.44728	7.127975
HSI Canned Test Data (400x640x270) x 15	1 16	25.22242	**30.62405**	5.401625
	10 16	24.77401	**29.85104**	5.077023



Existing AIST kernel driver requires replacing SCENIC's existing Linux kernel



New software driver approach relies on allocating kernel resources with existing drivers

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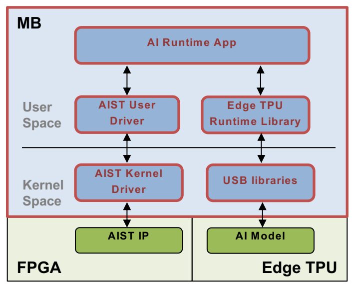
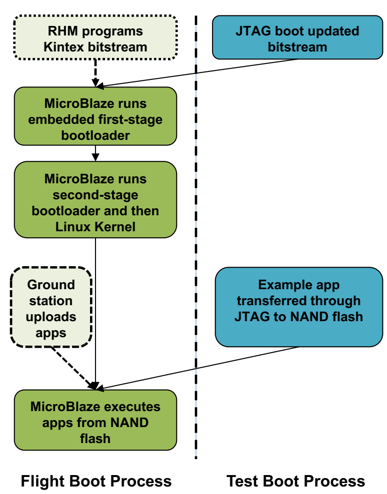
AI Application Runtime Software Framework

- Runtime software framework for executing models on SCENIC
- Preprocessing
  - Employs calls to SCENIC IP's user-space driver
  - Interacts with kernel driver to invoke processing pipeline within SCENIC IP core
- AI model inference
  - Employs calls to Edge TPU runtime library (libedgetpu)
  - Libedgetpu works with USB libraries (libusb) to send preprocessed data and model to Edge TPU for inference



Initial SCENIC Porting Efforts

- To port AIST app to SCENIC, started with running example Linux app on FlatSat
  - Ensures user driver is compatible with SCENIC FPGA/Linux configuration
  - Afterwards, user driver needs to be integrated with TPU and cFS code
- cFS is not present on KCU105 reference design equivalent to flight build therefore mimicked upload process was used
  - Only JTAG-booted updated bitstream with embedded first-stage bootloader, mimicking RHM bitstream update
  - Cross-compiled example app and JTAG-transferred to NAND flash data partition, mimicking app upload
- Initial example code runs successfully
  - Ran HSI Canned Test Data from earlier experiment
  - Execution takes about 10s longer than KCU105 due to longer memory copies
  - Likely result of slower DDR performance
    - KCU105 is 1200 MHz DDR4
    - SpaceCube v3.0 Mini is 667 MHz DDR3



AT	XT	KCU105 (s)	SCENIC (s)	Difference
1	16	30.62405	39.49477	8.870722
10	16	29.85104	39.45832	9.607287

64

JPL Clearance CL#23-3437

Dynamic Tasking

Steve Chien[1] (PI)
Alberto Candela[1], Juan Delfa[1] (Co-I)

AIST-QRS-23-0001 Annual Technical Review
12 July 2023

Team listing:
Marcin Kurowski[1], Abigail Breitfeld[1], Akseli Kangaslahti[1]

1 - Jet Propulsion Laboratory, California Institute of Technology

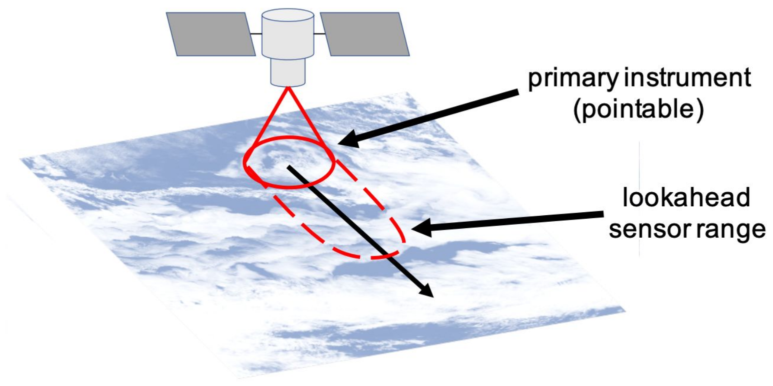
Dynamic Targeting

PI: Steve Chien, JPL

Objective

Mature dynamic targeting concepts, algorithms, and software to enable future missions to more effectively capture science data.

- Mature and enhance online instrument targeting and reconfiguration algorithms.
- Investigate dynamic targeting strategies for plausible wide-swath lookahead sensors, which can detect events of interest that can be dynamically targeted by trailing sensors that have higher resolutions or complementary sensing modes.
- Evaluate dynamic targeting in the context of use cases in Planetary Boundary Layer, Storms and Severe Weather, and Cloud avoidance.



A dynamic targeting use case: Lookahead sensor data analyzed to target primary sensor on key science features.

Approach

- Study dynamic targeting in the context of use cases in: Planetary Boundary Layer, Storms and severe weather, and Cloud avoidance, including investigation of potential instruments and science phenomena. The primary use case will be PBL, for which we will develop datasets to evaluate the impact of dynamic targeting. As a stretch goal we will evaluate a second use case using existing datasets, to the extent permitted by resources.
- Investigate generic families of algorithms for combinations of recurring problem subtypes based on pointing, consumable resources (e.g., energy, data volume), and setup times.
- Study lookahead sensor detectability for plausible wide swath sensors

Co-Is/Partners: A. Candela, J. Delfa, JPL

Key Milestones

• Targeting algorithms space defined; Scoping for PBL study, potential use subcases identified.	Mar-23
• Datasets for PBL study acquired; base targeting algorithms implemented.	Jun-23
• Targeting algorithms extended for variable utility maximization.	Sep-23
• empirical evaluation on PBL case; Second use case study results (stretch goal).	Jun-24
• Complete publications.	Dec-24

$TRL_{in} = 4$ $TRL_{current} = 4$

Presentation Contents

- Background and Objectives
- Technical and Science Advancements
- Summary of Accomplishments and Future Plans
- Actual or Potential Infusions and Collaborations
- Publications - List of Acronyms

Background and Objectives

Background

- Current Earth Science Missions “Mow the lawn” and observe blindly, *hoping* to acquire data on complex science phenomena
- Dynamic Targeting (DT) utilizes lookahead sensor data and other available sensor data to target areas and best configure instrument settings to improve science return and capture more of rare science phenomena, with many science use cases
  - Study of deep convective ice storms,
  - Planetary Boundary layer,
  - Disasters/hazards (plumes, air quality),
  - Cloud avoidance

Objectives

- **Advance DT Algorithms to more realistic constraints and utility models**
- **Mature Planetary Boundary Layer (PBL) DT Use Case**
- **Investigate flight opportunities as “stretch goals”**

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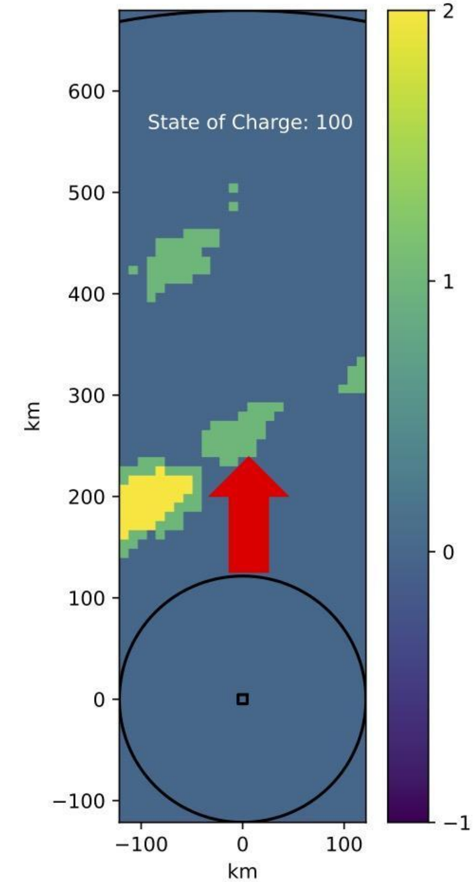
Earth Science Technology Office

DT Algorithm Enhancement

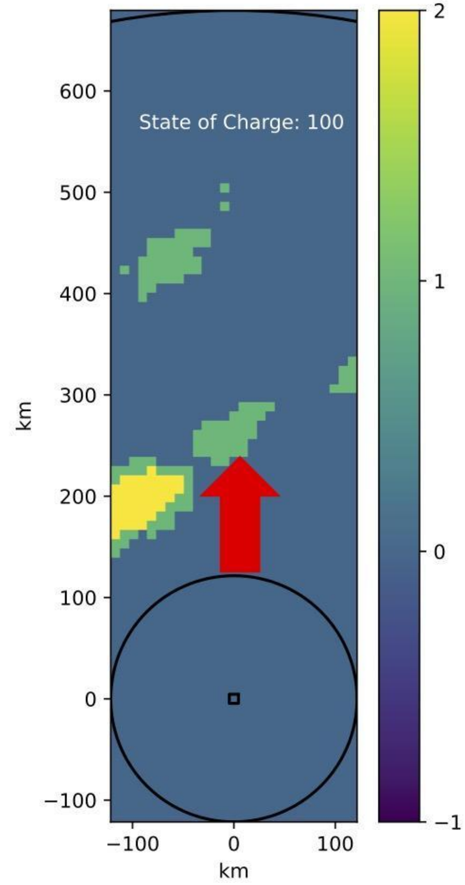
- Generalization and improvement of DT to more realistic costs and constraints
  - **slew time**, energy costs
- Algorithm searches ahead by next observation
  - variable time based on required slew duration
  - non-observation option does not commit to slew but grows reachable zone
- Algorithm considers beam (aka beam search) of top N candidate observations
- Testing algorithm on a range of datasets and slewing configurations (from SMICES and others)
- Being prototyped by **Akseli Kangaslahti**



DT uses a slewing model to understand which targets can be reached at which times during an overflight.

DT Algorithm Enhancement

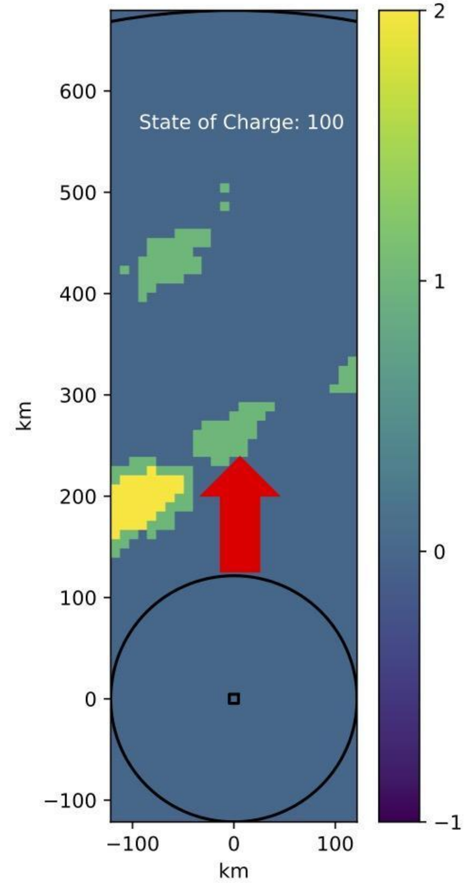
- Generalization and improvement of DT to more complex, realistic utility functions
  - Diminishing (or increasing) returns for repeated observations of the same point
  - Penalty (reward) for off-nadir measurements
  - Utility based on diversity in observation geometry
  - Incremental search updates utilities of potential observations after each observation selected
  - Being prototyped by **Akseli Kangaslahti**



DT uses a utility model to represent science goals of observation spatial diversity, geometric diversity, repeat observations, and nadir or off-nadir preferences.

DT Algorithm Enhancement

- Generalization and improvement of DT
- Deep Learning (DL):
  - Agents learn optimal actions through many trials/simulations
  - Potential to learn customized policies for different use cases, regions, seasons
  - Requires realistic datasets
  - Test using standard cross validation
  - Being prototyped by **Abigail Breitfeld**



DL for DT can learn observation policies to account for complex preferences, target distributions, with multiple models possible for different contexts

Planetary Boundary Layer Case Study

- Study of dynamic interactions between planetary surface and lower atmosphere
- Many rapid, complex interactions (e.g. sunset)
- Some rare and short duration
- Some can only be measured indirectly
- Decadal "Incubation Targeted Observable"

Figure 2-1. A schematic depiction of key aspects of the PBL.

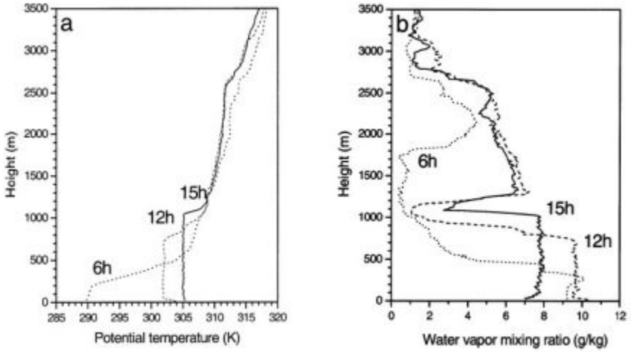
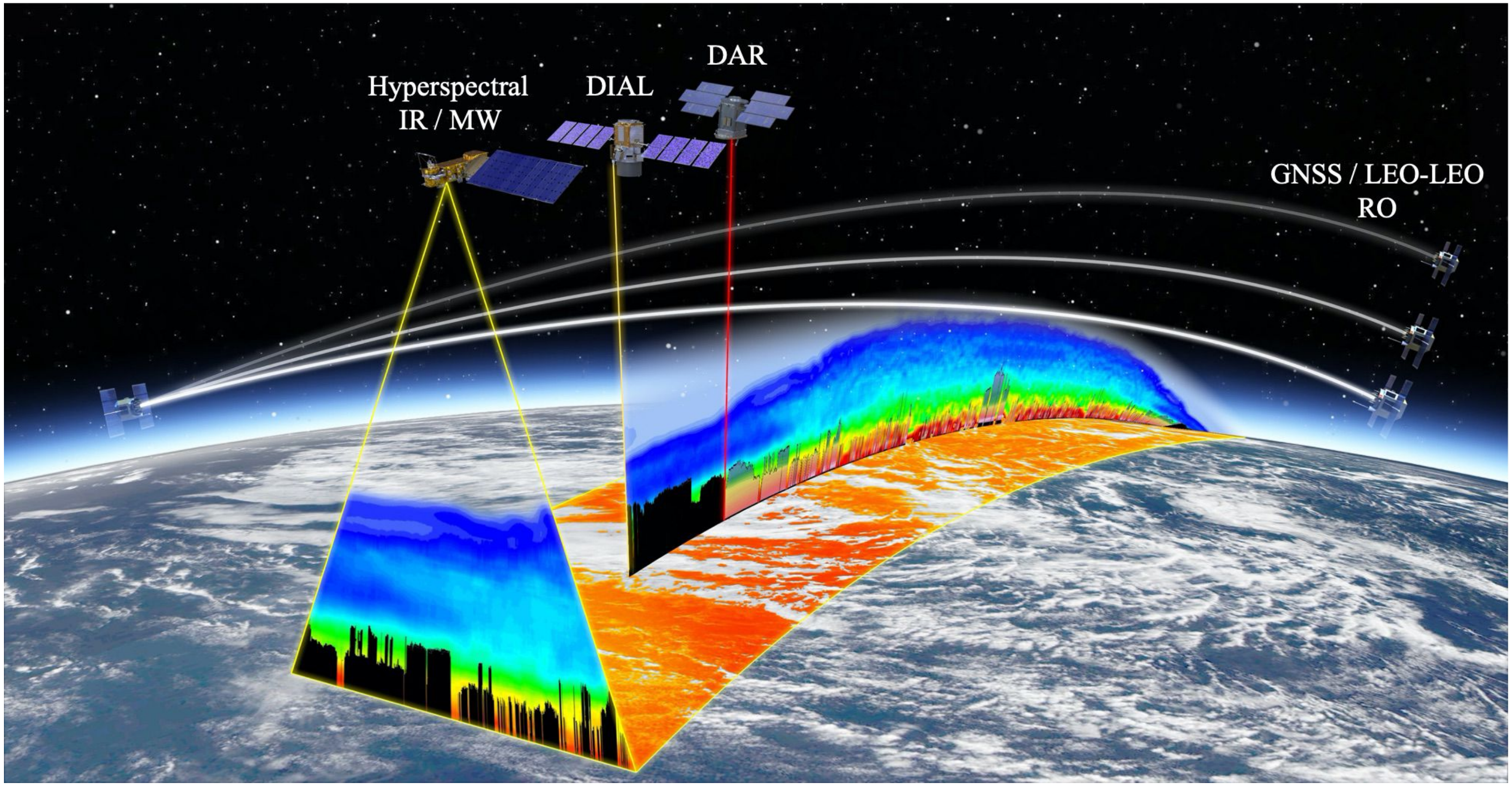


Figure 4-1. Example of dry convective PBL thermodynamic structures: Observed (a) potential temperature (K) and (b) water vapor mixing ratio (g kg-1) profiles from a field experiment in Southern Portugal during Northern Hemisphere (NH) summer at 6, 12 and 15 UTC. From Teixeira et al. (2004).

Planetary Boundary Layer Case Study



- Lookahead instrument:
  - Hyperspectral Infrared Sounder
  - Hyperspectral Microwave Sounder
- Primary Instrument
  - Differential Absorption Lidar
  - Differential Absorption Radar

Planetary Boundary Layer

- PBL science study team has shown great interest in integrated measurement of PBL phenomena

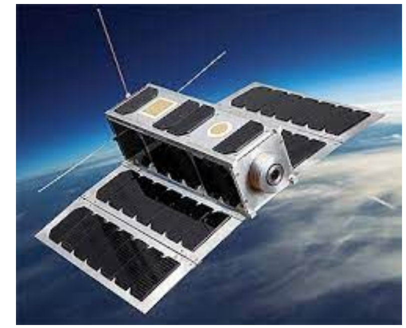
- Multi-instrument measurements are challenged by limitations on some constituent instruments
  - DIfferential Absorption LIDAR (DIAL) is narrow FOV and is best suited for clear sky applications
  - Differential Absorption Radar (DAR) is narrow FOV and power hungry

- The above operations constraints can be mitigated by DT "smarts"
- **Juan Delfa** working above concept(s) with Marcin Kurowski (PBL science)
- Working to identify datasets to validate above concepts (Marcin Kurowski, Qing Yue)

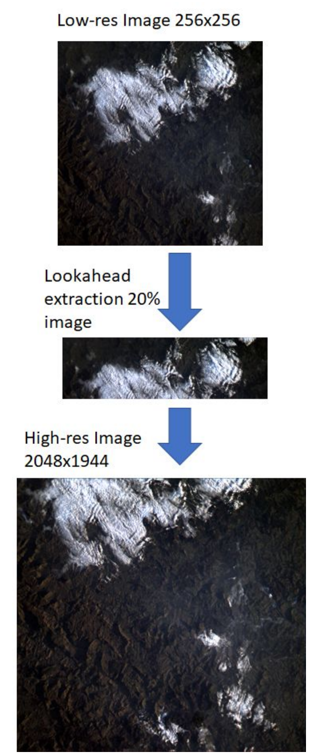
ESTO Earth Science Technology Office

ESA Ops Sat Experiment

- Cubesat with high-performance CPU
- Challenges for DT: limited access to onboard software; no lookahead instrument; slow slewing
- Dynamic Targeting without dedicated lookahead instrument:
  - Simulate Lookahead instrument using nadir image at lower resolution (ahead track segment)
  - Simulate nadir target instrument using high-res images (behind track segment)
- DT development
  - Detection of multiple targets per swath
  - Use of global cloud knowledge as heuristic
  - Prototype passed flatsat tests, possible scheduled for flight as early as *August 2023*
  - Conception, design, and development led by **Juan Delfa**



Artists rendering of OPSSAT



Planet Labs PBC

- Planet Labs PBC has shown considerable interest in flying DT on their Pelican 2 satellite(s) to implement cloud avoidance
- Steve Chien has been in consistent contact with Planet regarding this and other concepts
  - Cloud avoidance
  - Storm hunting
  - Thermal anomaly hunting (volcano, wildfire)
  - Plume tracking
- JPL and Planet PBC are jointly maturing several concepts under NDA.

Artists rendering of Planet Pelican Satellite.
Image courtesy Planet PBC.

Team Members: Students

Abigail Breitfeld, (Ph.D. student, Carnegie Mellon University, Advisor David Wettergreen)
Intern Summer 2023.

Working on Deep Learning to learn policies for Dynamic Targeting.

Akseli Kangaslahti, (undergraduate, University of Michigan)
Intern Summer 2023. Was intern Summer 2022 working on NOS-L Sensorweb.

Working on extensions of Dynamic Targeting to slewing models and multi-look utility models.

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Summary of Accomplishments and Future Plans

- DT Task initiated and making good progress.
  - Extensions of algorithms to incorporate slewing constraints
  - Extensions of algorithms to incorporate nadir/off nadir utility, multi observation variations in utility
  - **<u>Future:</u>** testing above extended algorithms on existing datasets
  - Developed preliminary concept for Planetary Boundary Layer observation
  - **<u>Future:</u>** develop datasets to assess PBL concept; assess value proposition of DT for PBL
  - OPS SAT Flight Experiment nearing Flight
  - **<u>Future:</u>** Flight on OPS SAT
  - Planet Pelican 2 Flight Experiment in negotiation
    <u>Future:</u> Complete agreement and identify funding.

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Actual or Potential Infusions and Collaborations

- Potential Infusions - NASA
  - DT in SMICES mission for hunting deep convective ice storms
    <u>POC:</u> Xavier Bosch-Luis, SMICES Concept Lead, JPL
  - DT in cloud avoidance for future OCO-3 follow on missions
    <u>POC:</u> Annemarie Eldering, OCO-3 Project Scientist
  - DT for focused measurement of PBL phenomena
    <u>POC:</u> Marcin Kurowski, PBL Science, JPL

- Potential Infusions - Commercial
  - DT on Planet PBC Pelican 2 for Cloud avoidance
    <u>POC:</u> Kiruthika Devaraj, VP Avionics and Spacecraft Technology, Planet PBC

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Publications

Juan Delfa, Alberto Candela, Steve Chien, “Enhanced Dynamic Targeting for the OPSSAT Cubesat,” *in International Workshop on Planning and Scheduling for Space (IWPSS 2023)*, Prague, CZ, July 2023.

James Mason, Tessa Holzmann, Jason Swope, Ashley Gerard Davies, Steve Chien, Joel Mueting, Tanya Harrison, Vishwa Shah, JJ Walter, “Fully Automated Volcano Monitoring And Tasking With Planet Skysat Constellation: Results From A Year Of Operations,” *In Intl Geoscience and Remote Sensing Symposium (IGARSS 2023)*, Pasadena, CA, July 2023.

Akseli Kangaslahti, Steve Chien, Jason Swope, James Mason, Joel Mueting, Tanya Harrison, “Using A Sensorweb For High-Resolution Flood Monitoring On A Global Scale,” *In Intl Geoscience and Remote Sensing Symp. (IGARSS 2023)*, Pasadena, CA, July 2023.

Alberto Candela, Jason Swope, and Steve Chien, Dynamic Targeting to Improve Earth Science Missions, *Journal of Aerospace Information Systems*, in press.

Steve Chien, Alberto Candela, Juan Delfa, Akseli Kangaslahti, Abigail Breitfeld, Expanding and Maturing Dynamic Targeting, 17th Symposium on Advanced Space Technologies in Robotics and Automation, Leiden, NL, October 2023 (in review)

List of Acronyms

- DT - Dynamic Targeting
- SMICES - Smart Ice Hunting Radar Mission Concept
- PBL - Planetary Boundary Layer
- DL - Deep Learning
- IR - Infrared
- MW - Microwave
- DIAL - Differential Absorption LIDAR
- LIDAR - Light Detection and Ranging
- DAR - Differential Absorption Radar
- GNSS - Global navigation satellite system
- LEO - Low Earth Orbit
- RO - Radio Occultation
- ESA - European Space Agency

Innovative Geometric Deep Learning Models for Onboard Detection of Anomalous Events

PI: **Yulia R. Gel** (UTD)

Co-Is: **Huikyo Lee** (JPL)**, Michael Garay** (JPL)
Baris Coskunuzer (UTD), **Matthew Dixon** (IIT)
Yuzhou Chen (Temple Univ./previously PostDoc Princeton)

AIST-21-0059 Annual Review
July 12, 2023

Other personnel: **Nick LaHaye** (JPL), **Deepisha Solanki** (UB), **Zhiwei Zhen** (UTD), **Jae Won Choi** (UTD), **Cheyenne Ward** (CSU), and **Ziheng Guo** (IIT)

Innovative GDL for Onboard Detection of Anomalous Events

PI: Yulia R. Gel, University of Texas at Dallas

Objective

We propose to develop a topology-based deep learning (DL), geometric deep learning (GDL), machine learning (ML) framework that can investigate spatiotemporal anomalies in the radiance observations from GOES-East (GOES-16) and GOES-West (GOES-17) satellites;

- Develop time-aware DL, GDL, and ML architectures with shape signatures from multiple spectral bands for (semi-)supervised on board learning of multi-resolution smoke observations.
- Detect smoke plumes and other anomalies in multi-resolution observations with time-aware DL/ML with a fully trainable and end-to-end topology-based module.
- Investigate the uncertainty in topological detection of smoke plumes and improve the efficiency of GDL for onboard applications.

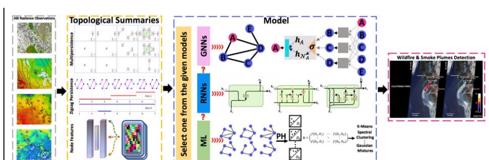

Illustration of topology-based representation learning architecture. Given ABI radiance observations we apply various TDA tools (e.g., multi-persistence and zigzag persistence), feed topological summaries into DL, GDL, or ML models, and utilize the outputs for tracking and detecting smoke plumes.

Approach

An end-to-end topology-based representation learning for wildfire and smoke plumes tracking and detection tasks. This framework is able to

- Integrate Advanced Baseline Imager (ABI) radiance observations and graph structural information to generate high-quality embedding at node level.
- Extract various topological summaries via different topological data analysis tools and utilize topological convolution operation to generate latent representation for topological summaries.
- Combine all representations of nodes and topological summaries and feed the concatenation to DL, GDL, or ML models to capture spatial and topology-based temporal correlation in multi-resolution observations.

Co-Is/Partners: H. Lee and M. Garay, JPL, M. Dixon, IIT, Y. Chen, Temple University; B. Coskunuzer, UT Dallas

Key Milestones

- ~~Develop time-aware GDL architectures~~ ~~01/23~~
- Demonstrate detection of smoke plumes and other anomalies 07/23
- Demonstrate uncertainty quantification in topological detection of smoke plumes 01/24
- Demonstrate improved efficiency of GDL for
- onboard applications 01/24

TRL_{in} = 2

Presentation Contents

- Background and Objectives
- Technical and Science Advancements
- Summary of Accomplishments and Future Plans
- Actual or Potential Infusions and Collaborations
- Publications - List of Acronyms

Background: Introduction

• ML/DL in Earth sciences gains popularity for analysis of massive datasets from observational records and climate models, particularly geometric deep learning (GDL) for non-Euclidean objects, can describe hidden structures that cannot be done with conventional analytic tools.

• The simultaneous use of spatial structures and temporal evolution from NASA's satellite observations in onboard ML/DL modeling is limited, due to the inability to efficiently characterize nonstationary spatiotemporal structures and to detect spatiotemporal anomalies .

• Most available DL tools are inherently static and do not systematically integrate time-dimension into the learning process of spatial data properties. As a result, such architectures often cannot learn, in case of the onboard exploration, many salient time-conditioned characteristics of complex interdependent Earth science systems.

• In GDL community, although some existing GNN-based models have been successfully applied in a wide variety of scenarios for spatial earth science data (Van den Ende et al. (2020) and Sun et al. (2021)), they can only collate information over neighbors of every node and cannot necessarily capture certain topological information (i.e., beyond node-level).

• The way that individual wildfire smoke plumes interact with the downwind environment is highly variable both temporally and spatially, and their representation remains a big challenge for both numerical simulations and ML.

Background: GDL on COVID-19

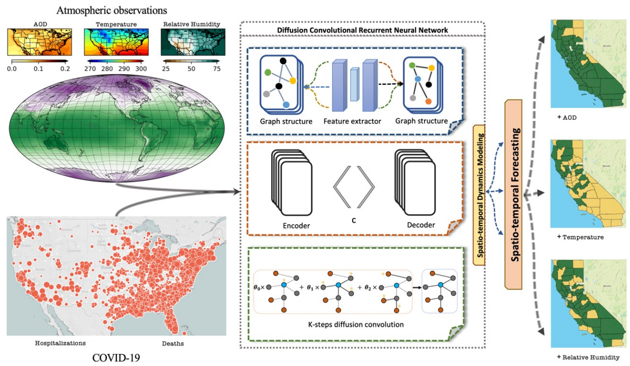

Illustration of the overall architecture, using GDL to model dynamics between atmospheric variables and COVID-19 clinical severity. One of the project's team achievements funded by NASA in 2020.

Our previous study focused on anomaly detection of COVID-19 clinical severity, measured in terms of hospitalization rates, in three U.S. states. This case of study represents a significant step forward because, to the best of our knowledge, there are not current GDL tools that have been used for spatio-temporal tracking of anomalies in Earth science observations.

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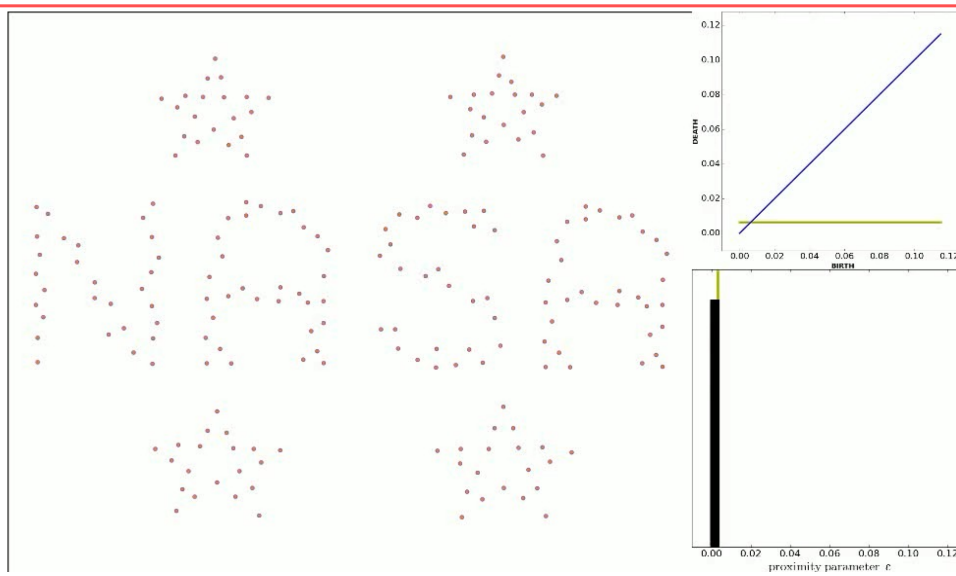
Background: TDA Example



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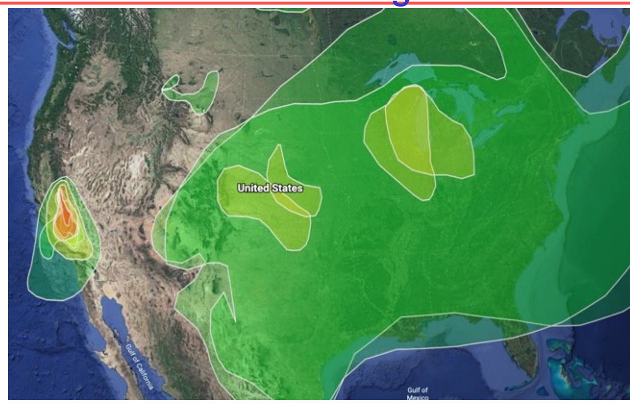
Background: Difficulties with plume modeling



Light (dark green), medium (green), and heavy (orange and red) smoke from wildfires over the contiguous United States on October 1st, 2021. The data retrieved from GOES-16 and 17 observations are from the Hazard Mapping System Fire and Smoke Product (https://www.ospo.noaa.gov/Products/land/hms.html).

The key to improving the smoke plume modeling is the use of topological information that provides compressed representation of complex smoke shapes.

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Objectives (1)

Using the radiance data from the Advanced Baseline Imager (ABI) available through NASA's GeoNEX project and High-End Computing (HEC) systems, we will address the following interlinked tasks:

•**T1.** Develop time-aware DL architectures with shape signatures from multiple spectral bands for semi-supervised onboard learning of multi-resolution smoke observations.

•**T2.** Detect smoke plumes and other anomalies in multi-resolution observations with time-aware DL with a fully trainable and end-to-end topology-based module.

•**T3.** Investigate the uncertainty in topological detection of smoke plumes.

•**T4.** Improve the efficiency of GDL for onboard applications.

In addition to developing the novel early-stage technology, topological and geometric DL methods for onboard exploration, we will disseminate all new topological and geometric DL tools in the form of publicly available Python packages. We will maintain all software in a public GitHub repository and use GitHub's built-in issue JIRA system for tracking issues and collaborative software management.

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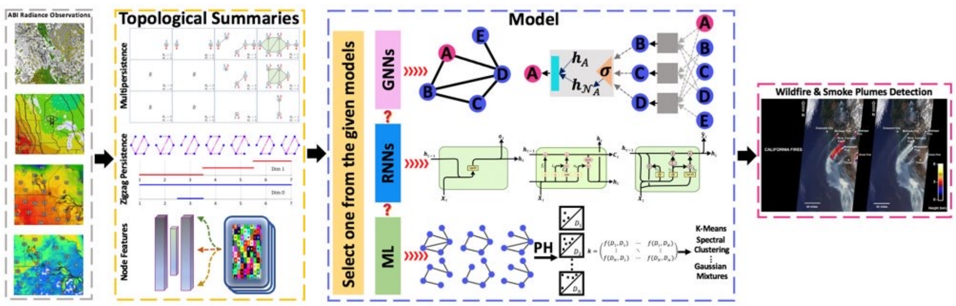
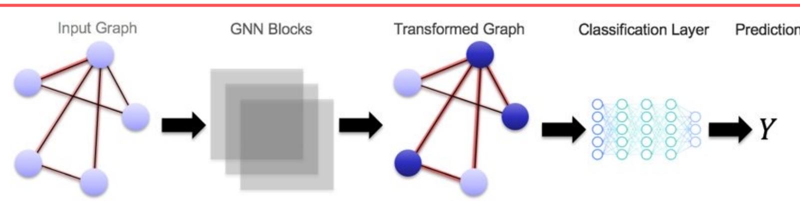
Objectives (2)

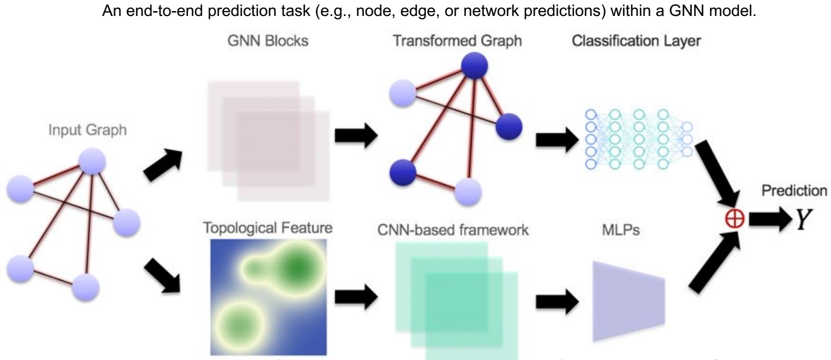
Given advanced baseline imager (ABI) radiance observations, we first apply various topological data analysis (TDA) tools to obtain the corresponding topological features (e.g., multipersistence image and zigzag persistence image). Then we feed these topological features into ML/DL/GDL models. More specifically, in our project, we provide three options including ML approaches (e.g., K-Means, spectral clustering, and Gaussian mixtures), DL (recurrent neural networks, e.g., RNN, LSTM, and GRU), and GDL (e.g., GNN-based models). Finally, we can utilize the output of the selected model for tracking and detecting smoke plumes.



Objectives (3)

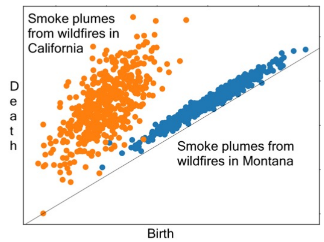


An end-to-end prediction task (e.g., node, edge, or network predictions) within a GNN model.



An end-to-end prediction task (e.g., node, edge, or network predictions) within a topological GNN model.

Objectives (4)



Hypothetical example from K-means clustering persistent images associated with smoke plumes from wildfires in two different regions.

Uncertainty Quantification for Topological Detection of Smoke Plumes. We will extend topological subsampling and meta-representations in a meta-learning framework to strengthen topological representation learning of spatio-temporal ABI aerosol data under uncertainties, to achieve a more systematic understanding of potential predictive fluctuations resulted from high dynamic and heterogeneous high-order interactions in ABI aerosol products.

At present, smoke plumes, retrieved from satellite and suborbital imagers, are classified at the pixel level using radiance observations within a pixel. Current pixel-wise approach requires more computational resources with increasing resolution and number of pixels. In contrast, the proposed GDL model will be sensitive to the spatio-temporal dynamics of smoke plumes, and the GDL-based anomaly detection method is particularly well suited for classifying objects with complex spatial structures.

Previous State: Literature (1)

- Zhen et al. (2022) Tlife-GDN: Detecting and Forecasting Spatio-Temporal Anomalies via Persistent Homology and Geometric Deep Learning. *PAKDD.*
- Chen et al. . (2022). TAMP-S2GCNets: When Time-Aware Multipersistence Meets Spatio-Supra Graph Convolutional Nets while Forecasting Time Series. *ICLR*, **Spotlight**.
- Segovia-Dominguez et al. (2021). Does Air Quality Really Impact COVID-19 Clinical Severity: Coupling NASA Satellite Datasets with Geometric Deep Learning. *KDD*
- Segovia-Dominguez et al. (2021) - TLife-LSTM: Forecasting Future COVID-19 Progression with Topological Signatures of Atmospheric Conditions. *PAKDD.*
- Chen et al. (2021). Z-GCNETs: Time Zigzags at Graph Convolutional Networks for Time Series Forecasting. *ICML*
- Ofori-Boateng et al. (2021). Application of topological data analysis to multi-resolution matching of aerosol optical depth maps. *Frontiers in Environmental Science: Environmental Informatics and Remote Sensing*.
- Sun et al. (2021). Explore Spatio-Temporal Learning of Large Sample Hydrology Using Graph Neural Networks. *Water Resources Research*.
- Van den Ende et al. (2020). Automated seismic source characterization using deep graph neural networks. *Geophysical Research Letters*.

To the best of our knowledge, GDL has never been used for anomaly detection and more generally, analysis of Earth Science data. Applications of TDA for Earth Science data are also nascent (Hoef et al., A Primer on Topological Data Analysis to Support Image Analysis Tasks in Environmental Science, *AI for Earth Systems,* 2022)

There are potential overlaps in terms of TDA between our project and Huikyo Lee's project on Open Climate Workbench to support efficient and innovative analysis of NASA's high-resolution observations and modeling datasets, but the science use cases & integrations are independent. We have been exploiting the synergy by working together.

Previous State: Activities within the Team (2)

- Deepisha Solanki (Ph. D. candidate, Department of Mathematics, SUNY Buffalo)
  - 2022 Summer Intern at JPL by winning a grant from the NSF Mathematical Sciences Graduate Internship Program.
  - Project title: **Evaluating spatial structures of aerosols simulated by climate models**
- NASA GPU Hackathon 2022 (https://www.nas.nasa.gov/hackathon/; September 18 & 26-28)
  - Nick LaHaye and Huikyo Lee's application was selected
  - Project title: "Development and Application of Unsupervised Machine Learning for Smoke Plume and Active Fire Identification from the FIREX-AQ Datasets"
- Nick LaHaye (Data Scientist, JPL)
  - Dr. LaHaye attended the ECMWF–ESA Workshop on Machine Learning for Earth Observation and Prediction in Reading UK (November 14-17, 2022)
- After advancing the TRL of our project, we plan to submit proposals to the ACCESS, AIST New Observing Strategies (NOS), Technology Development for Support of Wildfire Science and Disaster Mitigation programs.

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Presentation Contents

- Background and Objectives
- Technical and Science Advancements
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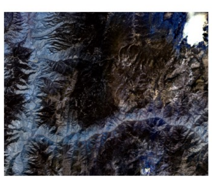
Overview

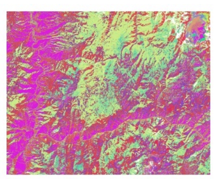
- **Benchmark Datasets and Self-Supervised Contrastive Learning for Wildfire Prediction**
- **Time-Aware Topological Graph Neural Networks for Wildfire Prediction**
- **Evaluating spatial structures of simulated aerosols**
- **Application of Topological Data Analysis and Deep Learning to Predict Active Wildfires:**
  - ❑ **Uncertainty Quantification of Wildfires**
  - ❑ **Detection of wildfire spread**
- **Firetech Proposal: Multi-Sensor Wildfire and Smoke Identification and Tracking using SIT-FUSE to Support Innovative Evaluation of Smoke Forecasting System**

Benchmark Datasets and Self-Supervised Contrastive Learning for Wildfire Prediction (1)

- Propose FIRE-D benchmark datasets – the surface reflectance and top of atmosphere (TOA) brightness data from several satellites over the contiguous United States.
- Create FIRE-D user interface, i.e., providing smooth access to geospatial imagery from multiple platforms and data sources (that is, both NASA and non-NASA-centric products).



(a) LandSat RGB reference.



(b) SIT-FUSE scene segmentation.

(c) Fire labels.

```
from GeoQuery import GeoInterface, \
                     SentinelAdapter, \
                     EarthDataAdapter

geo = GeoInterface()
sentinel = SentinelAdapter()
hls = EarthDataAdapter("earthdata")
geo.AddAdapter("sentinel1", sentinel)
geo.AddAdapter("hls", hls)
result = geo.Query(target="sentinel1^instrument=sar,product=slc",
                   lon1=-121.827, lat1=46.805,
                   lon2=-121.6255, lat2=46.92621,
                   sdate="20230228", edate="20230301",
                   projection="EPSG:32610",
                   resolution=30)
```

```
import sys
from geoquery import GeoInterface, SentinelAdapter, EarthDataAdapter
import numpy as np

lon1 = float(sys.argv[1])
lat1 = float(sys.argv[2])
lon2 = float(sys.argv[3])
lat2 = float(sys.argv[4])
sdate = sys.argv[5]
edate = sys.argv[6]
projection = sys.argv[7]
res = float(sys.argv[8])
geo = GeoInterface()
hls = EarthDataAdapter('v4uz9', provider='osf')
geo.AddAdapter("hls", hls)

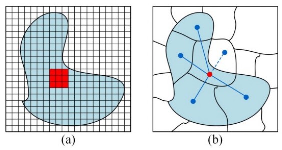
result = geo.Query('hls', lon1, lat1, lon2, lat2, \
                   sdate, edate, projection, res)
np.save('fire.npy', result['fire'])
```

```
python3 test_utility.py <lon1> <lat1> <lon2> <lat2> <sdate> <edate> <projection> <resolution>
```

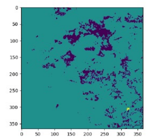
```
python3 test_utility.py -116 46 -115 47 20220901 20220930 EPSG:32611 30
```

Benchmark Datasets and Self-Supervised Contrastive Learning for Wildfire Prediction (2)

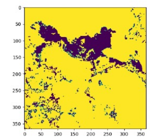
- **Challenge**: Wildfire presence tends to be scarce and ground truth labels of wildfire occurrence are not readily available, while the labeling process is resource-consuming.
- **Goal**: Conduct self-supervised learning and illustrate the utility of FIRE-D as a benchmarking platform for unsupervised wildfire prediction on both images and graphs.



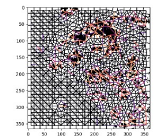
Illustrations of the CNN and GCN convolution.



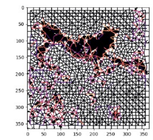
(a) A toy example of a FIRE-D image with wildfire.



(b) A toy example of a FIRE-D image without wildfire.



(c) A toy example of a RAG of a FIRE-D image with wildfire.



(d) A toy example of a RAG of a FIRE-D image without wildfire.

Model	KMeans	RF	ResNet18	ResNet50	SimCLR
FIRE-D	0.1238±0.0001	0.1233±0.0001	0.0177±0.0003	0.0225±0.0002	0.0001±0.0001

Model	MVGRL	GraphCL	BRGL	InfoGraph
FIRE-D	0.0503±0.0095	0.0002±0.0573	0.0037±0.0102	0.0812±0.0463

- Tables (*top row*) show comparison in performance among 9 models in terms of the reconstruction error (without labels). Neural network-based and GNN-based models achieve competitive results and substantially outperform more traditional ML methods.

Model	KMeans	RF	ResNet18	ResNet50	SimCLR
FIRE-D	85.25±0.19	85.20±0.26	90.47±0.53	90.48±0.43	90.40±0.01

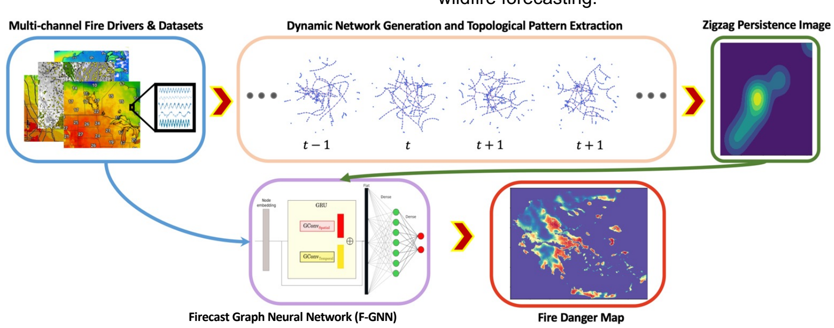
Model	MVGRL	GraphCL	BRGL	InfoGraph
FIRE-D	90.34±0.11	90.44±0.30	90.55±0.41	90.44±0.39

- Tables (*bottom row*) show comparison in performance among 9 models in terms of the accuracy (with labels). Similarly, neural network-based models significantly outperform ML methods. Moreover, all considered GNNs deliver on par performance with CNNs.

• Time-Aware Topological Graph Neural Networks for Wildfire Prediction

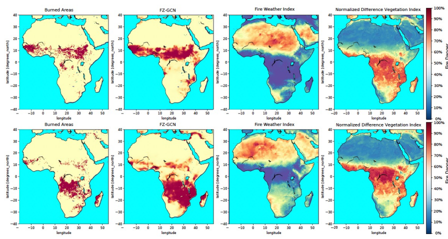
Goal: Develop novel Time-Aware Topological Graph Neural Networks (GNNs) for wildfire prediction using multi-source spatio-temporal data.

- Design and test time-aware (semi)-supervised DL models with multi-source data; e.g., ERA-5, MODIS (vegetation-Index & surface temperature), Copernicus EU-DEM (Elevation & Slope), and Copernicus Corine Land Cover.
- Model probability of future wildfire occurrence and spread using multiple disparate resolution information, related to weather, vegetation and human activity.
- Advance state-of-the-art Geometric Deep Learning by integrating time-aware topological information of various fire drivers at different resolutions, by examining the concept of zigzag persistence on wildfire forecasting.



F-GNN: Time-Aware Topological Graph Neural Networks for Wildfire Prediction

- Fire Danger Maps (*right side*) obtained via F-GNN are compared with the Burned Areas, Fire Weather Index (FWI; i.e., widely used in practice for wildfire forecasting), and Normalized Different Vegetation Index.
- The F-GNN model includes topological & nonlinear interactions and dynamic spatio-temporal evolution of the fire drivers, (e.g., vegetation information, relative humidity, and surface temperature) in contrast to the static FWI.
- Note that FWI is limited to the spatial resolution of 9km x 9km, in contrast to resolution of the F-GNN model which relies on the fire drivers' resolution.



- F-GNN outperforms competitors for the wildfire prediction tasks on African continent across multiple metrics.
- yields lower variability of the delivered forecasts.
- is more robust, under scenarios of limited fire data records.

Year 2019	Precision	Recall	F1-Score	Accuracy	AUC	AUCPR
ConvLSTM	0.949 ± 0.005	0.984 ± 0.007	0.966 ± 0.004	0.966 ± 0.004	0.997 ± 0.001	0.997 ± 0.001
GCN	0.965 ± 0.011	**0.994** ± 0.001	0.979 ± 0.005	0.979 ± 0.006	0.999 ± 0.000	0.999 ± 0.000
F-GNN	**0.979** ± 0.006	0.992 ± 0.002	**0.986** ± 0.002	**0.985** ± 0.002	**0.999** ± 0.000	**0.999** ± 0.000
Year 2020	**Precision**	**Recall**	**F1-Score**	**Accuracy**	**AUC**	**AUCPR**
ConvLSTM	0.966 ± 0.005	0.967 ± 0.006	0.966 ± 0.004	0.966 ± 0.004	0.996 ± 0.001	0.996 ± 0.001
GCN	0.972 ± 0.010	0.986 ± 0.003	0.979 ± 0.004	0.979 ± 0.005	0.998 ± 0.000	0.999 ± 0.000
F-GNN	**0.978** ± 0.006	**0.987** ± 0.002	**0.982** ± 0.003	**0.982** ± 0.003	**0.999** ± 0.000	**0.999** ± 0.000

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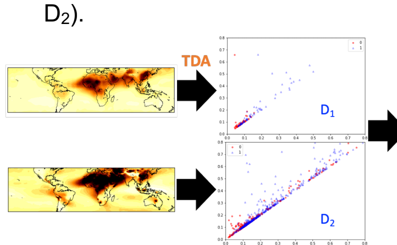
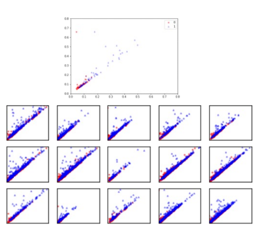
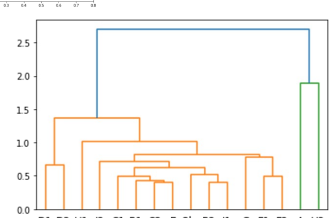
Evaluating spatial structures of simulated aerosols : Application of topological data analysis (TDA)

- In terms of the latent topology, two aerosol optical depth (AOD) maps from NASA's MISR and a climate model can be compared via Wasserstein distance (i.e., optimal transport) between their respective persistence diagrams (D_1 and D_2).



$$W_r(D_1, D_2) = \left(\inf_{\gamma} \sum_{x \in D_1} \|x - \gamma(x)\|_\infty^r\right)^{1/r}$$





- To the best of our knowledge, there is no quantitative metric to measure similarity/difference in spatial patterns between Earth science datasets at different spatial resolutions.
- Persistent homology (PH), one of TDA tools, allows us to compress two-dimensional AOD maps from MISR and models into persistence diagrams.

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TDA and Deep Learning for Wildfire Prediction

Current Research

- Novel Time-Aware Graph Convolutional Networks with a Fully Trainable Topological Layer to predict geographic location of the next day's wildfire occurrence.
- Learning topological representations of multi-channel fire drivers (i.e., different filtrations, graph representations, similarity measures, resolution scales).
- The current region of study is centered around Africa and covering a total area of 1,253km x 983km. Note that we use 25 features with historical burned areas from years 2009-2020.

Future Work

- Transfer learning of the zigzag-based graph neural networks to different geographic locations around the globe.
- Uncertainty quantification and robustness analysis with respect to noisy and incomplete data records.
- To evaluate the utility of capturing long-range dependencies by using time-aware TDA approaches over spatio-temporal datasets.
- We will provide more advanced capabilities for all researchers and practitioners working at the interface of ML and Earth Sciences.

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Uncertainty Quantification of WildFires

Summary

- We have developed a new topological method for uncertainty quantification of wildfire detection from satellite radiance images.
- By applying TDA with sublevel set filtration, fire is detected by dimension 1 homology points appearing on the persistent diagram with longer birth-death time intervals
- The effectiveness and robustness of the methodology relies on thermodynamics: the higher the radiance, the higher the probability of a wildfire
- Uncertainty quantification is based on an data-depth index, assessing outlyingness of the extracted topological features with respect to the distribution of all observed topological features.

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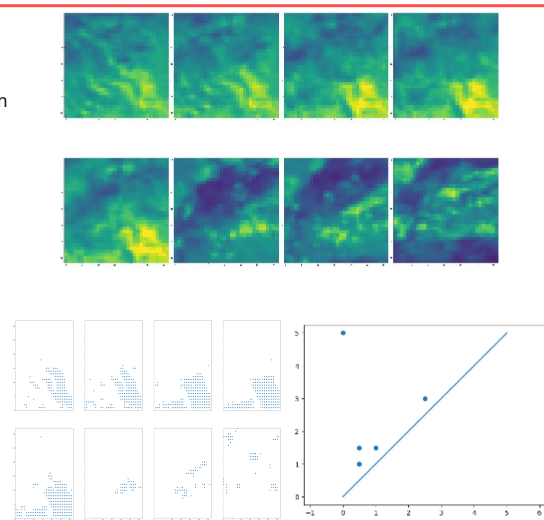
Wildfire Spread Detection

Summary

- We have developed a new spatio-temporal TDA algorithm for fire detection called 'Zig-Zag PD'
- It uses the history of satellite radiance images to capture the dynamics and characterize the spread of the wild-fire
- The algorithm shows promising results on early studies in detection and keeping track of wildfires by using satellite data
- The algorithm is data-driven and is backed by mathematical guarantees, with minimal reliance on heuristics and ad-hoc rules
- Leads to new insights about topological structures in wildfire dynamics



FireTech Proposal

Summary

- At present, JPL's Segmentation, Instance Tracking, and data Fusion Using multi-SEnsor imagery (SIT-FUSE), utilizes an unsupervised machine learning framework that allows users to segment instances of objects like wildfires and smoke plumes in single and multi-sensor scenes from NASA's satellite instruments with minimal human intervention, in low and no label environments.
- Recognizing the need of our stakeholder partner, the National Oceanic and Atmospheric Administration (NOAA) Air Resources Laboratory (ARL), we propose to augment SIT-FUSE with the capability to track wildfires and associated smoke plumes within NASA and NOAA's satellite observations, in a way that is suitable for systematic evaluation of the wildfire-induced smoke plumes simulated by the Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model.
- This will allow NOAA and other potential stakeholders, such as the United States Forest Service (USFS) and Environmental Protection Agency (EPA), to initialize and evaluate modeled smoke plume distribution with moderate- to high-resolution smoke plume properties from multiple satellite instruments.
- Stage II to be submitted by September 15 deadline

Presentation Contents

Summary

- Our ultimate goal is to develop efficient, systematic, and reliable learning mechanisms for the onboard exploration by explicitly integrating both space and time dimensions into the knowledge representation at multiple spectral and spatial resolutions.
- Topological and geometric methods in deep learning allow us to address these goals but remain virtually unexplored in Earth science applications.
- Our current results show that TDA and Geometric Deep Learning with topological layers achieve promising performance in anomaly detection and representation learning of spatio-temporal Earth science processes, with limited labelled information or even without any ground truth labels.

Plan Forward

- Topological transfer learning for hybrid ‘knowledge’ transfer
- Analysis of 2-D and 3-D reconstruction capabilities
- Topological uncertainty quantification for anomaly detection within GNNs in semi-supervised and unsupervised settings (i.e., attention mechanism, topological contrastive learning, topological ensembles, extreme value theory)
- Topological multi-channel fire index (statistical data depth)
- Physics-inspired GNNs with a topological layer

Actual or Potential Infusions and Collaborations (if any)

- Summary of actual or potential infusions
  - All developed software will be publicly available in the form of Python packages and maintained in a public GitHub repository. We will use GitHub's built-in issue JIRA system for tracking issues and collaborative software management.
- Summary of actual or potential collaborations:
  - NASA AIST OCW Project: Data benchmarks and use-cases of the developed ML tools for wildfire analytics with onboard processing
  - "Urban form and environmental risks: untangling relationships with structural racism through deep learning methods." (PI: Dr. Jankowska at the City of Hope): Submitted to Interdisciplinary Research in Earth Science
  - "Multi-Sensor Wildfire and Smoke Identification and Tracking using SIT-FUSE to support innovative evaluation of smoke forecasting system" (PI: Dr. LaHaye): Step-1 proposal encouraged and Step-2 is being written for A53. Technology Development for Support of Wildfire Science and Disaster Mitigation
  - Society of Actuaries (SOA): stakeholders for proposed methodology for wildfire risk analytics

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Publications

1. "**Segmentation of wildfires, smoke plumes, and burn scars using multi-sensor input and unsupervised and supervised machine learning for improved spatiotemporal coverage and facilitation of automated tracking**" at *ECMWF-ESA Workshop on Machine Learning for Earth Observation and Prediction,* Nov, 2022.

2. "**Application of Topological Data Analysis to Detect Extreme Cold and Heat Waves**" at *AGU2022*, Dec 2022.

3. "**Segmentation of wildfires, smoke plumes, and burn scars using multi-sensor input and unsupervised and supervised machine learning for improved spatiotemporal coverage and facilitation of automated tracking**" at *TIES2022*, Nov, 2022.

4. "**Time-Conditioned Dances with Simplicial Complexes: Zigzag Filtration Curve based Supra-Hodge Convolution Networks for Time-series Forecasting**", *NeurIPS'2022*

5. "**Learning on Health Fairness and Environmental Justice via Interactive Visualization**", *IEEE BigData 2022*

7. "**Automatic Smoke Plume and Wildfire Instance Tracking across Multi-Sensor Scenes**" (*IGARSS2023*)

8. H^2-Nets: Hyper-Hodge Convolutional Neural Networks for Time-series Forecasting *(ECML/PKDD 2023)*

9. "**Time-Aware Topological Graph Convolutional Networks for Wildfire Prediction**" (submitted)

10. "**Environmental Justice and COVID-19 Outcomes: Uncovering Hidden Patterns with Geometric Deep Learning and New NASA Satellite Data**", submitted.

11. **FIRE-D: NASA-centric Remote Sensing of Wildfires** (submitted)

12. **2023 Workshop on Fragile Earth: AI for Climate Sustainability From Wildfire Disaster Management to Public Health and Beyond (**ACM SIGKDD, Long Beach, CA)

Acronyms

List of Acronyms

ABI	Advance Baseline Imager
CNN	Convolutional Neural Network
DL	Deep Learning
GDL	Geometric Deep Learning
GNN	Graph Neural Network
GOES	Geostationary Operational Environmental Satellite
ML	Machine Learning
TDA	Topological Data Analysis
UQ	Uncertainty Quantification

Intelligent Long Endurance Observing System (ILEOS)

Meghan Chandarana (PI, NASA Ames)

Jeremy Frank (co-I, NASA Ames)
Richard Levinson (co-I, NASA Ames)
Eugene Turkov (co-I, NASA Ames)
Douglas Caldwell (co-I, NASA Ames)
Vinay Ravindra (co-I, NASA Ames)
Bryan Duncan (co-I, NASA GSFC)
Sarah Strode (co-I, NASA GSFC)
William Swartz (co-I, JHU JHU)
Kristen Manies (co-I, USGS)

AIST-21-0098 Annual Technical Review
July 12, 2023

1

Intelligent Long Endurance Observing System

PI: Meghan Chandarana (NASA Ames Research Center)

Objective

Intelligent Long Endurance Observing System (ILEOS):

A *Science activity planning* system to enable NOS consisting of satellites and *HALE UAS-mounted instruments.*

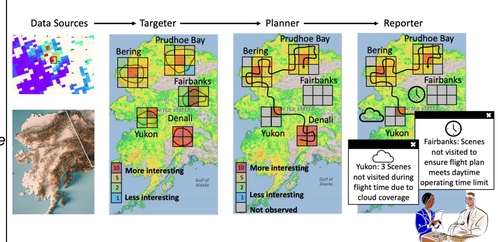
Optimize *fine-grained spatio-temporal resolution data collection of Earth observations, such as GHG-relevant gases,* using HALE UAS.

Incorporates *coarse-grained satellite data* and near real-time environmental (e.g., wind, weather, airspace constraints) data to generate high-value fine-grained resolution data collection plans.

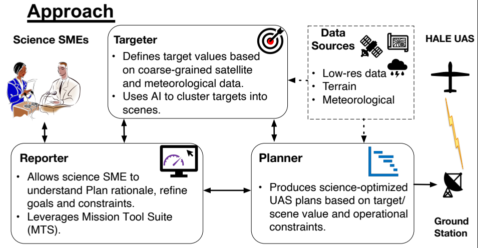
Designed for human operators; *plan explanation and data provenance features* will ensure science mission planners understand all key choices made while generating targets and plans.

IMPACT: Reduced cost for Earth observations in environments ranging from arctic to urban to offshore (some previously inaccessible), continuous observations not possible for current field/in-situ campaigns, improved science outcomes

ILEOS Functional Flow



Approach



Co-Is/Partners: NASA GSFC, USGS, JHU/APL

Key Milestones

• Complete ILEOS requirements / design	Jan 2023
• Prototype ILEOS for NO2 science use case	Oct 2023
• Prototype ILEOS for CH4 science use case	Jan 2024
• 3rd year proposal to AIST program	Jan 2024
• User testing and evaluation of ILEOS	July 2024
• Airborne Science Program integration reqts/design	Oct 2024
• Infusion into Airborne Sciences Program	July 2025
• Final Report / Project Closeout	July 2025

$TRL_{in} = 3$
$TRL_{out} = 5$

Earth Science Technology Office

2

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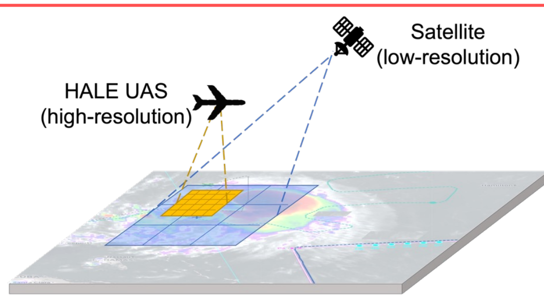
Concept of Operations



- Current satellites and fine-pointing aircraft do not provide sufficient spatio-temporal resolution to observe stochastic, ephemeral events between observations
- HALE UAS provide mechanism for collecting higher spatio-temporal data
  - Operate for months and loiter over targets

ILEOS will provide a science activity planning system to enable NOS
  - Fuse coarse-grained sensor data to target and plan HALE UAS flights

Relevance to Earth Science

- ILEOS will focus on use cases related to NO_2 and CH_4, which both high relevance to the science and application priorities presented in the 2019 Decadal Survey:
  - NO_2, here a proxy for combustion emissions (e.g., CO_2), and CH_4 over oil and natural gas extraction areas of the Gulf of Mexico.
    - Estimation of these emission sources(e.g., point - large rigs, line - shipping lanes, and area - small wells and support ships).
  - NO_2 down to the city block level in urban environments
    - Human health (unhealthy to breathe) and environmental justice
  - NO_2 generated from lightening (collected from above storm clouds)
    - Important ingredient in formation of upper tropospheric ozone, expensive to collect with crewed aircraft
  - CH_4 over Artic-Boreal zone
    - Characterize how the water table and air temperature affect the rate of emission
  - CH_4 from various anthropogenic sources such as industrial processes and leaky natural gas distribution pipelines, in complex urban environments
    - Pinpoint sources needing migration for safety reasons or to reduce the GHG footprint of urban areas

Objectives

- Optimize fine-grained spatio-temporal resolution data collection of Earth observations, such as GHG-relevant gases

Novel automated target generation technology

- Incorporates *coarse-grained satellite data* and near real-time environmental (e.g., wind, weather, airspace constraints) data to generate high-value fine-grained resolution data collection plans.

State-of-the-art automated planning and scheduling algorithms

- Designed for human operators; *plan explanation and data provenance features* will ensure science mission planners understand all key choices made while generating targets and plans.

Innovative techniques for user control and review of decision making

IMPACT: Reduced cost for Earth observations in environments ranging from arctic to urban to offshore (some previously inaccessible), continuous observations not possible for current field/in-situ campaigns, improved science outcomes

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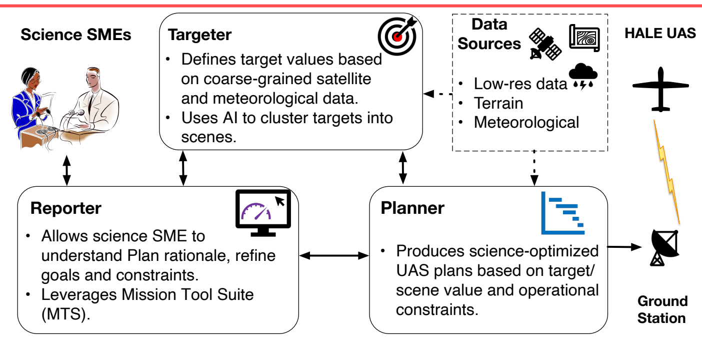
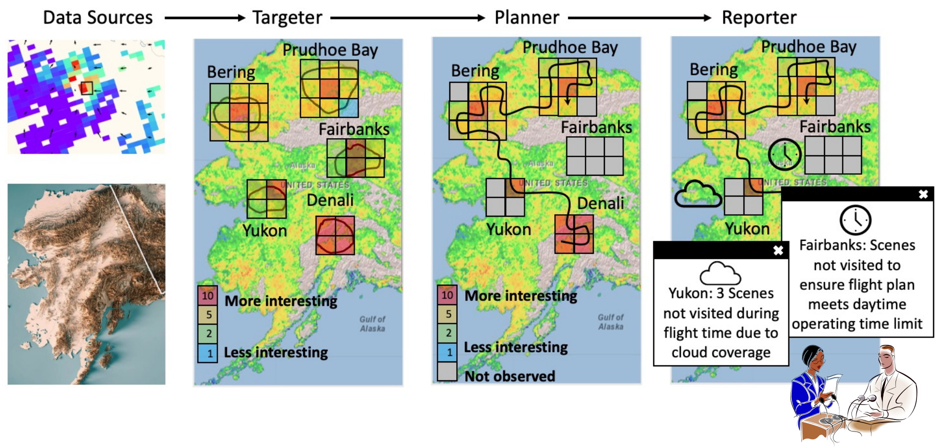
ILEOS Architecture



- Targeter – leverages Science SME domain knowledge to fuse available coarse-grained data into pixel value maps to generate target scenes
- Planner – generate flight plan to observe best identified target scenes while enforcing HALE UAS operating constraints
- Reporter – allow users to configure Targeter and Planner, visualize all data and outputs, and request explanations

Full ILEOS Pipeline



Technical Advancements

- Developed the ILEOS planning pipeline architecture design leveraging Science SME domain knowledge
- Identified key coarse-grained data sources
- Identified regions of interest and constraints (general, use case specific, and vehicle) for use cases
- Developed logic structure for interpreting coarse-grained data sources for NOx and Methane use cases
- Identified pertinent clustering and segmentation algorithms for use in scene generation
- Developed Targeter module and produced high interest science targets
- Developed Planner module to optimize HALE flight path by leveraging target interest values, vehicle constraints, and environmental constraints
- Provided user feedback on key factors used to generate targets and plans via the Reporter interface

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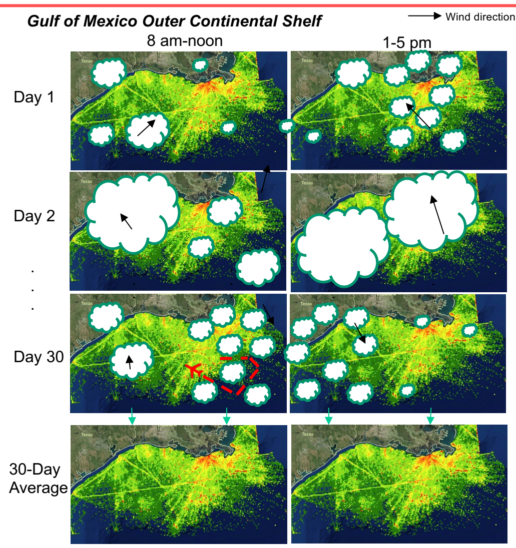
Summary

Milestone	Month after task start
ILEOS Architecture requirements/design	6
NO_2 Targeter	9
CH_4 Targeter	12
NO_2 Planner	12
CH_4 Planner	15
NO_2 Reporter	15
CH_4 Reporter	18
3rd year proposal	18
Integration Testing	21
Human-in-the-loop user testing	24
MTS/ETM migration/integration architecture requirements/design	27
MTS migration	30
ETM integration	33
MTS/ETM integration testing	36

Example NO_2 Use Case



Duncan BN. 2020. NASA resources to monitor offshore and coastal air quality. Sterling (VA): U.S. Department of the Interior, Bureau of Ocean Energy Management. OCS Study BOEM 2020-046. 32 p. https://espis.boem.gov/final%20reports/BOEM_2020-046.pdf

Intelligent Long Endurance Observing System (ILEOS)

ILEOS is a data collection planning system that generates optimal flight tracks based on mission parameters and various input datasets. It may be applied to numerous aircraft platform-instrument configurations, including in the use case study presented next.

ILEOS Use Case Study Example – Offshore Oil & Natural Gas Operations

The Outer Continental Shelf Lands Act (OCSLA) requires the US Dept. of Interior Bureau of Ocean Energy Management (BOEM) to ensure compliance with the National Ambient Air Quality Standard (NAAQS) so that Outer Continental Shelf (OCS) oil and gas exploration, development, and production do not significantly impact the air quality (AQ) of any state. BOEM has partnered with NASA to explore the use of satellite data to meet this goal.

One air pollutant, nitrogen dioxide (NO_2), is emitted during fossil fuel combustion, including during oil and natural gas extraction activities (e.g., from ships, platforms, flaring), and is readily detected from instruments on satellites. Therefore, it is an excellent tracer of anthropogenic activities.

ILEOS would use data of offshore and onshore NO_2 sources (in figure at left) with weather data to efficiently generate optimal flight plans, such as for a HALE UAS fitted with a NO_2 sensor. The NO_2 sensor, with its small pixel size (30x30 m^2; 4.5 km swath), can easily collect data at the platform-scale, including between broken clouds that stymie coarsely-resolved satellite instruments (e.g., TROPOMI; 3.5x7 km^2 pixel size). Therefore, in this configuration, ILEOS would enable the efficient collection of data for BOEM's applications, including spatio-temporal emission quantification.

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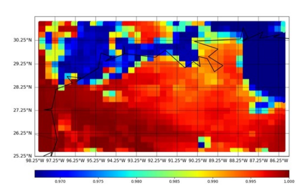
Targeter

Interest values:
- Unique for each use case
- Based on available coarse-grained data (satellite measurements, meteorological, etc.)
- Leverage Science SME domain knowledge to provide priority

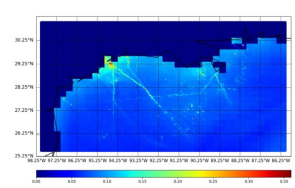
NO_2 Use Case Coarse Grained Data:
- Land cover (target water)
- Measured satellite NO_2
- Cloud cover
- Aerosol optical thickness

Methane Use Case Coarse Grained Data:
- Land cover (target wetlands)
- Cloud cover
- Inundation
- Measured Methane

Sample Value Map for NO_2 BOEM Inventory Use Case



Cloud Feature



Interest Values

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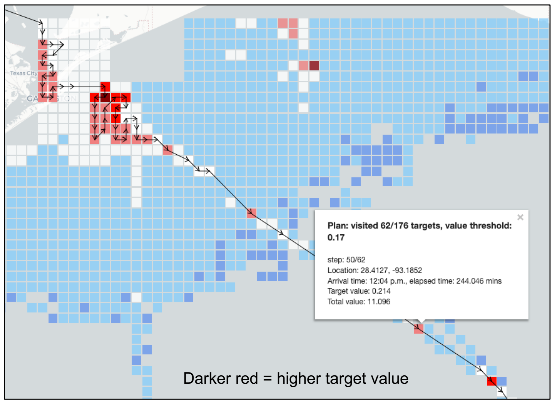
Planner

Task: Decide which locations to visit and when

- Modeled as a Multi-Profit Orienteering Problem (MPOP)
- Solution optimizes plan based on rewards at different times for each potential target



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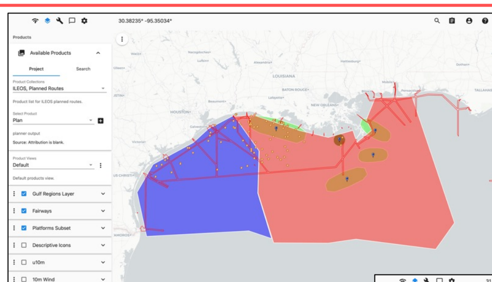
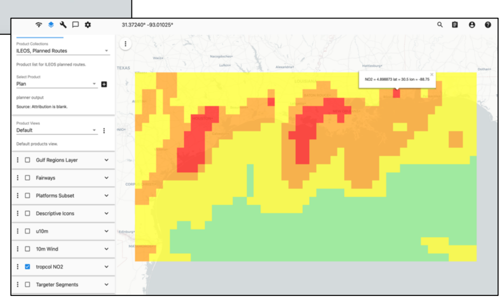
Reporter: Input Data Sources



Shipping lanes and platform sources



Tropospheric column density of NO_2

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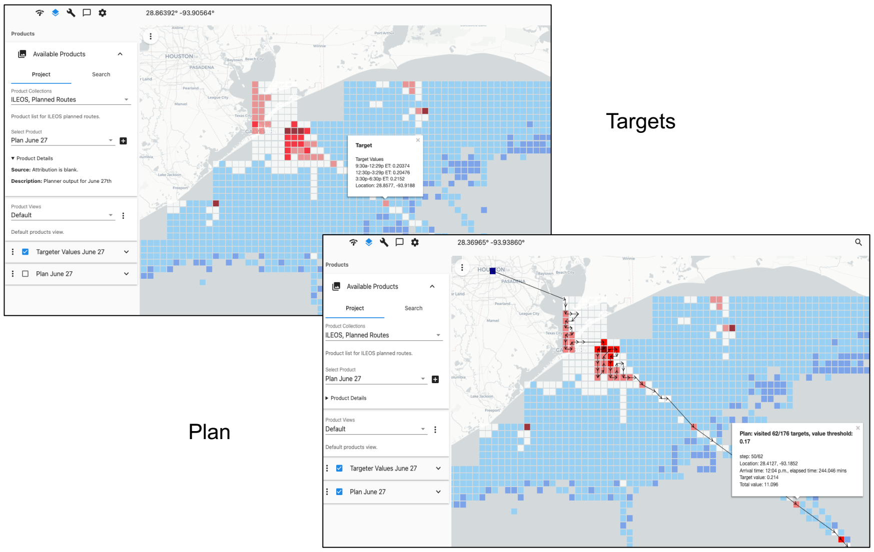
Reporter: Targets and Plans



Targets

Plan

System Evaluation

- ILEOS' first 2 years will culminate with a capstone demo featuring simulated observing campaigns overseen by SMEs
  - Evaluated on at least 2, ideally 4 climate-relevant gas sensing science use cases

Sensing Domain	Use Case Type	
	Nominal	Stressing
Methane	Urban emissions	Artic permafrost thaw
Nitrogen Dioxide	Urban emissions	Upper atmospheric lightening

- Assess users' ability to generate desired plans and understand relationship between scenes, priority, constraints, and their impact on plan
  - Human-in-the-loop evaluation

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Technology Infusions and Collaborations

Tentative 3rd Year Infusions and Collaborations

- Technology infusion into NASA Airborne Sciences Program (ASP) via integration with:
  - Heritage Mission Tool Suite (MTS) application
  - Upper-E Traffic Management (ETM) Project
- Collaborate to integrate with NOS-T platform to evaluate mission concepts using ILEOS planning architecture

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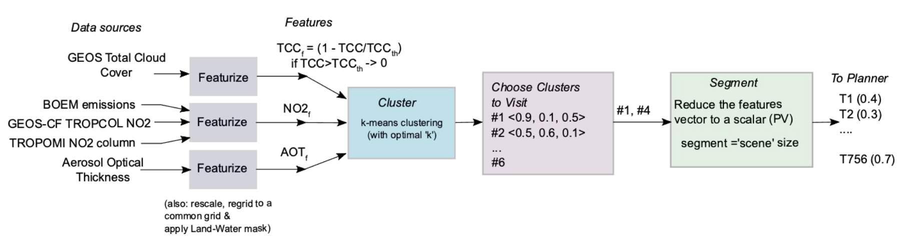
Acronyms

List of Acronyms

• NOS	New Observing Strategy
• GHG	Greenhouse gas
• NO_2	Nitrogen Dioxide
• CO_2	Carbon Dioxide
• CH_4	Methane
• HALE UAS	High Altitude Long Endurance Uncrewed Aerial System
• MTS	Mission Tool Suite

BACKUP

Targeter Pipeline



- Data sources selected based on science case

- Build the 'features' of a 'pixel'
- Pixel resolution ~1km

- Cluster regions with similar feature spaces

- Choose Clusters based on their mean values of the features

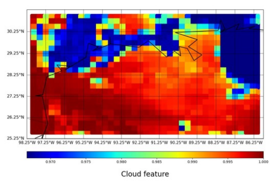
- Segment Clusters of interest
- Assign Segment Value based on formulation by SMEs

Features(1/3)

Cloud feature

$$cld = cldtot_{GEOSFP}$$
$$x = 1/cld_{thresh} * (cld_{thresh} - cld)$$
$$if \quad cld > cld_{thresh} \; -> \; x = 0$$
$$f_{cloud} = x$$

- Less clouds => good observation possible
- If clouds are above a threshold, then the area is completely deprioritized.



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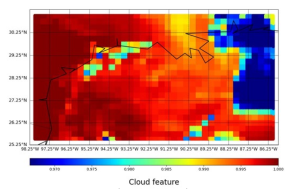

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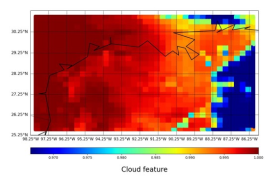

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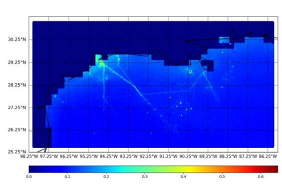
Features (2/3)

$$tropomiNO2 = mask_{water} * tropomiNO2$$
$$f_{NO2} = a\ \overline{PlatformEmis} + b\ \overline{nonPlatformEmis} + c\ \frac{tropomiNO2}{tropomiNO2_{max}}$$

NO2 feature

The weights ‘a’, ‘b’, ‘c’ depend upon the GEOS-CF TROPCOL-NO2 which is a measure of continental influence. If the GEOS-CF TROPCOL-NO2 is above a threshold, the Tropomi NO2 reading is deemphasized.
(Land-water mask has been applied prior to normalization of the Tropomi NO2 data)



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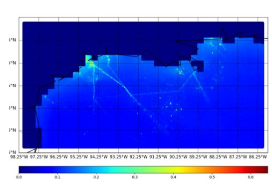

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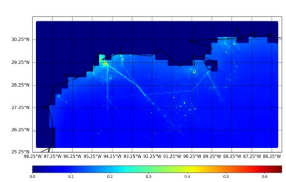


(15:30 ET)

Features (3/3)

$$AOT = AOT_{GEOSFP}$$

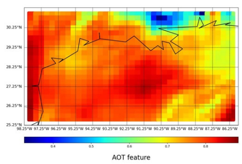
$$x = 1/AOT_{thresh} * (AOT_{thresh} - AOT)$$

$$if \quad AOT > AOT_{thresh} \; -> \; x = 0$$

$$f_{AOT} = x$$

AOT feature

- Less AOT means a better observation.
- Like in the case of clouds, when the Aerosol Optical Thickness is greater than a threshold, the area is completely devalued.



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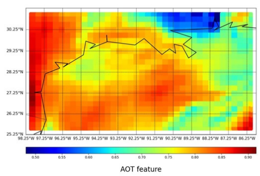

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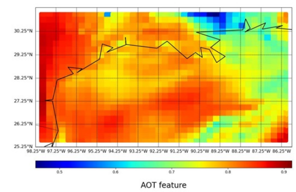

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Clustering

- Clustering was applied with <cloud feature, NO2 feature, AOT feature>
- Looking at the centroid values (of the features), clusters could be selected.

TIME	Clusters to be devalued to 0 (fall on Land)	Clusters to be considered (tradeoff b/w good visibility & NO2)
9:30 ET	#1, #2, #3, #5	#0, #4
12:30 ET	#1, #3, #4	#0, #2, #5
15:30 ET	#1, #3, #5	#0, #2, #4

```
Centroid 0:[0.99689402 0.09428842 0.80126798]
Centroid 1:[9.77492551e-01 6.94805408e-05 7.56075764e-01]
Centroid 2:[ 9.75385516e-01 -5.59274849e-15  4.91762706e-01]
Centroid 3:[9.95863201e-01 2.73699363e-06 8.36105321e-01]
Centroid 4:[0.98449536 0.10991961 0.71720205]
Centroid 5:[9.77639960e-01 5.45534421e-04 6.47565975e-01]
```

```
Centroid 0:[0.9773663  0.10152901 0.69901884]
Centroid 1:[9.99729780e-01 1.36929560e-06 8.49629249e-01]
Centroid 2:[0.99368389 0.11960303 0.76286309]
Centroid 3:[9.85745194e-01 2.14804811e-06 5.90253910e-01]
Centroid 4:[9.92937477e-01 8.41505628e-05 7.62709311e-01]
Centroid 5:[0.99705372 0.08887723 0.81468544]
```

```
Centroid 0:[0.99613391 0.08649785 0.82443154]
Centroid 1:[9.97362464e-01 8.27451833e-05 7.82542125e-01]
Centroid 2:[0.99433646 0.11778618 0.78066517]
Centroid 3:[9.99926501e-01 1.40020914e-06 8.53498595e-01]
Centroid 4:[0.98125586 0.10213357 0.71393262]
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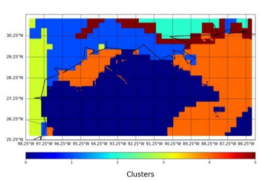

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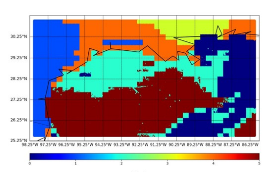

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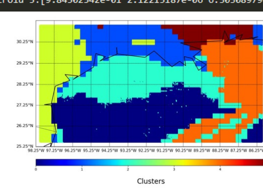


(15:30 ET)

Warning: Do *not* compare the colors across the cluster maps over time.

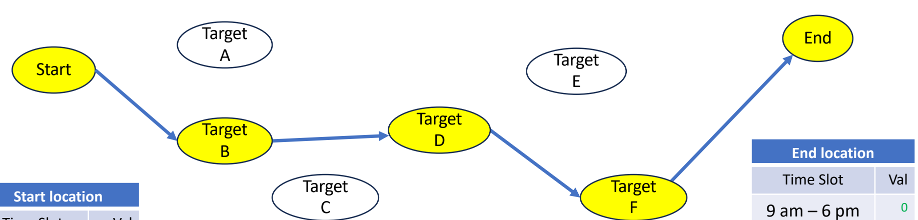
Next time: Remove the land pixels completely from analysis upstream. Why bother to cluster it at all?

Algorithm: The Multi-Profit Orienteering Problem (MPOP)*

- The Orienteering Problem (OP) is like a scavenger hunt game with a time limit
- Multi-Profit means the reward (profit) for visiting each location depends on the time of the visit
- MPOP has many applications, including travel and city tour planning
  (Plan a tour of multiple places of interest with different rewards at different times)
- Planning problem: *Decide which locations to visit, and when to visit them*
- MPOP is a formal *math model* (equations) for optimizing a sequence of location visits, within a given time limit
  - Targets are modeled as vertices in a graph
  - Model is constructed in Python then solved by Gurobi Optimization software (fastest optimization engine available)

*[Kim et al., *Hybrid dynamic programming with bounding algorithm for the multi-profit orienteering problem*, European Journal of Operational Research 303 (2022)]

MPOP Example



Start location

Time Slot	Val
9 am – 6 pm	0

Target B

Time Slot	Val
9 am - 11:59 am	5
12 pm – 2:59 pm	8
3 pm – 6 pm	10

Target D

Time Slot	Val
9 am - 11:59 am	10
12 pm – 2:59 pm	5
3 pm – 6 pm	9

Target F

Time Slot	Val
9 am - 11:59 am	3
12 pm – 2:59 pm	12
3 pm – 6 pm	6

End location

Time Slot	Val
9 am – 6 pm	0

Total value: 18

Total value: 25

Blue route is selected for total value 25, Delayed arrival at B until 3 pm to collect B's max value of 10

[Kim et al., *Hybrid dynamic programming with bounding algorithm for the multi-profit orienteering problem*, European Journal of Operational Research 303 (2022)]

MPOP Model

Decision Variables (planner must choose values) $x_{ij},\ y_{kd} \in \{0, 1\},\ s_i \geq 0$

$$x_{ij} = \begin{cases} 1 \text{ if the vehicle visits vertex } v_j \text{ right after vertex } v_i \\ 0 \text{ otherwise} \end{cases}$$

$$y_{id} = \begin{cases} 1 \text{ if vertex } v_i \text{ is visited at } d\text{th time slot} \\ 0 \text{ otherwise} \end{cases}$$

$s_i =$ start time of the visit of the vehicle at vertex v_i

Objective: Maximize sum of profit collected for all visited targets

$$\text{Max} \sum_{i=1}^{n} \sum_{d=1}^{D_i} P_{id} y_{id}$$

where P_{id} = profit for visiting vertex i during timeslot d

[Kim et al., *Hybrid dynamic programming with bounding algorithm for the multi-profit orienteering problem*, European Journal of Operational Research 303 (2022)]

An Intelligent Systems Approach to Measuring Surface Flow Velocities in River Channels

Carl J. Legleiter (PI, USGS, Observing Systems Division)

Uland Wong (Co-I, NASA Intelligent Systems Division)

AIST-21-0049 Annual Technical Review

July 12, 2023

Team listing:

USGS: Carl Legleiter, Paul Kinzel, Elizabeth Hyde, Isaac Anderson

NASA: Uland Wong, Michael Dille, Massimo Vespignani, Jonathan Bruce

Earth Science Technology Office

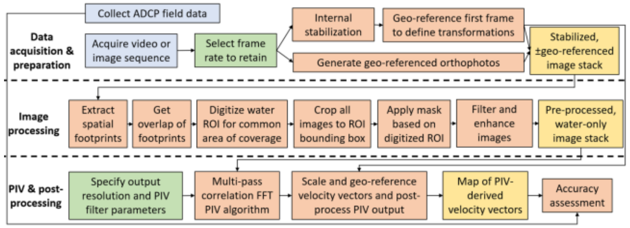
An Intelligent Systems Approach to Measuring Surface Flow Velocities in River Channels

PI: Carl Legleiter, U.S. Geological Survey

Objective

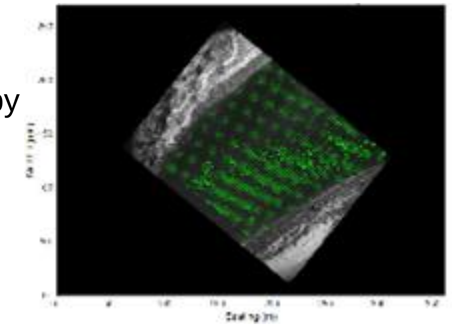
Advance hydrologic monitoring capabilities by developing a UAS-based intelligent system for streamflow measurement.

1. Enhance the prototype UAS payload developed jointly by USGS and NASA by enabling onboard particle image velocimetry (PIV) analysis to provide river surface velocity fields in real-time.
2. Develop an intelligent systems framework for characterizing the uncertainty associated with velocity measurements and use this information to enhance streamgaging quality control via stationing autonomy.
3. Improve flood response and contaminant mapping by establishing a framework for an instrumented UAS to use autonomous route-finding during an event to focus data collection on areas of interest, such as high or low velocity zones.



Overview of image pre-processing and particle image velocimetry (PIV) workflow

Surface flow velocity vectors inferred from a sequence of visible (RGB) images acquired by a prototype USGS-NASA streamflow measurement payload during September 2021 test flight on the Sacramento River using the workflow above



Approach

Our work plan is structured around five major thrust areas:

1. Develop a simulation environment encompassing the UAS, sensors, & river to guide stationing autonomy in discharge measurement using real-time, onboard PIV
2. Improve payload hardware to support autonomy
3. Implement pipelines for stationing autonomy and route-finding during discharge measurement & flood response
4. Validate streamflow measurement system using high-cadence testing in simulation and three test flights on the Sacramento River with supporting field observations
5. Disseminate results through software and publications

Co-Is/Partners: Paul Kinzel, USGS; Uland Wong, Michael Dille, and Massimo Vespignani, NASA

Key Milestones

- Field test IMU, payload enclosure, & ground station 09/22
- Field test real-time PIV & stationing autonomy 10/23
- Field test integrated system, autonomous navigation 06/24
- Deliver UAS-based flow measurement software 09/24

$TRL_{in} = 3$ $TRL_{current} = 3$

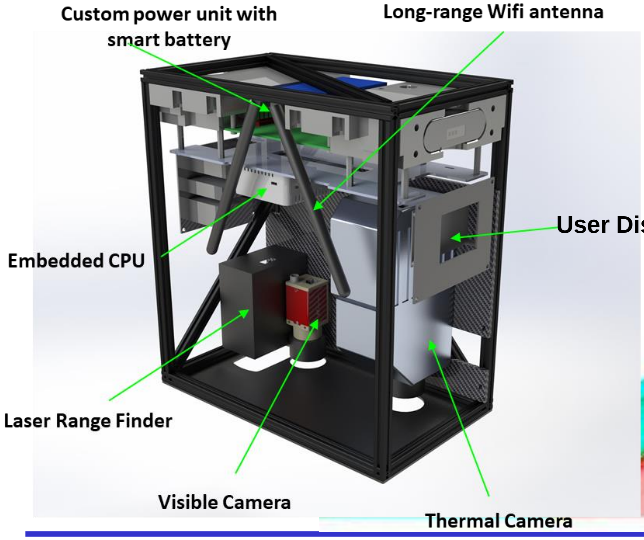
ESTO Earth Science Technology Office

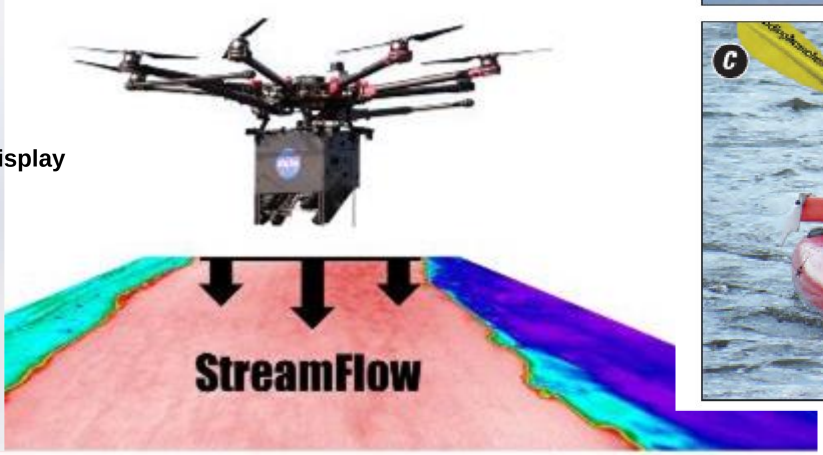
Presentation Contents

- Background and Objectives
- Technical and Science Advancements
- Summary of Accomplishments and Future Plans
- Actual or Potential Infusions and Collaborations
- Publications - List of Acronyms

Background and Objectives

- Traditional, field-based methods of measuring streamflow in river channels are laborious, expensive, and pose safety risks to staff
    - Limits number of rivers that can be gaged conventionally
    - Constrains water supply monitoring and flood response
- Overarching goal is to develop a novel, UAS-based approach to streamflow measurement to facilitate USGS hydrologic monitoring
    - Help meet the goals of several cross-cutting science areas: Water & Energy, Disasters, Water & Food, and Weather
- **Objective 1:** Enhance the prototype UAS-based streamflow measurement payload developed jointly by USGS and NASA by enabling onboard particle image velocimetry (PIV) analysis to provide river surface velocity fields in real-time.

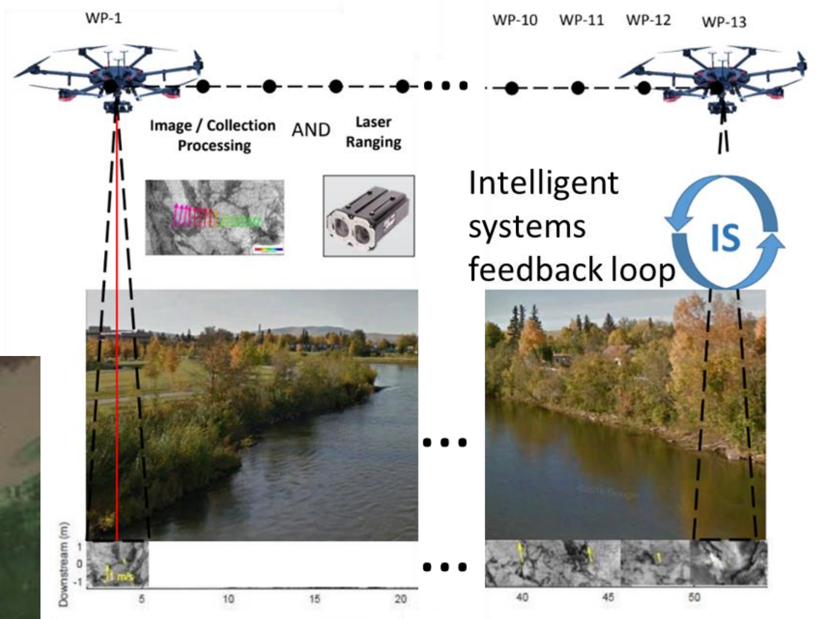


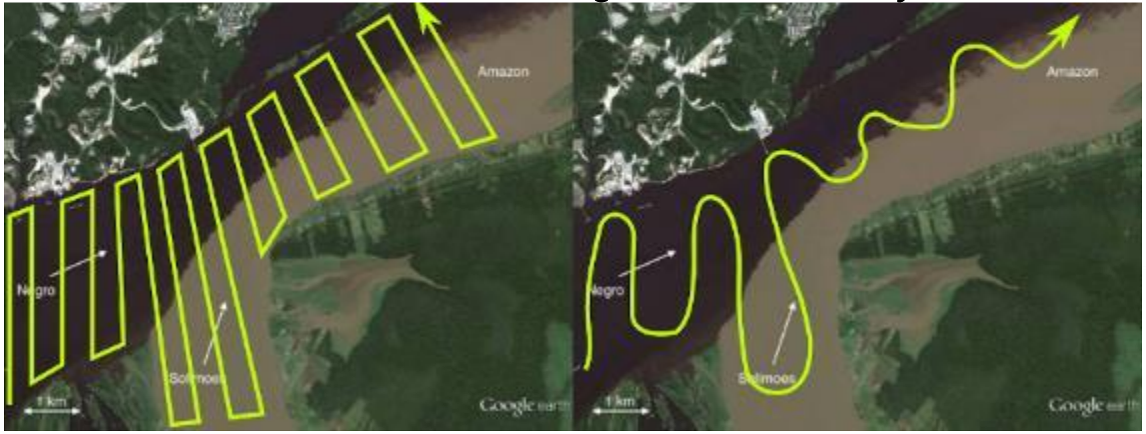


(Conaway et al., 2019)

Background and Objectives

- **Objective 2:** Develop an intelligent systems framework for characterizing the uncertainty associated with surface velocity measurements and use this information to enhance streamgaging quality control via stationing autonomy.
- **Objective 3:** Improve flood response and contaminant mapping by establishing a framework for an instrumented UAS to use autonomous route-finding during an event to focus data collection on areas of interest, such as high or low velocity zones





Rather than a typical exhaustive coverage pattern, intelligent system adaptively generates trajectory to focus on interesting areas

ESTO
Earth Science Technology Office

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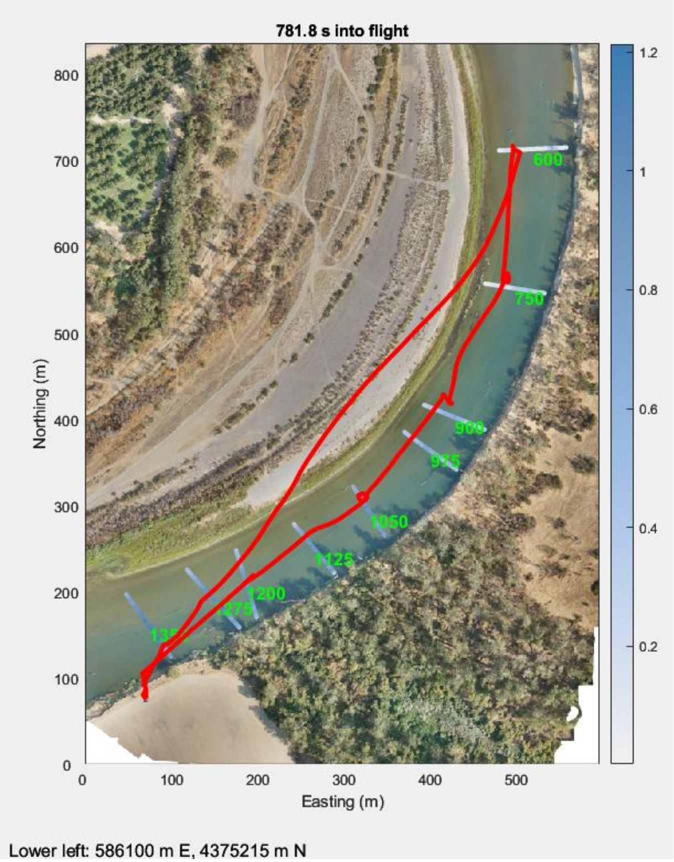
Technical and Science Advancements
Test Flight

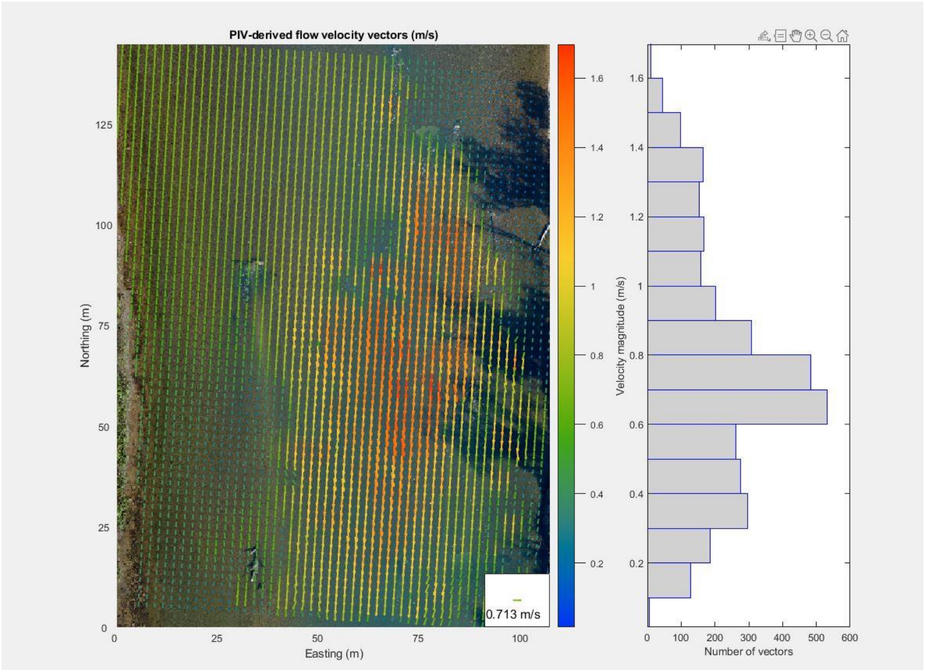
- Initial test flight conducted September 16, 2022, along the Sacramento River near Willows
- Deployed RiOS payload from sUAS on six flights focused on channel-spanning transects
- Data collected with visible and thermal cameras and laser range finder
- Simultaneous field measurements of flow velocity made from boat with NOAA colleagues
- Key outcomes from this test flight include:
    - Confirmed compatibility of payload components: sensors, CPU, power supplies, control module …
    - Demonstrated ability to live preview images at ground station in real time during flight
    - Acquired remotely sensed and field-based data from a natural river to use in developing workflows

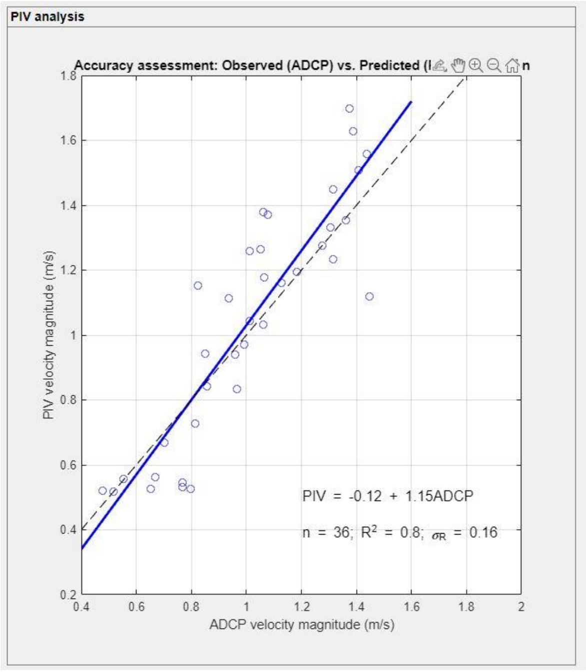


- Further field testing planned throughout project; next flight scheduled for October 2023

Technical and Science Advancements
PIV analysis of visible image data

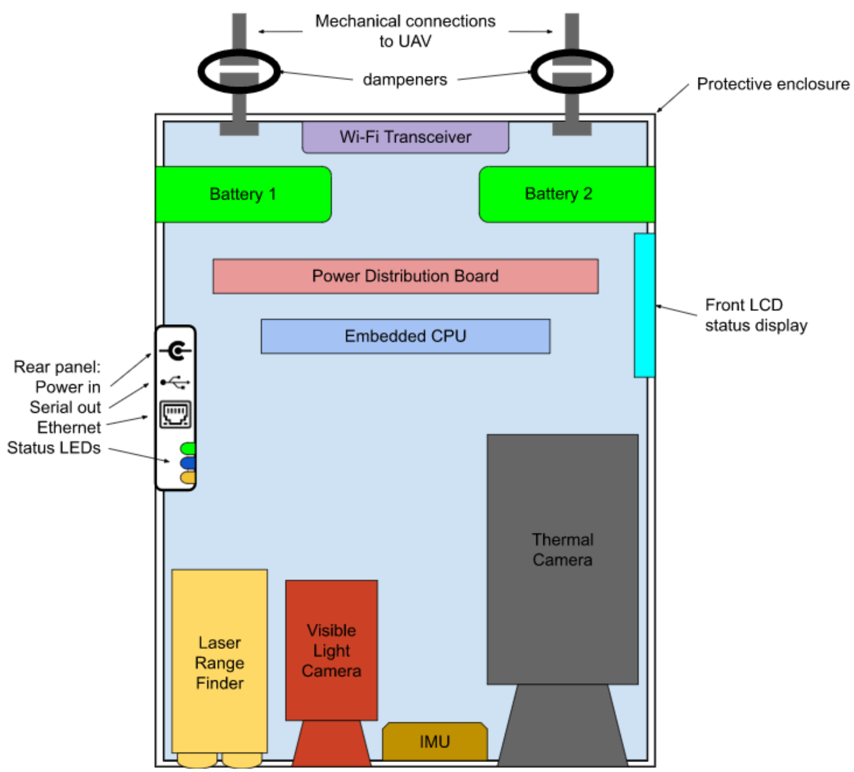
- Field test occurred under late summer, low flow conditions when the water was very clear
- Even at maximum permitted flying height, thermal camera field of view was not wide enough to see both banks, so stabilization was not possible, and we could not attempt thermal PIV
- RGB videos captured the entire channel, but few water surface features were visible
  - **Environmental conditions are a major constraint on feasibility of velocity mapping**
- Some features were detected and tracked, primarily sun glint from the water surface
- **New ensemble PIV algorithm led to much better agreement with direct field measurements than previous implementation based on individual frame pairs**
- Algorithm development and testing provides a foundation for port to embedded environment

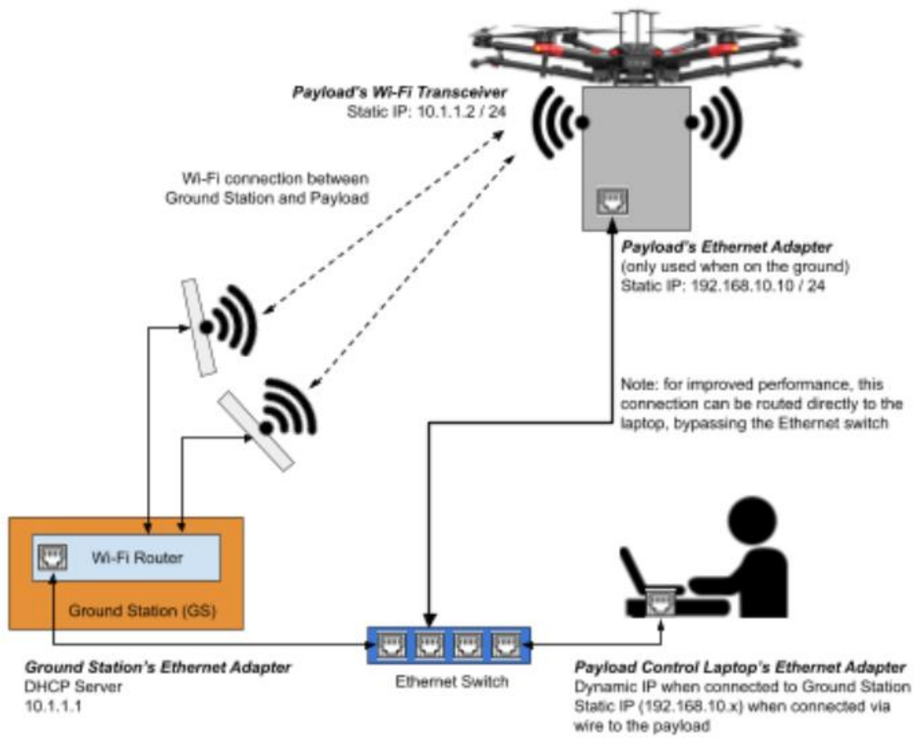




Technical and Science Advancements
Payload documentation

- Developed documentation for operating RiOS payload and detailed design documents
- Information needed for end users to deploy the RiOS sensor suite on a UAS included in:
  - **User's Manual** with a thorough overview of system architecture and specifications
  - **Getting Started Guide** provides step-by-step instructions for powering and connecting to payload, starting/stopping data acquisition, and offloading data
  - **Payload Design Documents** with technical data (mechanical and electrical drawings, datasheets, bills of materials, cabling instructions, software) for building RiOS payload





Technical and Science Advancements
Thermal camera characterization

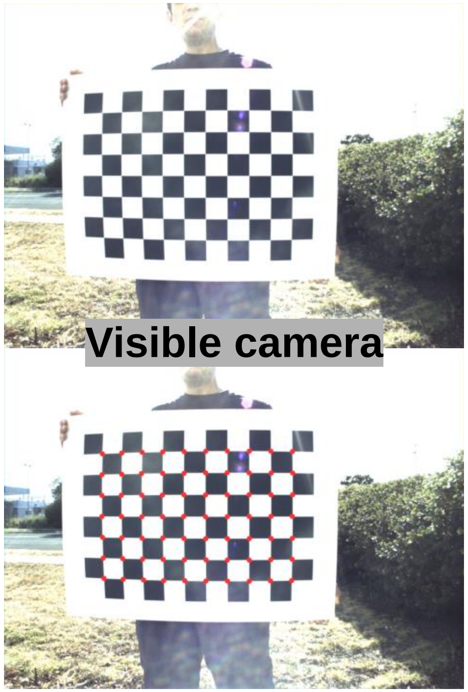
- Original thermal camera (ICI Mirage) is highly sensitive, but also large, heavy, and expensive
  - Motivated evaluation of a smaller, cheaper option (ICI 8640)
- Need to assess whether the smaller camera would be adequate
  - Sufficient sensitivity to support PIV? (30 mK for 8640 vs. 12 mK for Mirage)
    - Ongoing *in-situ* validation
  - Performed tests to confirm that 8640 periodic non-uniformity correction does not interfere
- Comparison initially complicated by different lenses and fields of view for the two cameras
  - Replaced lens on Mirage so that both cameras now have roughly the same field of view

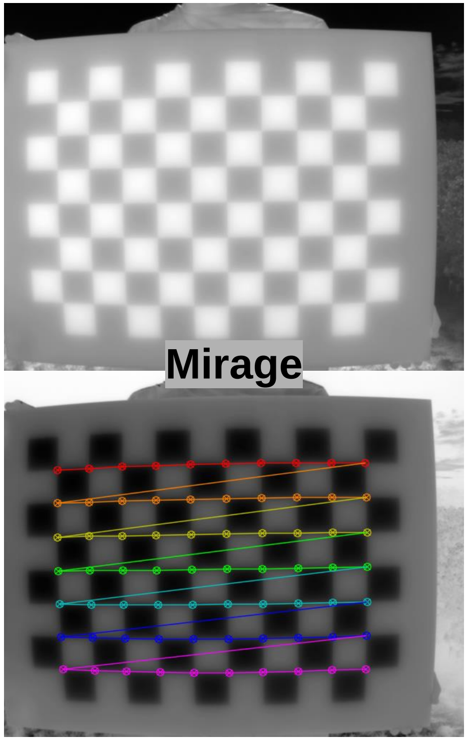
Mirage (16 cm long, 800 g)

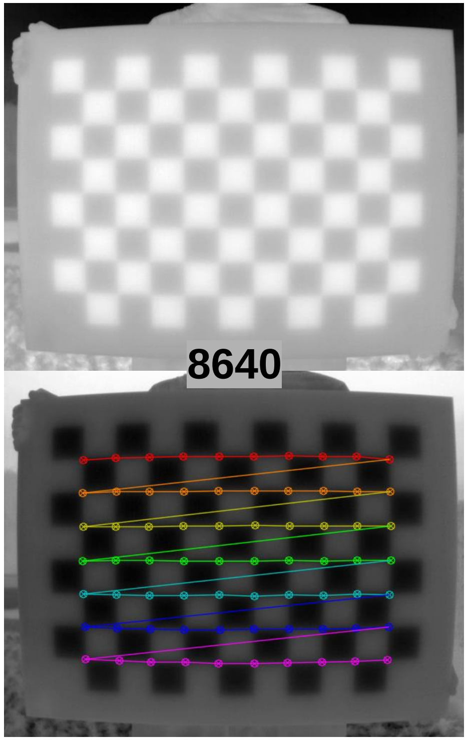
8640 (7 cm long, 150 g)

Technical and Science Advancements
Thermal camera characterization

- Geometric calibration needed to inform subsequent processing steps
    - Includes relative calibration offset between sensors
- Traditional printed checkerboard patterns cannot be used for thermal cameras because ink/toner is generally transparent in the infrared
    - Procured a printed target with highly infrared-absorptive ink on highly infrared-reflective substrate, with high thermal mass and low thermal conductivity







Targets will be used to calculate camera focal lengths, intrinsic parameters, and relative pose needed to support image stabilization

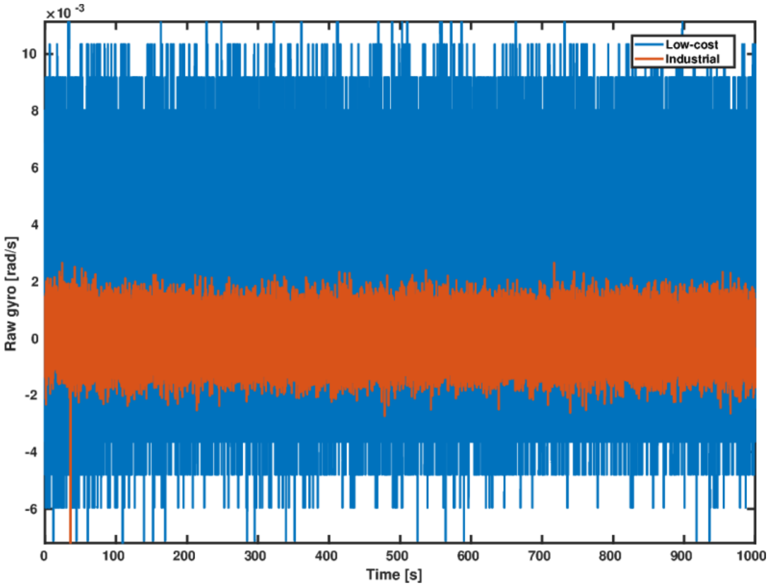
Technical and Science Advancements
Inertial Measurement Unit (IMU) characterization

- Currently comparing low-cost ($150) IMU used in previous flights to an industrial-grade ($1000) alternative in the same class: micro-size/weight
- Low-cost IMU exhibiting good performance (< 2° error) in lab settings over typical flight durations but showed poor drift and repeatability in a previous field test
  - Environmental conditions during flight (interference, heat, power noise) likely led to corrupted data
  - Industrial IMU was less sensitive to these external factors
- Performed side-by-side comparison while stationary and while in varied motion
  - ○ Low-cost IMU has 2-3x gyro noise and 1.3-x accelerometer noise, but a similar drift rate
  - ○ Fitting noise/drift models for sim

Low-cost IMU

Industrial IMU

side-by-side data collection

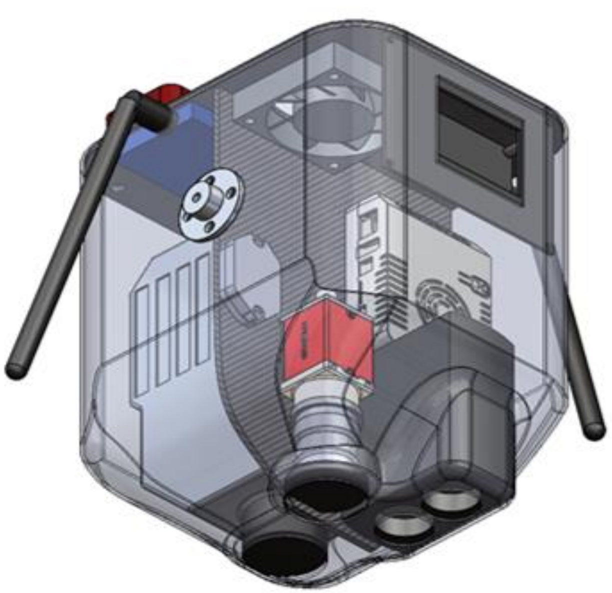


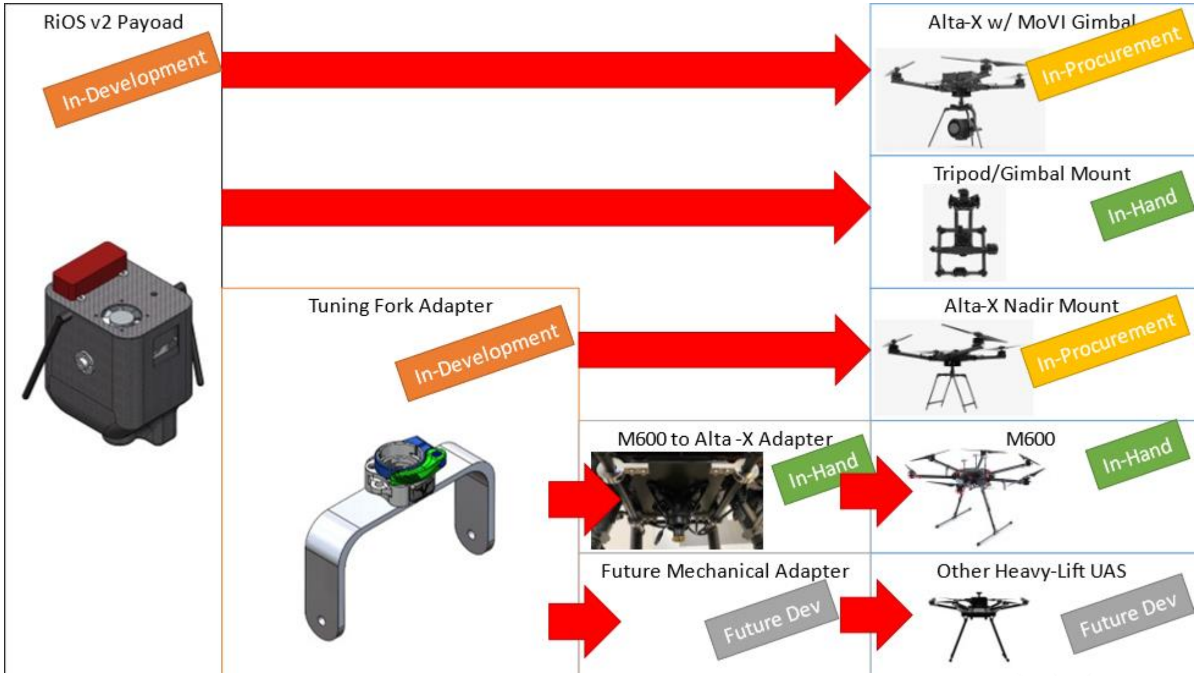
comparative noise magnitudes

- Will proceed with industrial IMU given marginally greater cost and similar low size and weight
  - Comparison exercise provided valuable cross-check and validated process

Technical and Science Advancements
Evolving RiOS payload design

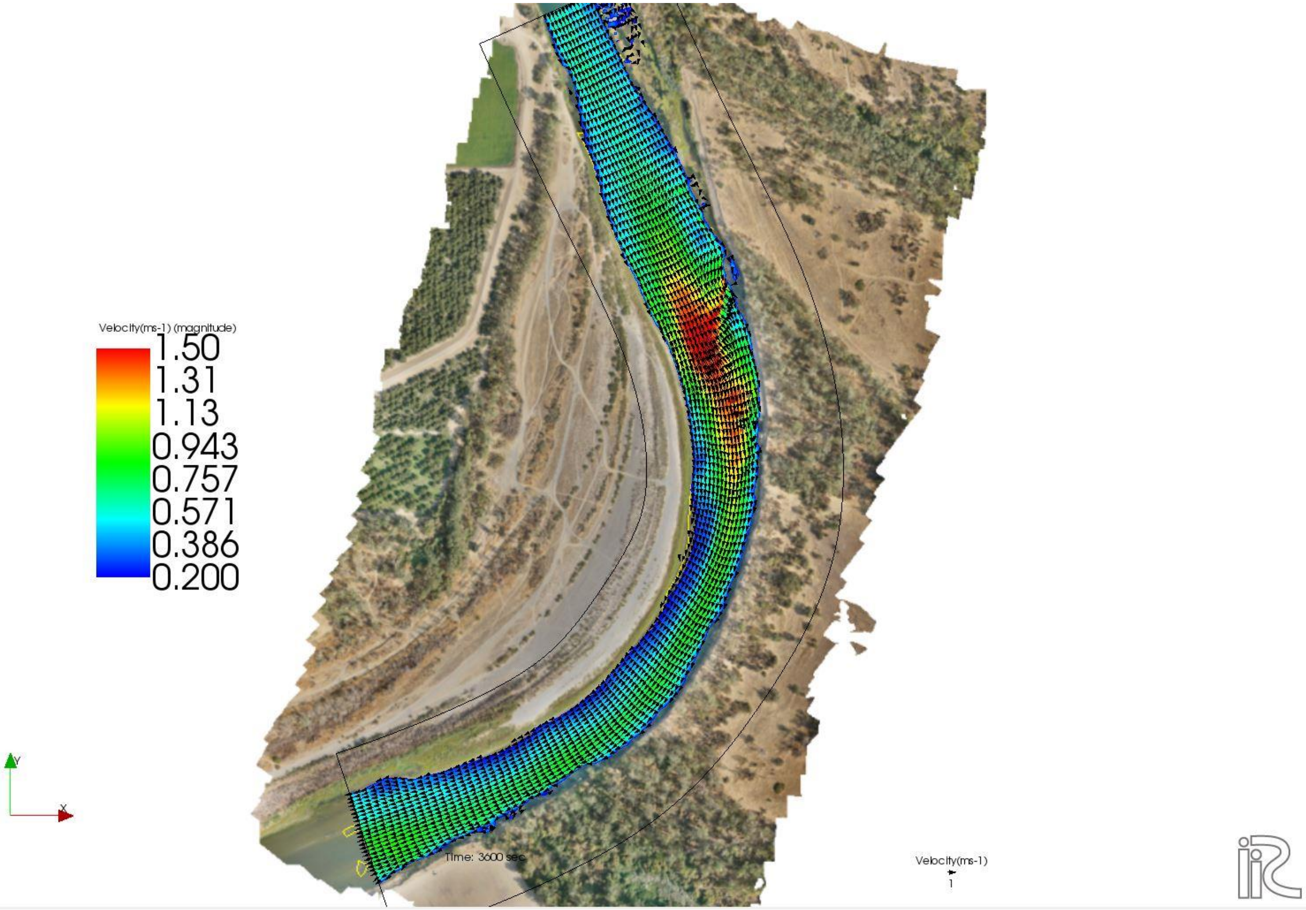
- Initial RiOS payload (v1) based on legacy design to quickly provide workable payload
- More robust payload design (v2) to optimize performance under real-world field conditions and provide flexibility to accommodate changes in types of UAS platforms available for use
  - Compact interior skeleton structure with components positioned close to one another
  - Retains platform agnostic status so we can adapt to changing UAS regulations
  - Exploring possibility of integration with an external gimbal system to improve stability
  - Working to improve aerodynamics, reduce weight, and optimize balance to smooth flight





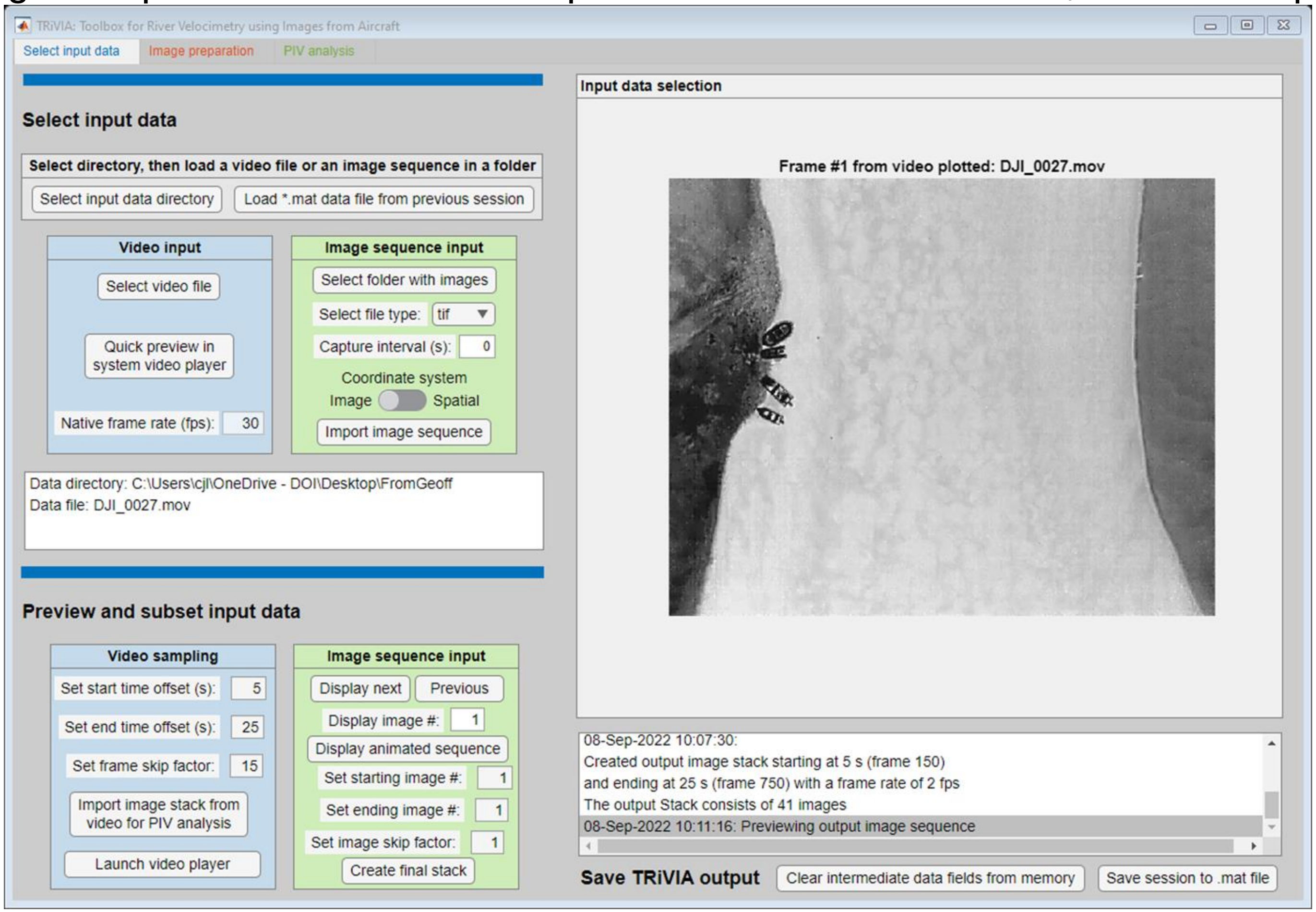
Technical and Science Advancements
Hydrodynamic modeling

- Hydrodynamic models of the flow field will support development of simulation environment for prototyping stationing autonomy and data-driven route-finding workflows
- Performed trade study of 2D flow models and selected iRIC interface with Nays2DH solver
- Created model for Sacramento River reach where September 2022 test flight occurred



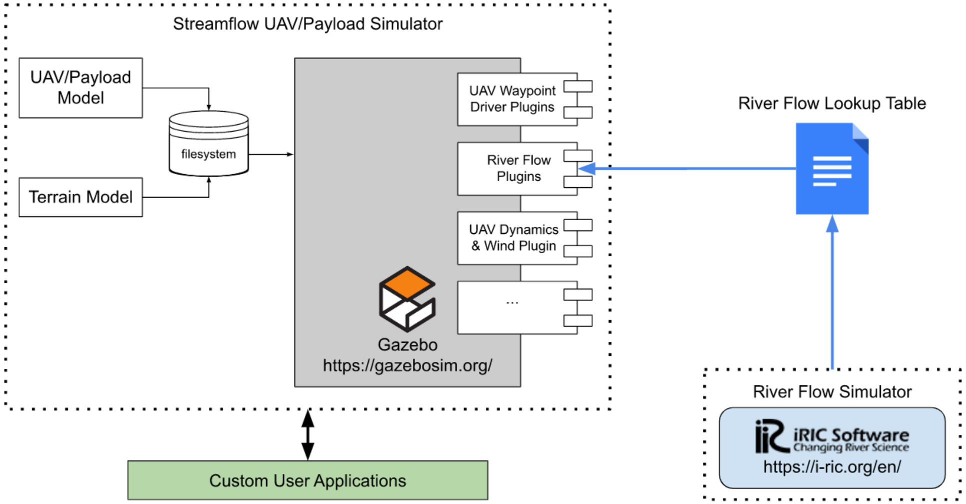
Technical and Science Advancements
Software framework development

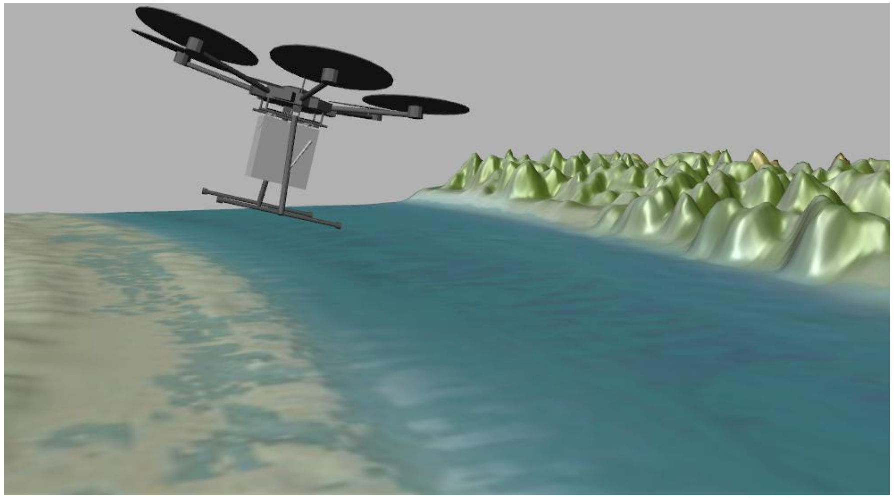
- Toolbox for River Velocimetry using Images from Aircraft (TRiVIA) USGS scientific software
- Provides end users with an integrated, end-to-end workflow for image processing and PIV
- Designed for USGS hydrologic technicians to perform PIV in the field right after UAS flight
- Underlying code provides a foundation upon which to build real-time, onboard implementation



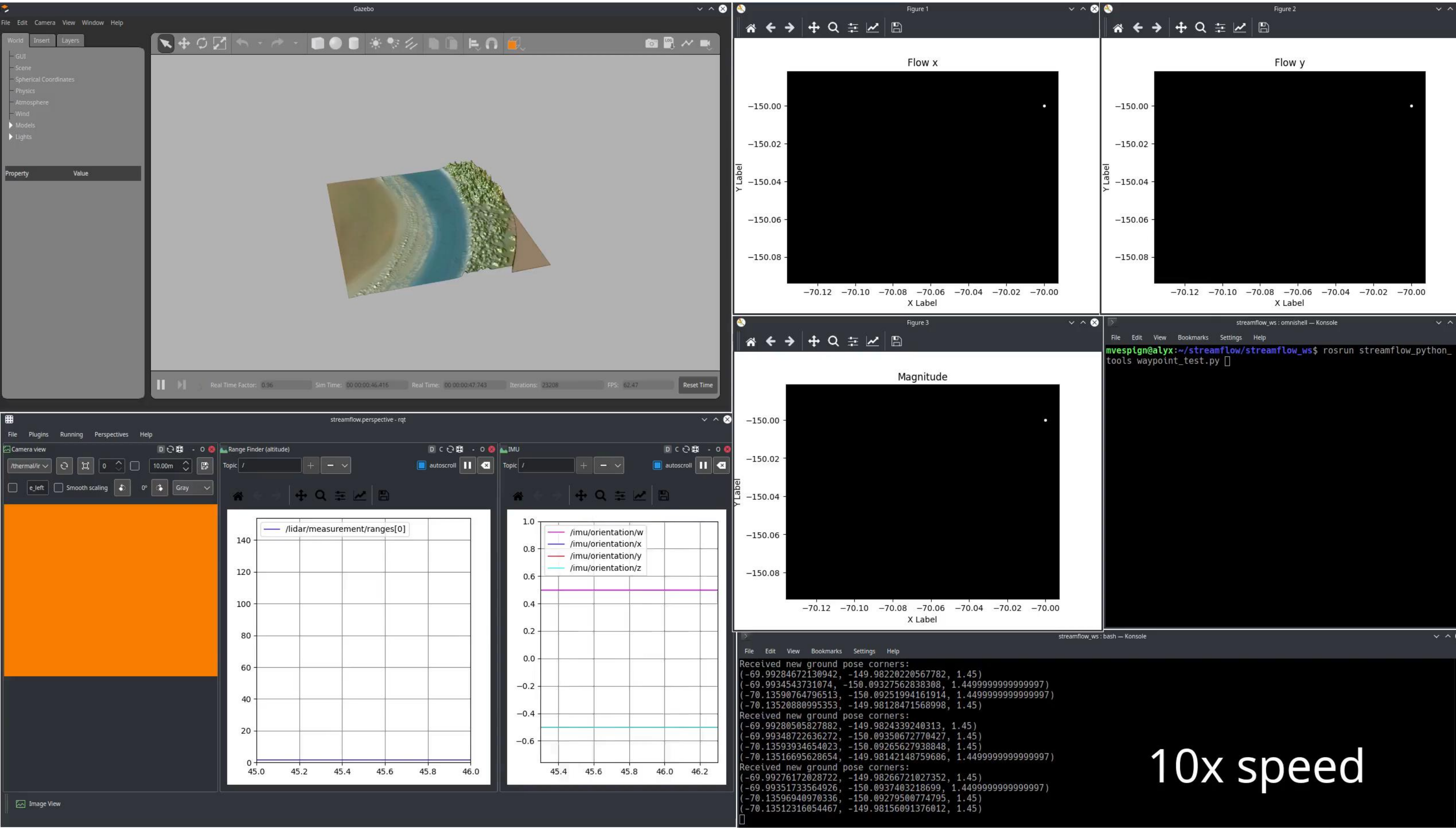
Technical and Science Advancements
Simulation Environment

- Established foundation for a physics-based ROS1/Gazebo simulation environment for the UAV/payload that will support development and testing of new route-finding algorithms
- The simulation uses modular plugins to facilitate incremental development of new features, as detailed in the document "*Simulation Architecture and Plan*"
- Current state:
  - UAV/payload structure modeled based on CAD drawings
  - Terrain imported from real-world digital elevation models from Sacramento River field test
  - Site-specific flow data, simulated with iRIC, saved in a Flow Lookup Table
  - Custom plugin parses flow data from lookup table based on current location
  - UAV plugin controls flight dynamics of the UAV
  - UAV flight controller provides waypoint control and navigation





Technical and Science Advancements
Simulation Environment



Technical and Science Advancements
Prototype for embedded PIV

- Implementing PIV workflow in edge computing environment is challenging but crucial to project
- Ported original MATLAB codebase to ROS to integrate with sensors and execute in real time
- Established functional prototype ROS network that incorporates all phases of the PIV process, from ingesting, stabilizing, and enhancing images, through correlation calculations, to vectors
- Developed on desktop PC but also tested on Odroid like that on payload, along with field laptop

pivEntry.m
Input: PivParams structure array with parameters for PIV algorithm and post-processing, as well as ROS nodes
Output: PivArams.yaml file that can imported into ROS with a launch file produced by addRosnode.m

addRosNode.m
Helper function to make MATLAB code into a ROS node via codegen, etc. Also creates a launch file that can be used to import ROS parameters from PivParams.yaml

ROS parameters
/intArea
/pixSize
/minvel
/maxvel
/stdThresh
/medianFilt
/infillFlag
/smoothFlag
/step
/subpixMode
/timeout
/maxX
/maxY
/minX
/minY
/numX
/numY
/subPixOffset

ROS topics
/camera/image_raw
/preProc1
/preProc2
/deltaTlist
/mergeIA
/cor
/ensCor
/xPiv
/yPiv
/uPiv
/vPiv
/uPivFilt
/vPivFilt

rosPivEntry (for simulated images)
First, run streamflowpiv.launch file to read PivParams.yaml
par out: everything in PivParams
TO-DO: add local function for pre-processing
sub in: /camera/image_raw
pub out: /preProc1, /preProc2, /deltaTlist

rosReadRaw (for real data in recorded bag file)
First, run streamflowpiv.launch file to read PivParams.yaml
par in: frameInterval
sub in: /camera/image_raw
pub out: /rawGray1, /rawGray2, /deltaTlist

rosImgPrep
par in: ptThresh, window
sub in: /rawGray1, /rawGray2
pub out: /preProc1, /preProc2

rosGetIA
sub in: /preProc1, /preProc2
par in: intArea, step, timeout
par out: minY, minX, maxY, maxX, numY, numX, subPixOffset
pub out: /mergeIA

rosPyMultiFFT
sub in: /mergeIA
par in: timeout, intArea, numX, numY
pub out: /cor

rosMergeFFT
sub in: /mergeIA
par in: timeout, intArea, numX, numY
pub out: /cor

rosEnsemble
sub in: /cor
par in: timeout, intArea, numX, numY
pub out: /ensCor

rosPeak
sub in: /ensCor, /deltaTlist
par in: intArea, minX, step, maxX, minY, maxY, subPixOffset, subpixMode
pub out: /xPiv, /yPiv, /uPiv, /vPiv

[OPTIONAL] rosPostProc
sub in: /uPiv, /vPiv
par in: minvel, maxvel, stdThresh, medianFilt, infillFlag, smoothFlag
pub out: /uPivFilt, /vPivFilt

CONOPS: Odroid XU4 embedded CPU onboard the UAS handles interaction with sensors and publishes images at desired frame rate. Raw frames are transmitted to ground station via Wi-Fi, where subsequent steps are performed within network of ROS nodes on a field laptop

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Summary of Accomplishments and Future Plans
Overview

Summary of current state

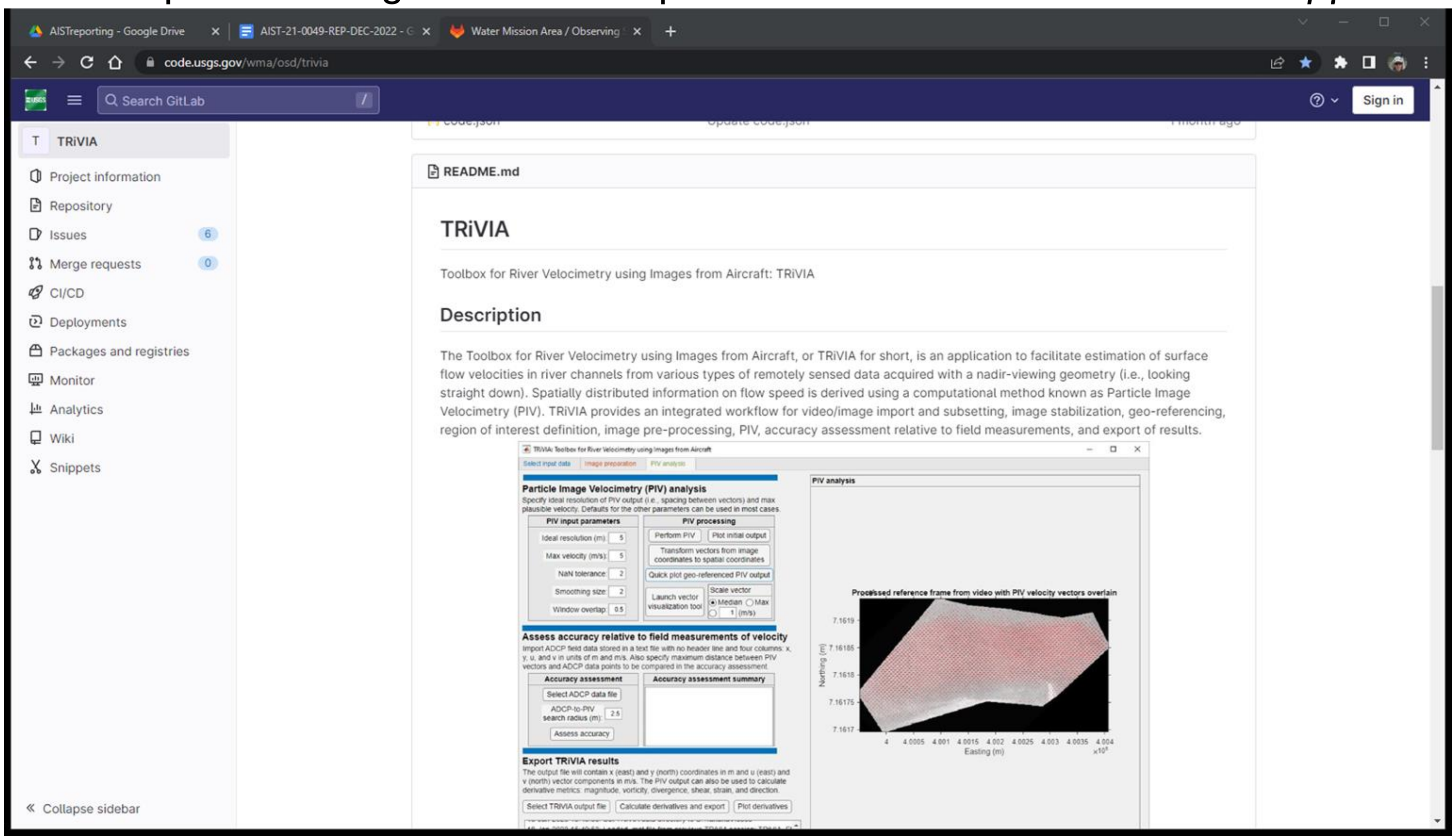
- Completed successful test flight of RiOS on the Sacramento River in September 2022
- Favorable comparison to field data despite clear water and paucity of trackable features
- Documentation includes Getting Started Guide, User's Manual, & Payload Design Documents
- Compared heavy/expensive thermal camera with lighter/more economical alternative
- Initial design work on Version 2 of RiOS payload in anticipation of shift to new platform
- Hydrodynamic modeling of Sacramento River flow field provides input to simulation environment
- Software release: Toolbox for River Velocimetry using Images from Aircraft (TRiVIA)
- Established simulation environment to facilitate testing of autonomous route-finding algorithms
- Developed functional prototype for embedded PIV by porting MATLAB code to ROS nodes

Anticipated results

- Field demonstration of the functionality of the RiOS payload and ground station
- Ability to perform PIV analysis in real time to direct stationing autonomy for discharge measurement and inform autonomous route-finding for hazard response
- Publications documenting the RiOS framework and results from test flights
- Software for end users and for implementing workflow in an edge computing environment

Summary of Accomplishments and Future Plans
TRiVIA software release

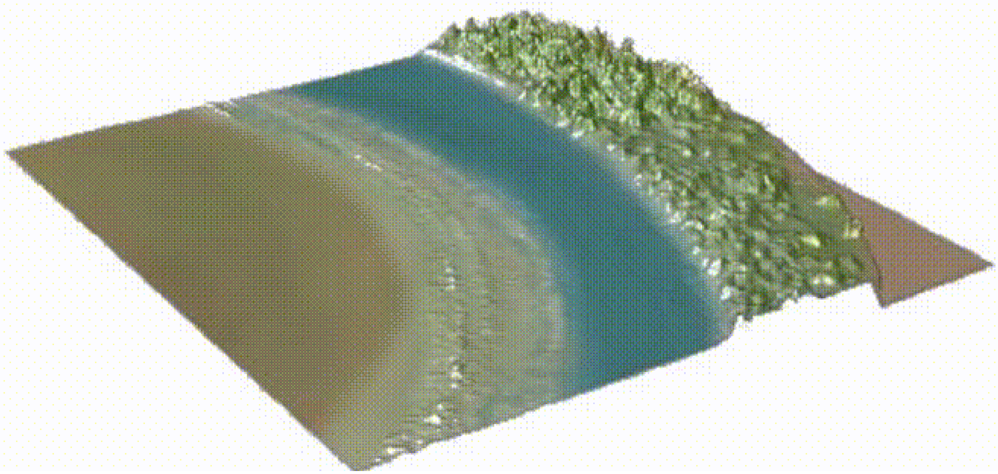
- Publicly available as a standalone USGS scientific software product from GitLab repository
  - https://code.usgs.gov/wma/osd/trivia OR https://doi.org/10.5066/P9AD3VT3
- Single zip file includes installer and a tutorial that provides an example and documentation
- GitLab repository includes issues board for posting requests for improvement, bug reports, …
- TRiVIA will be incorporated into the curriculum of several upcoming USGS training courses
- Manuscript describing the software published in *River Research and Applications* (DOI link)



Summary of Accomplishments and Future Plans
Integrating hydrodynamic model into simulation

- Flow modeling is performed separately in iRIC (NAYS2DH), outside simulation environment
- Information on flow field from NAYS2DH incorporated into Gazebo via specialized plugins
- Hydrodynamic data stored in lookup table with spatial coordinates and velocity components
- Plugin uses ray casting to identify the portion of river within sensor's field of view and then query lookup table to retrieve velocity vectors for this region
- UAS uses flight controller to follow user-defined waypoints

Data collected at this station will dictate location of next waypoint



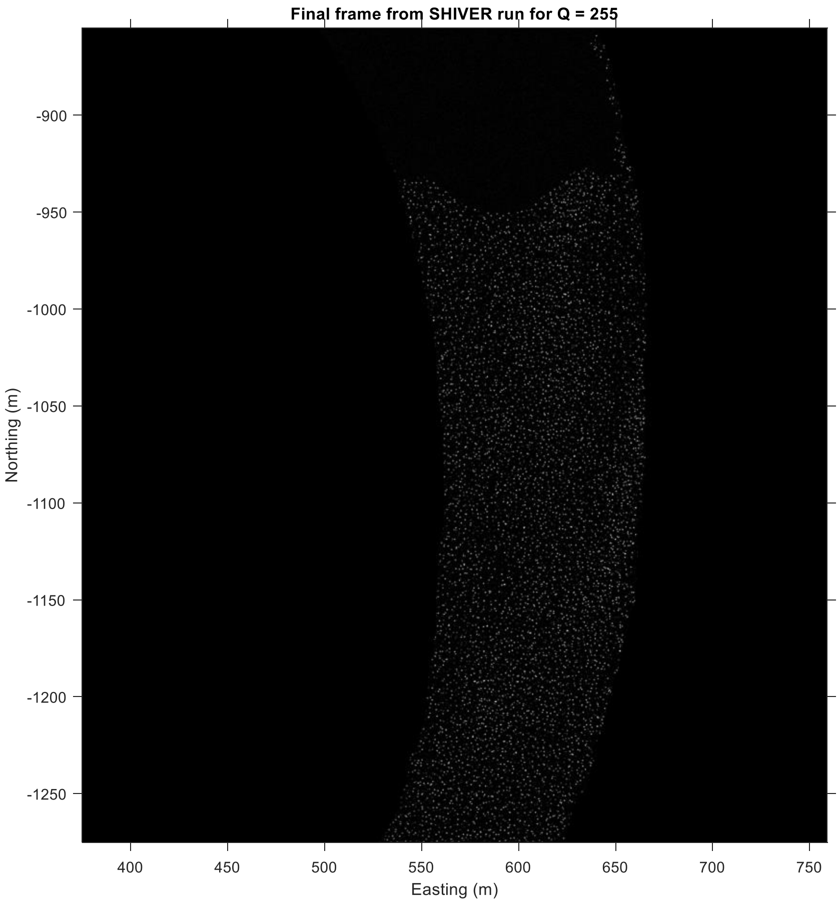
Next steps:

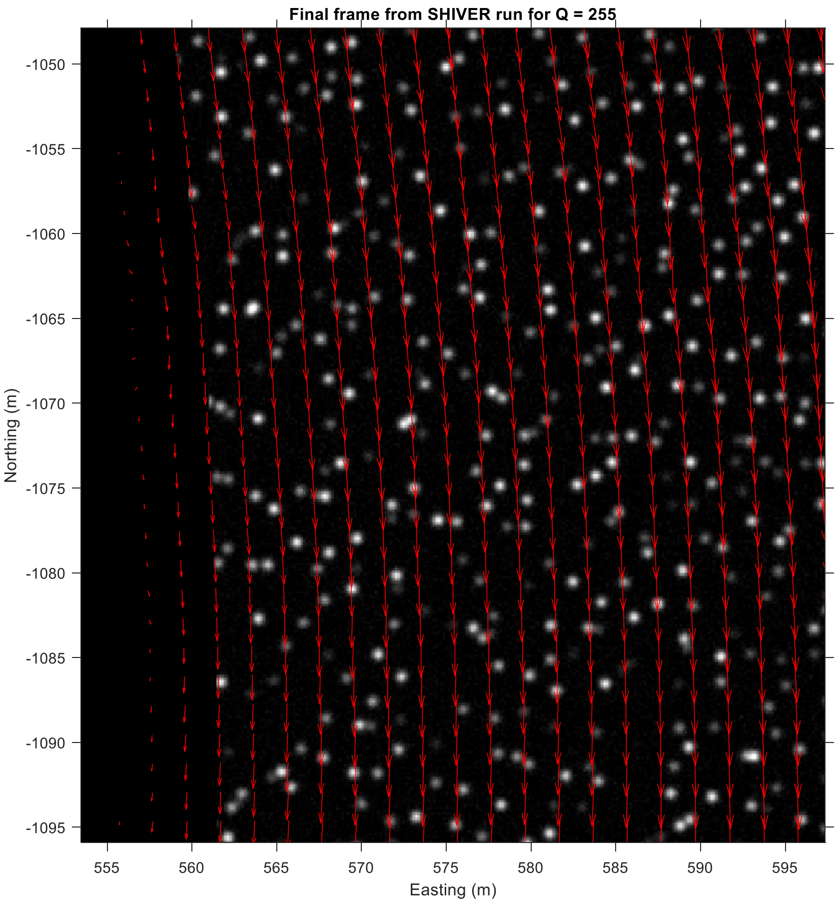
- Develop autonomy algorithms that programmatically generate waypoints (e.g., to find and follow fastest flow along river)
- Introduce noise to simulate camera distortion, motion blur, etc.

Summary of Accomplishments and Future Plans

Simulating images for PIV uncertainty characterization

- **SHIVER:** Simulating Hydraulics & Images for Velocimetry Evaluation & Refinement
  - Use velocities from flow model to direct the advection of particles in synthetic images, from which the flow field can be inferred via PIV



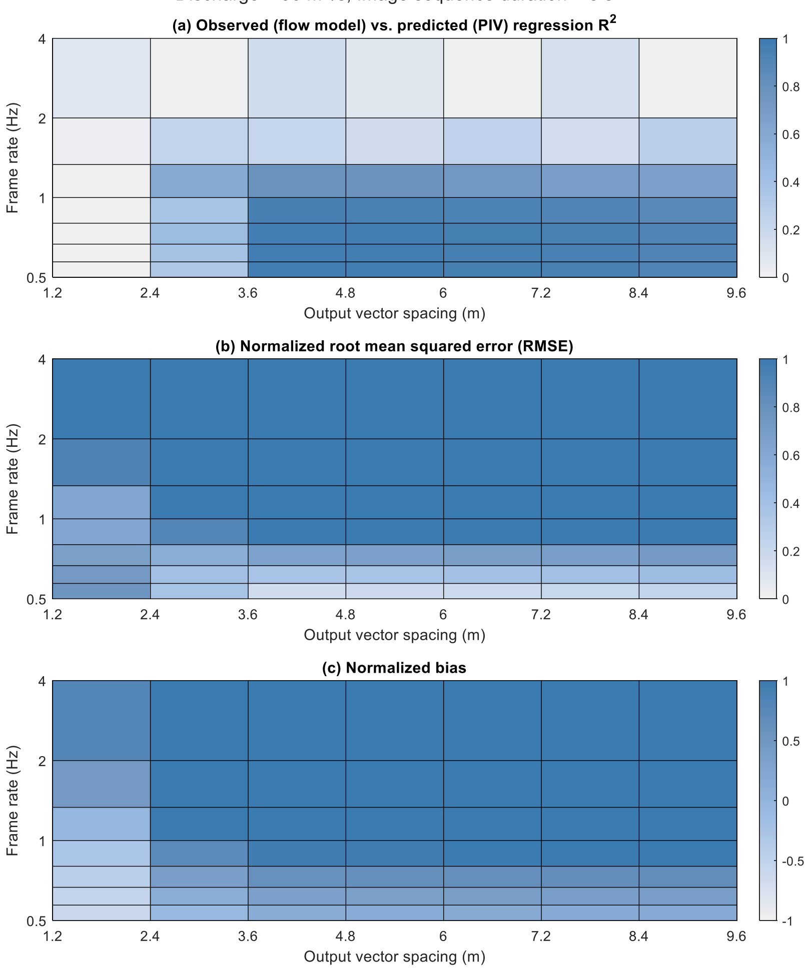


Summary of Accomplishments and Future Plans

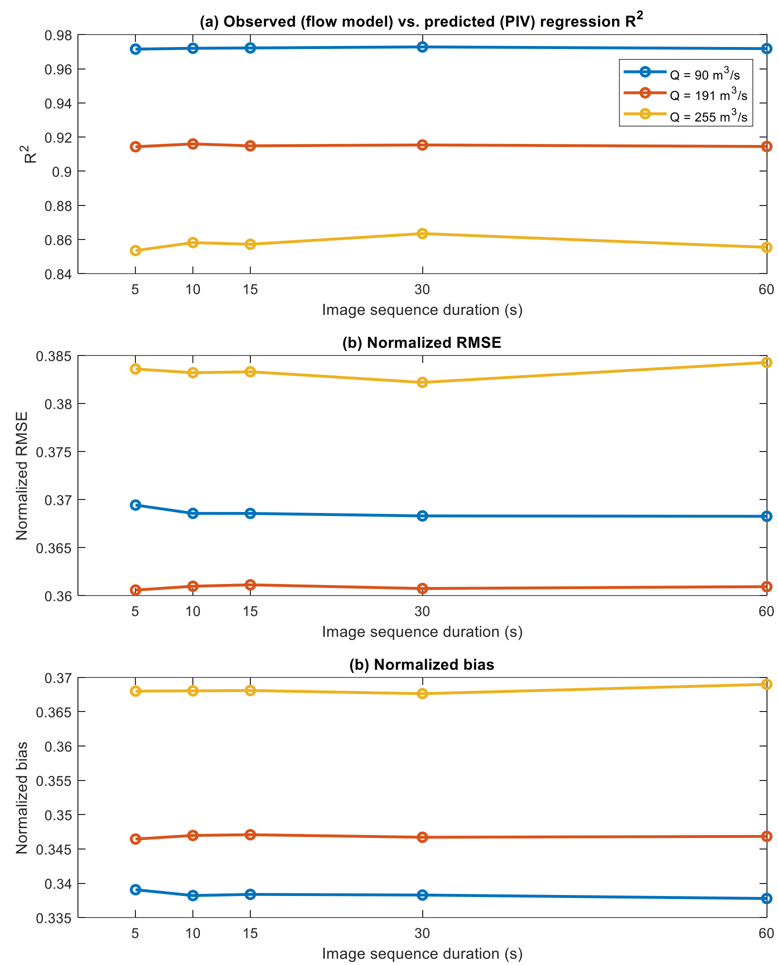
Simulating images for PIV uncertainty characterization

- **SHIVER:** Simulating Hydraulics & Images for Velocimetry Evaluation & Refinement
  - Provides a means of characterizing uncertainty via numerical experiments
  - Effects of frame rate, spatial resolution, flow velocity, & image sequence duration

Discharge = 90 m³/s, Image sequence duration = 5 s

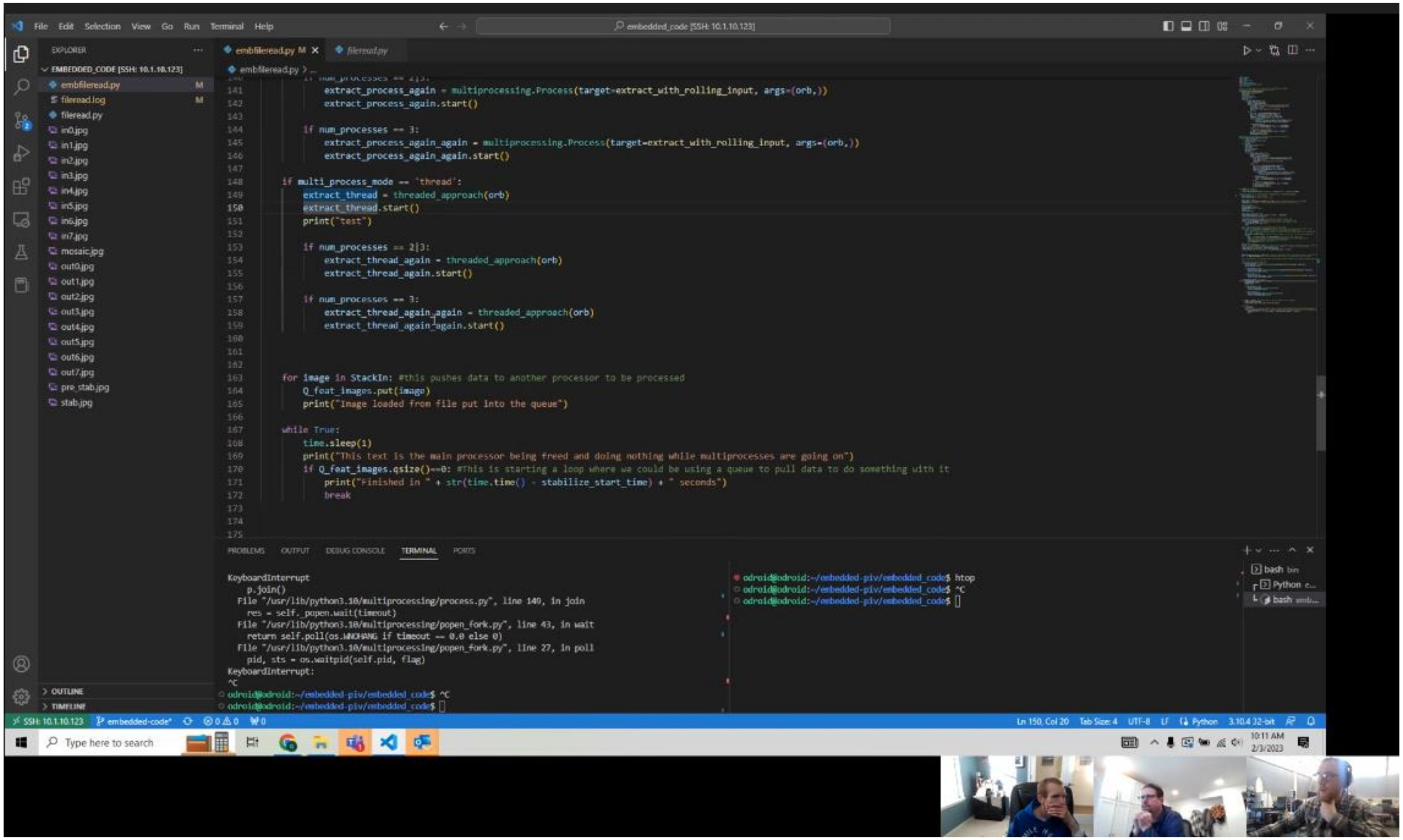


Frame rate = 0.66667 Hz, Output vector spacing = 3.6 m



Summary of Accomplishments and Future Plans
Porting workflow to embedded computing environment

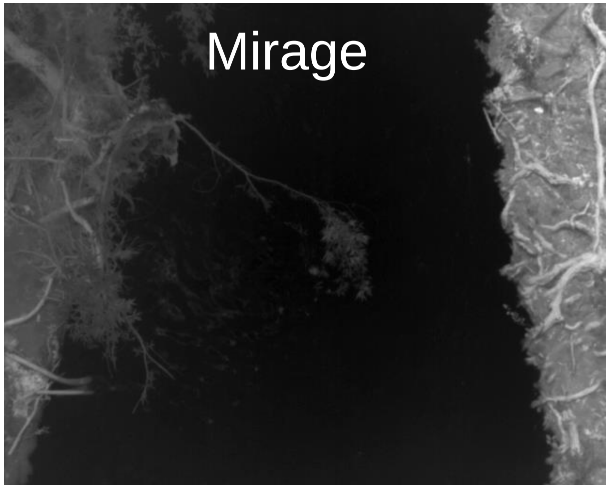
- Completed initial port of MATLAB codebase into ROS nodes for real-time PIV analysis
- Currently have a functional, end-to-end prototype, but processing speed is a concern
- Seeking to optimize computations via multiprocessing capabilities available in Python
- The SHIVER framework provides a rigorous means of benchmarking code performance

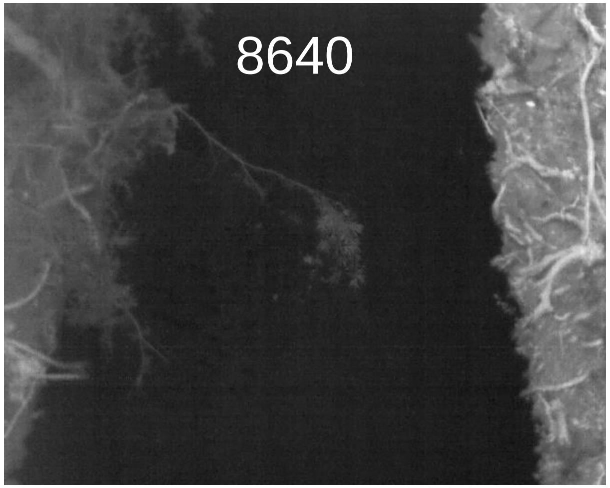


Collaborating with Greg Hewitt of Deep Analytics, LLC, to explore Python-based multiprocessing to optimize computational efficiency of PIV

Summary of Accomplishments and Future Plans
Local field testing

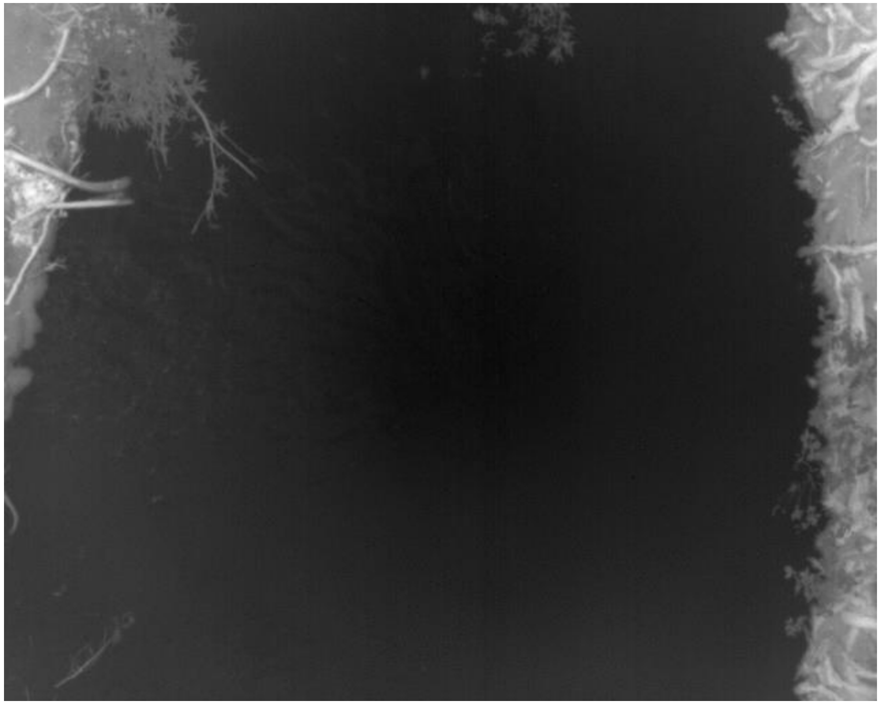
- Opportunistic data collection at park near NASA Ames
  - Enabled by period of high water following rains
- Allowed us to obtain data under real-world conditions from a small stream analogous to test site on the Sacramento
  - “Flying height” and channel width provided a rough scale model for UAS flight along the Sacramento
- **First outdoor dataset jointly recording data from all three cameras and the IMU**
  - Will be used to characterize thermal camera noise and test image stabilization methods



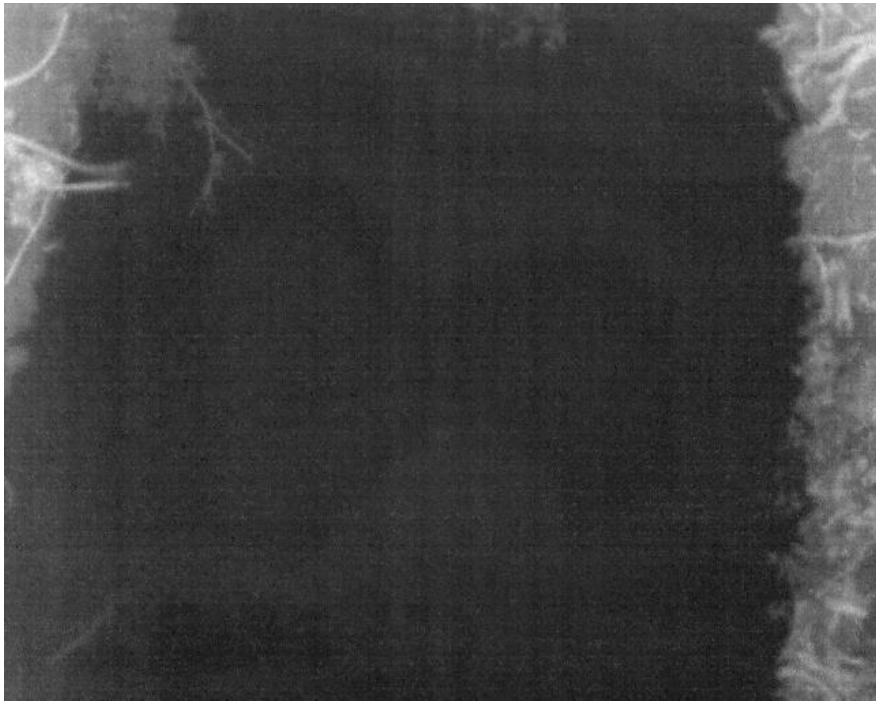


Summary of Accomplishments and Future Plans
Evaluating compatibility between thermal cameras

- Mirage (high quality, but expensive & heavy) vs. 8640 (cheaper & lighter, but lower quality)
- Replacement lens for Mirage provides wider field of view (FOV) comparable to that of 8640
- Repeated side-by-side testing to assess whether 8640 is sensitive enough to support PIV
- Confirmed FOV for Mirage is wider, which should allow full coverage at flying heights allowed
- Mirage images qualitatively superior to 8640 and we have decided to proceed with this camera
- Issues with temperature calibration persist, but absolute temperatures are not required for PIV



Mirage



8640

Summary of Accomplishments and Future Plans
Risk assessment and mitigation plan

- **RISK:** Uncertainty as to which UAS platforms we can use and how they will perform
- **MITIGATION:** Develop modular, entirely platform-independent payload to allow flexibility

- **RISK:** Implementing full PIV workflow on embedded, onboard CPU might not be feasible
- **MITIGATION:** Transmit resampled image stream to ground station via WiFi, run on laptop

- **RISK:** Long run times might limit number of images that can be analyzed per unit time
- **MITIGATION:** Extended hovering observations to improve signal-to-noise via ensembling

- **RISK:** Multiple flights and lengthy occupations →consume large amounts of battery power
- **MITIGATION:** Plan on using a generator during field tests to recharge batteries in a cycle

- **RISK:** Current thermal camera has not been tested in field setting with new lens
- **MITIGATION:** Perform initial outdoor ground testing on a local stream

- **RISK:** Computationally intensive image-based stabilization could be a workflow bottleneck
- **MITIGATION:** Incorporate IMU data to estimate pose and initialize image-based algorithm

- ***Note that most of the computational issues are dictated by current hardware and could be reduced by upgrading to more powerful processors***

Summary of Accomplishments and Future Plans
Work Plan for Next Reporting Period

1. Complete conversion of PIV source code from MATLAB into a coherent ROS package consisting of several interconnected nodes for all aspects of the workflow

2. Continue development of simulation environment by incorporating flow model output, synthetic images, and ROS nodes for full PIV workflow

3. Confirm that ROS nodes are fully functional on embedded CPU and ground station

4. Develop and test Wi-Fi transmission of images from payload to ground station

5. Use information from IMU on platform orientation to estimate sensor pose and provide a refined starting point for more demanding image-based stabilization

6. Characterize sensor responses/transformations as a step toward full error budget

7. Incorporate natural spatial and temporal variations in the flow field into the overall characterization of uncertainty by identifying indices of velocity error

8. Improve robustness of RiOS enclosure and ground station for future test flights

Summary of Accomplishments and Future Plans

- Significant progress to date: test flight, documentation, software release, established hydrodynamic model and simulation environment, functional prototype for embedded PIV
- Current work focused on incorporating information from IMU, optimizing real-time PIV, integrating flow model and synthetic image generator with simulation environment, characterizing uncertainty, and selecting algorithms for autonomous route-finding
- Overall, project is on track and advancing steadily

Presentation Contents

- Background and Objectives
- Technical and Science Advancements
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- Actual or Potential Infusions and Collaborations
- Publications - List of Acronyms

Actual or Potential Infusions and Collaborations

- Summary of actual or potential infusions
  - Infusion: PIV workflow → TRiVIA software for end users in USGS and beyond
  - Knowledge transfer: Exploring additional use cases for edge computing within USGS
  - Technology transfer: TRiVIA software freely available, developing real-time analog
  - Transition: Incorporate real-time PIV into more widespread ground-based sensors
  - Transition: NASA IRAD “Adaptive Automated Airborne Mapping of Dynamic Flows”

- Summary of actual or potential collaborations
  - Collaborating with NOAA Southwest Fisheries Science Center to collect field data during test flights on the Sacramento River
  - Established Cooperative Research and Development Agreement (CRADA) with Deep Analytics, LLC, to advance embedded computing capabilities for real-time PIV
  - Working with UC Berkeley student to port TRiVIA codebase to Python, funded by Universities Space Research Association
  - Exploring partnership with Civil Air Patrol to extend PIV to moving fixed-wing aircraft
  - Collaborating with US Fish and Wildlife Service to collect data from rivers in Alaska
  - Preparing proposal to apply PIV methods to support hazard response to spills of oil and other contaminants on large rivers in Alaska

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Earth Science Technology Office

Publications

Journal Papers

- Legleiter, C.J., and Kinzel, P.J. 2023, The Toolbox for River Velocimetry using Images from Aircraft (TRiVIA). *River Research and Applications,* https://doi.org/10.1002/rra.4147.

Software

- Legleiter, C.J., 2023, TRiVIA - Toolbox for River Velocimetry using Images from Aircraft (ver. 1.7.01, May, 2023): U.S. Geological software release, https://doi.org/10.5066/P9AD3VT3.

Presentations

- Legleiter, C.J. 2022, sUAS-based, non-contact measurement of flow velocities in river channels: Fifth Federal UxS Workshop, Moffet Field, CA.
- Legleiter, C.J. 2022, Panel session: Emerging Sensors for UAS-Borne Science. Fifth Federal UxS Workshop, Moffet Field, CA.
- Legleiter, C.J., 2023, USGS software for airborne PIV: Introduction and demonstration. USGS Water sUAS Focus Group: PIV and more, Online.
- Legleiter, C.J., 2023, The River Observing System (RiOS): A collaboration between the USGS and NASA to develop an intelligent systems framework for real-time, UAS-based river velocimetry. USGS Imagery Data at the Edge Workshop: Advancing USGS imagery data edge computer processing, Online.
- Legleiter, C.J., 2023, Toolbox for River Velocimetry using Images from Aircraft (TRiVIA). Hydraulic Measurements and Experimental Methods Conference, Fort Collins, Colorado.

List of Acronyms

2D	Two-dimensional
ADCP	Acoustic Doppler Current Profiler
AIST	Advanced Information Systems Technology
CAD	Computer-Assisted Drafting
CONOPS	Concept of Operations
CPU	Central Processing Unit
FOV	Field of View
ICI	Infrared Cameras Incorporated
IMU	Inertial Measurement Unit
iRIC	international River Interface Cooperative
NOAA	National Oceanographic and Atmospheric Administration
PIV	Particle Image Velocimetry
RiOS	River Observing System
RGB	Red Green Blue
ROS	Robot Operating System
sUAS	Small Unoccupied Aircraft System
TRiVIA	Toolbox for River Velocimetry using Images from Aircraft
TRL	Technology Readiness Level
UAS	Unoccupied Aircraft System
USGS	United States Geological Survey

OSSE / Trade Space Capability for NOAA's Future Mission Design

Derek Posselt (Co-PI, Jet Propulsion Laboratory)
Paul T. Grogan (Co-PI, Stevens Institute of Technology)

NOS Group Technical Review
July 12, 2023

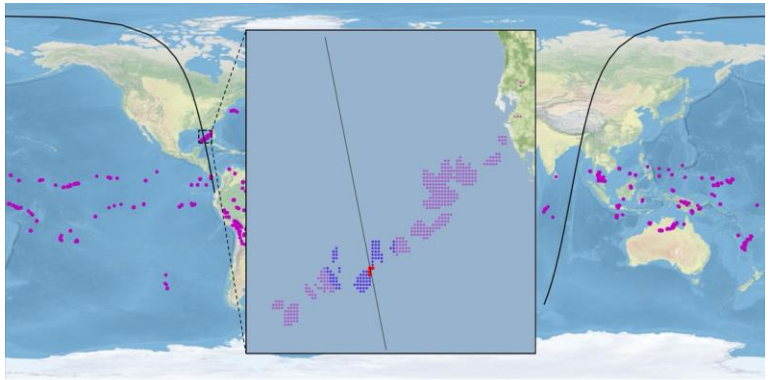
Julia Cairns, Zackary Horton (Stevens Institute of Technology)

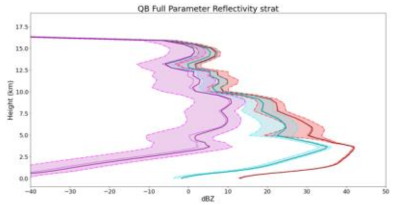
OSSE / Trade Space Capability for NOAA's Future Mission Design

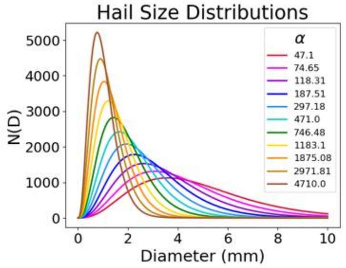
PIs: Derek Posselt, Jet Propulsion Laboratory; Paul Grogan, Stevens Institute of Technology

Objective:

- Develop automated trade space exploration and assessment tools to evaluate performance metrics under dynamic conditions
- Leverage tools developed in NASA ESTO-AIST funded projects to assist in NOAA's future mission design activities
- Evaluate system for diverse weather scenarios.
- Interface with NOAA's ASPEN trade space evaluation tool.







Automatically explore trade space of alternate mission architectures and evaluate their performance under dynamic conditions.

Approach:

- Integrate the parallel observing system simulation framework (ParOSSE) with the tradespace analysis toolkit for constellations (TAT-C)
  - ParOSSE is a parallel framework that can manage the vast search spaces needed to evaluate instrument metrics and uncertainties (developed under SRTD, AIST-18)
  - TAT-C is an automated trade space exploration tool that can evaluate alternate constellation architectures (AIST)
- Evaluate on use cases selected from existing missions and future mission architectures.
- Package as a pre-processor module for NOAA's ASPEN mission evaluation tool.

Key Milestones:

• Evaluation of dynamic performance metrics for use cases based on existing missions.	Apr. '23
• Automated trade space exploration of future constellation architectures	Oct. '23
• Interface with NOAA ASPEN trade tool	Jul. '24

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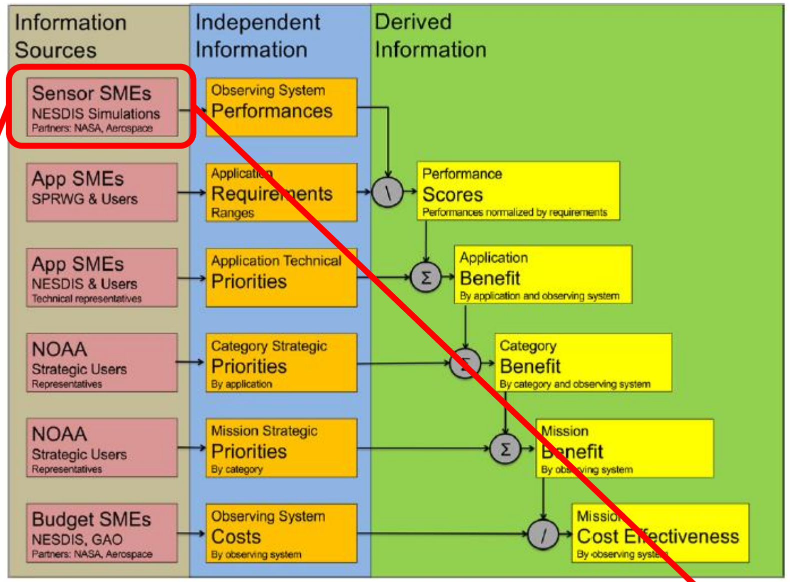
Background: Advanced Systems Performance Evaluation tool for NOAA (ASPEN)

- ASPEN is a decision support tool for observing systems: comparative assessment, trades, optimization
- Solution agnostic: compare observing system performance to requirements
- ASPEN process is driven by subject matter experts (SMEs) which is time-intensive and cost prohibitive for exploration of large trade spaces
- **Objective**: automate a subset of ASPEN inputs for future observing systems using two ESTO-funded tools: TAT-C and ParOSSE

Boukabara and Hoffman (2022)



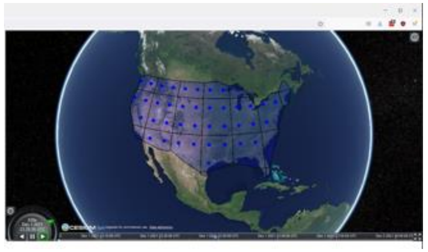
Geophysical Variables:
- Atmosphere Domain
- Hydrosphere Domain

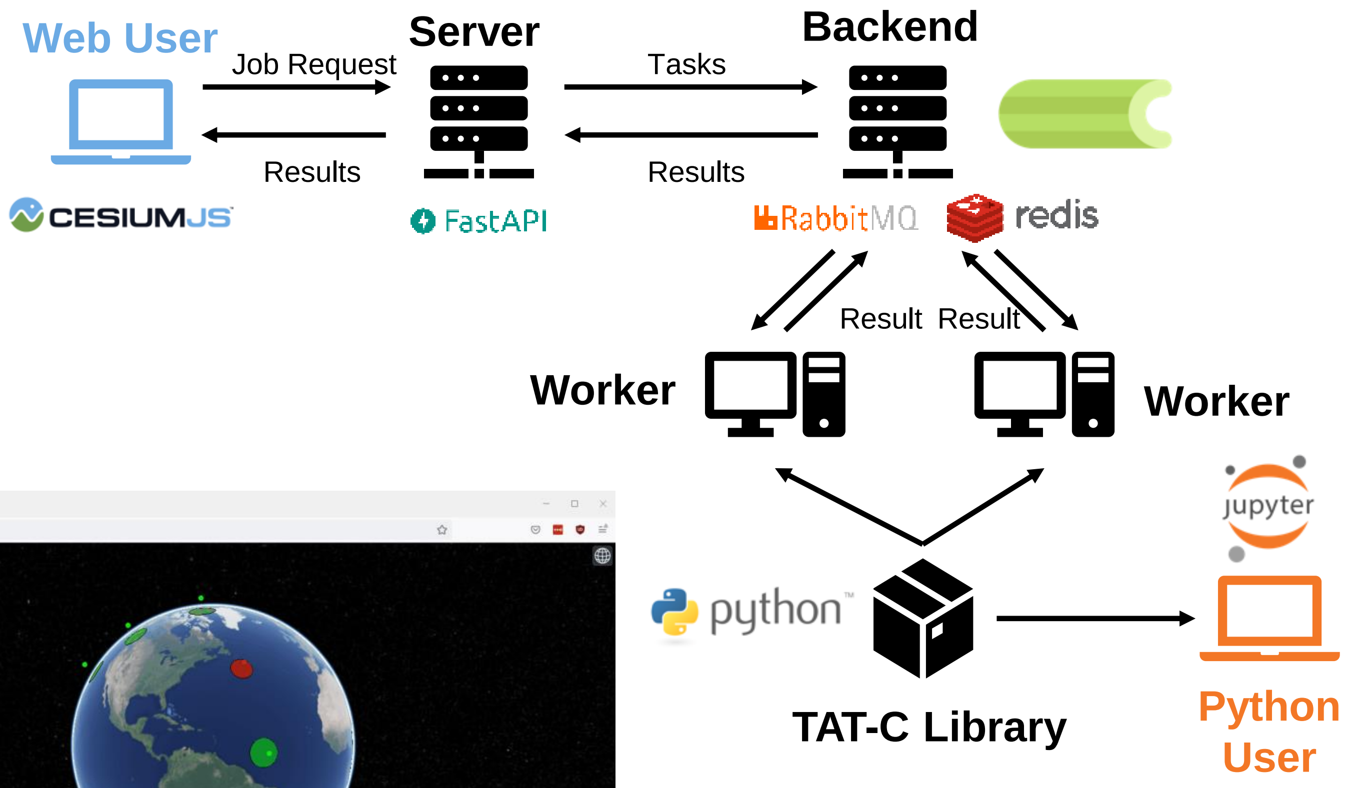
Attributes:
- Temporal Refresh
- Accuracy
- Validity Range Low
- Validity Range High
- Data Latency

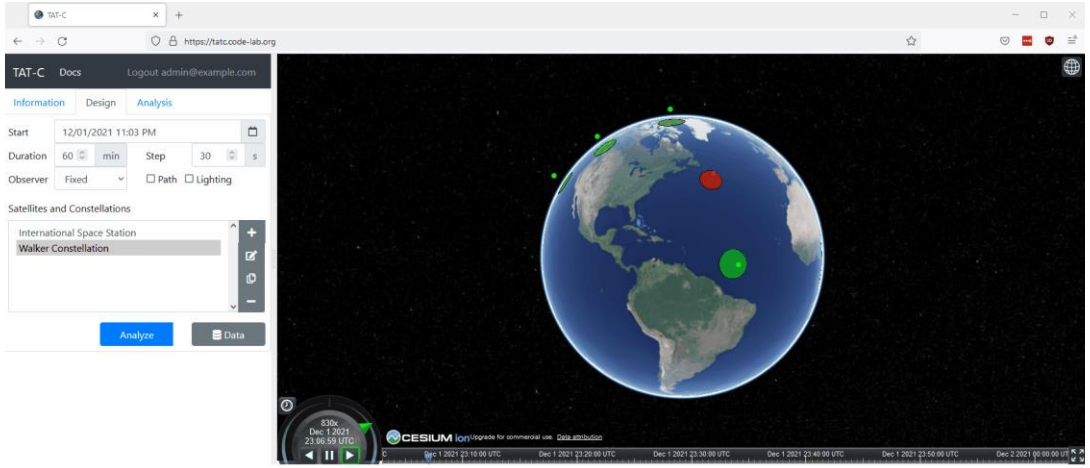
Tradespace Analysis Tool for Constellations (TAT-C)

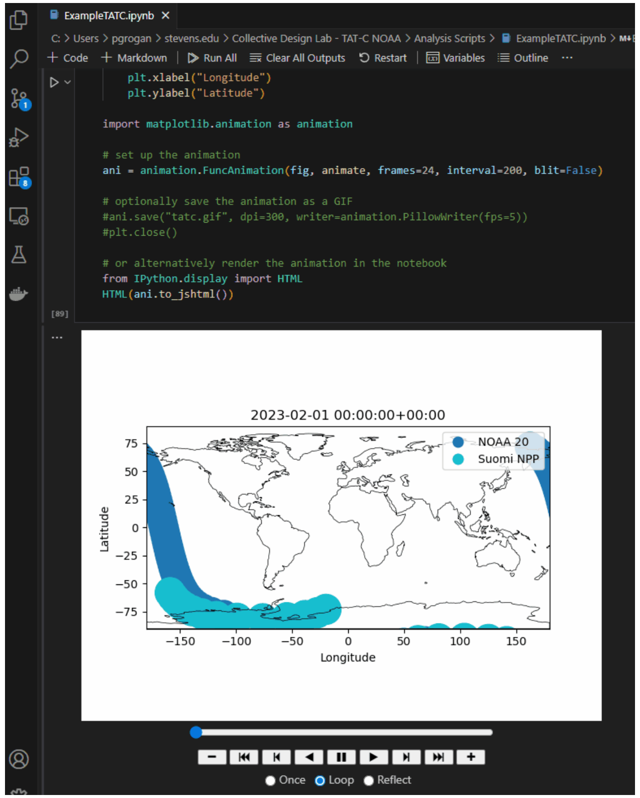
- TAT-C was funded by NASA's Earth Science Technology Office under the Advanced Information Systems Technology program (2014: v.1, 2016: v.2) and rewrite with external interfaces (JSON Schema, OpenAPI) in 2020: v.3
- Designed to efficiently model and simulate key mission performance attributes of satellite constellations suitable for tradespace exploration
- Currently used to interface with nature run and historical data sets to evaluate mission performance for precipitation and snow observing systems
- TAT-C v.3 available under an open-source license (github.com/code-lab-org/tatc)
  - Python-language library suitable for Jupyter Notebooks
  - Browser-based web application

TAT-C v.3 Software Environment









github.com/code-lab-org/tatc

tatc.readthedocs.io

Parallel Observing System Simulation Experiment (ParOSSE)

- ParOSSE was funded by NASA's Earth Science Technology Office under the Advanced Information Systems Technology program (2018)
- Designed to produce quantitative estimates of measurement sufficiency in a flexible parallel framework
- Used to aid in the 2017 Earth Science Decadal Survey ACCP (now AOS) mission formulation study
- Workflow consists of several modules, each a key OSSE component
  - Nature run interface
  - Radiative transfer model interface
  - Instrument model interface
  - Estimation (retrieval) algorithms
  - Quantitative measures of information

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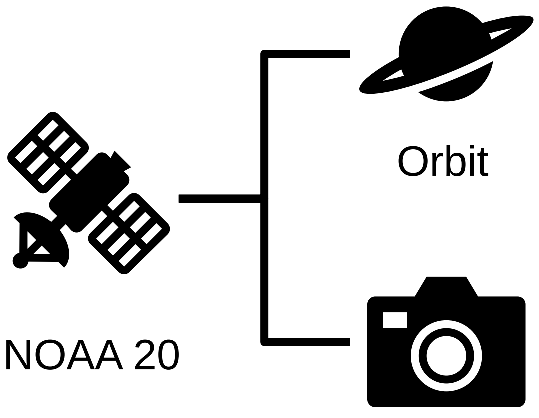
TAT-C Model Example (NOAA-20 VIIRS)

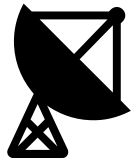


Orbit (TLE format):

```
1 43013U 17073A   23040.26276357  .00000206  00000+0  11864-3 0  9996
2 43013  98.7417 340.3662 0001620  85.7652 274.3709 14.19555145270826
```

Instrument:

- 3000 km swath width @ 834 km altitude = 111.6° field-of-regard
- Require sunlit target



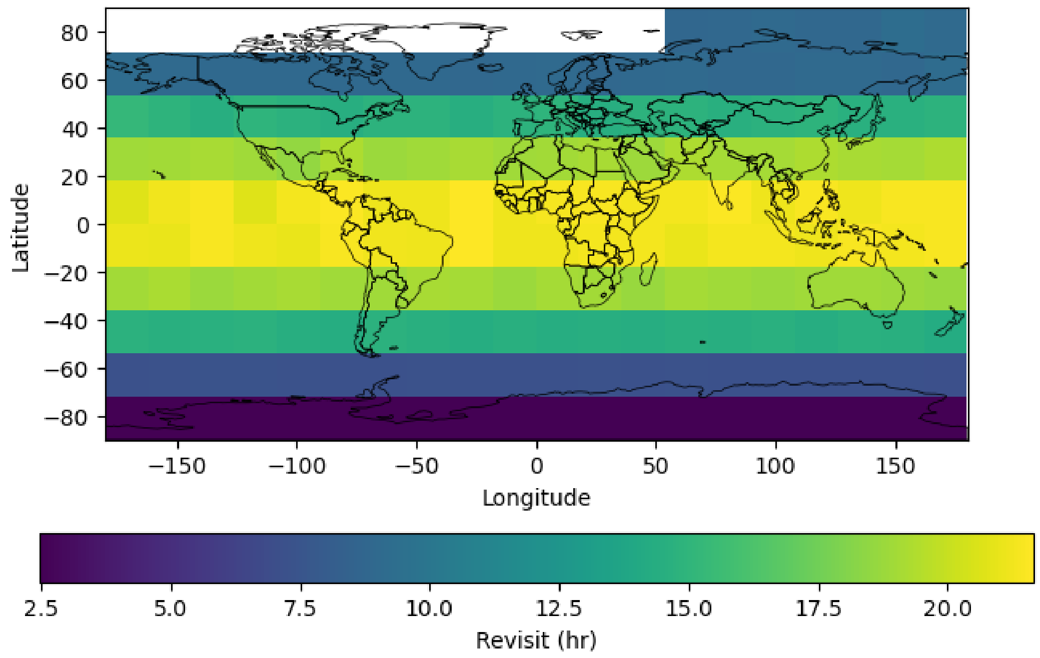
Ground station(s):

- Latitude = -77.846323, longitude = 166.668235, elevation = 0
- Minimum elevation angle = 10°

TAT-C Refresh Analysis (NOAA-20 VIIRS)

- Generate globally-distributed sample points (e.g., 1000 km cubed sphere; averaged to 2000 km cells)
- Simulate orbital motion for time interval (e.g., 1 month)
- Track observations of each sample point using criteria: field-of-regard → minimum elevation angle, sunlit
- Compute time intervals between successive observations
- Compute descriptive statistics

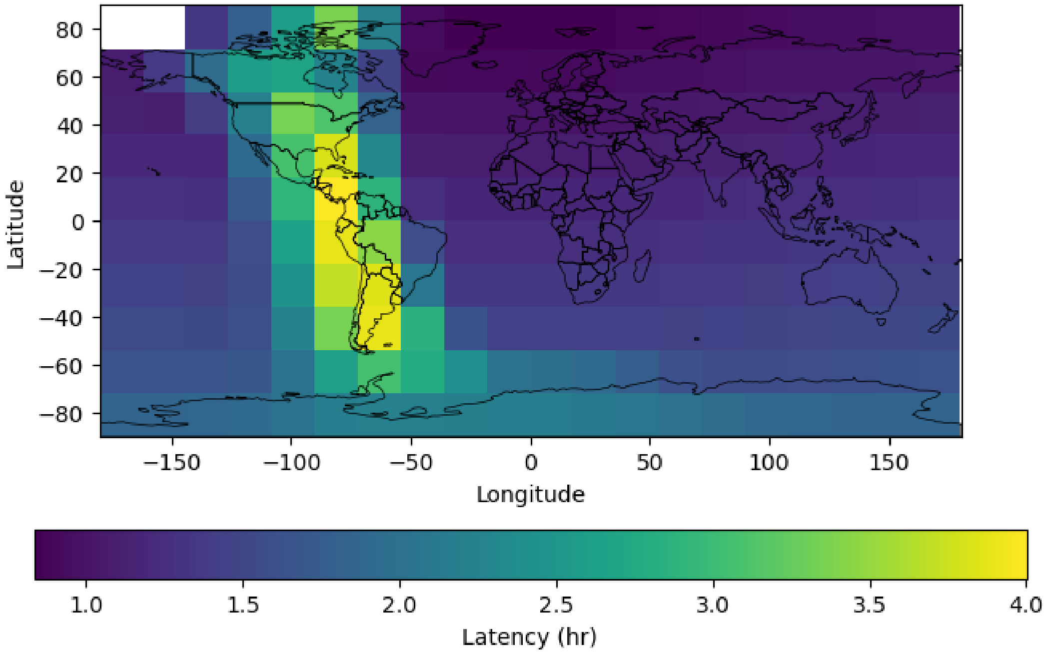
- Feb. 1, 2023 + 30 days
- Global Mean: 13.96 hr
- Global Max: 23.09 hr



TAT-C Latency Analysis (NOAA-20 VIIRS)

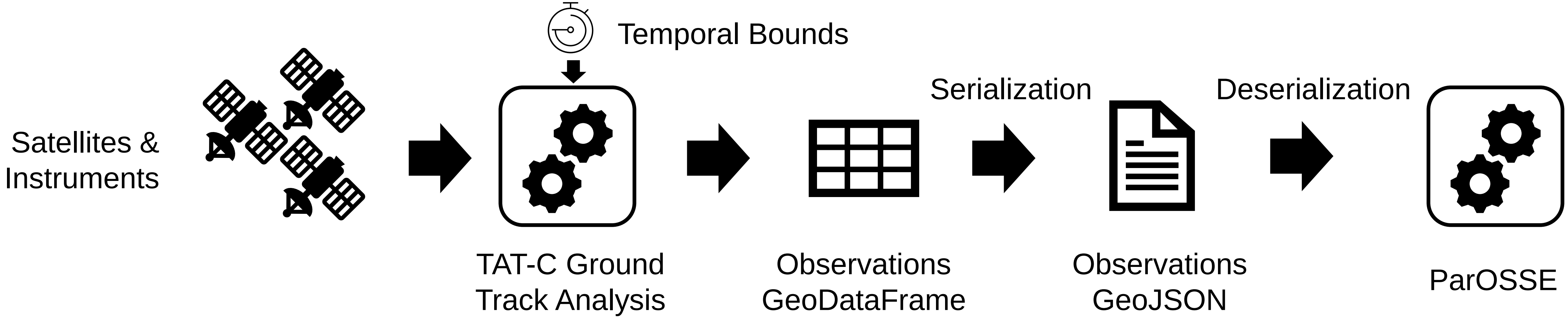
- Same as refresh analysis to track observations of sample points
- Track downlink opportunities to ground station locations based on minimum elevation angle criterion
- Compute duration between each observation and the next downlink opportunity
- Compute descriptive statistics

- Feb. 1, 2023 + 30 days
- Global Mean: 1.62 hr
- Global Max: 4.29 hr



TAT-C/ParOSSE Interface

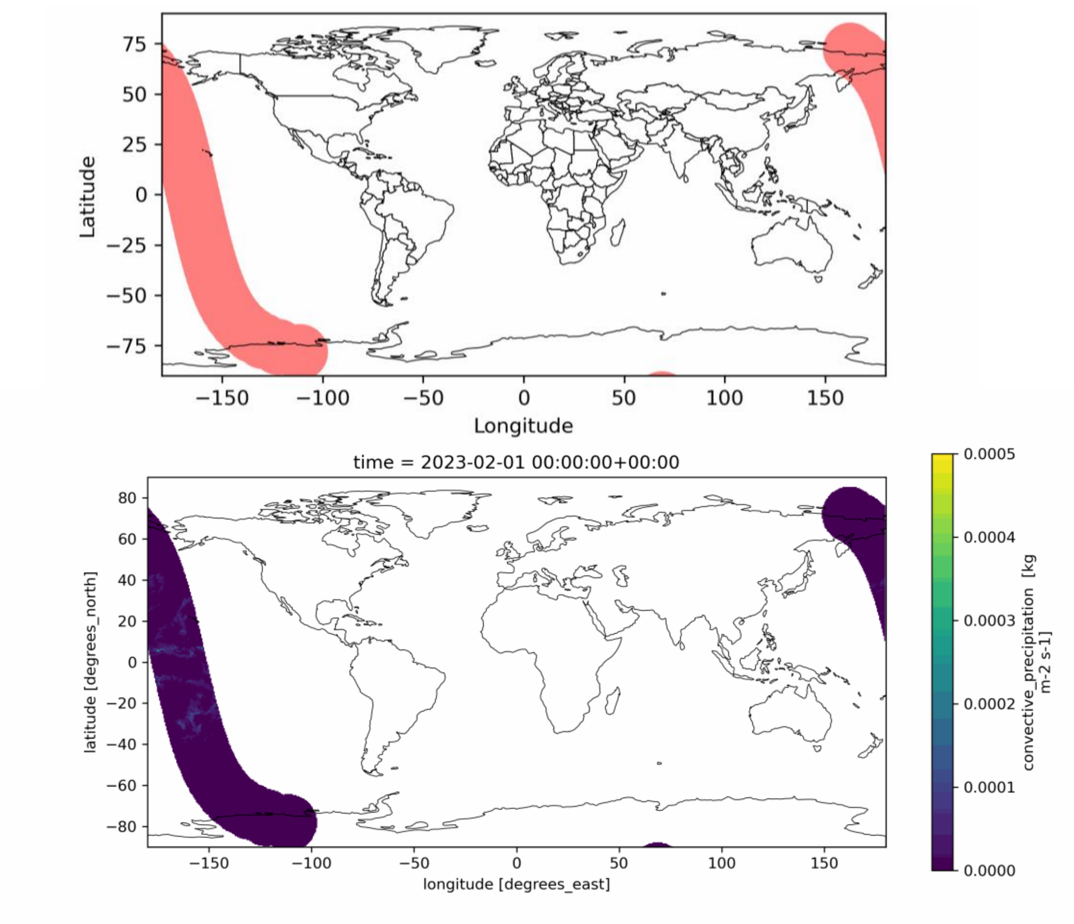
- TAT-C computes observable regions to feed to ParOSSE
  - Planar geometry polygons computed at time step interval (e.g., 1 minute)
  - Integrate/aggregate polygons over frame duration (e.g., 1 hour)
  - Collection of time-stamped geometries over a mission (e.g., 1 month)
  - Data serialized to GeoJSON and exported to ParOSSE



Example Interface (NOAA-20 VIIRS)

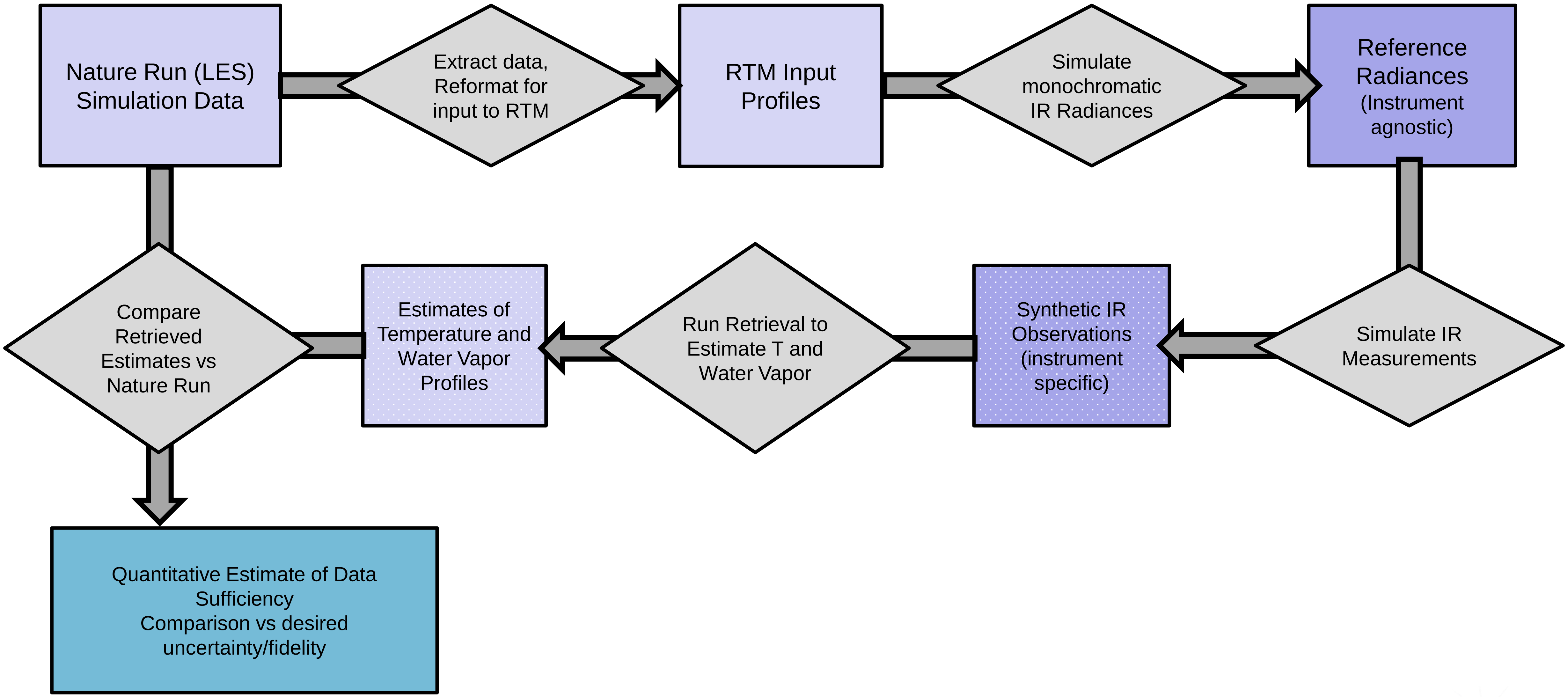
- Simulate orbital motion for mission (e.g., 1 day) using small time steps (e.g., 1 minute) aggregated to frames (e.g., 1 hour) aligned with data set
- Project each sub-satellite point to a Cartesian CRS (e.g., EPSG:4087), buffer the swath width to create a planar geometry (multi-)polygon, and project back into WGS 84 CRS
- Compile time-stamped (multi-) polygons into a single data structure and serialize to JSON

- Feb. 1, 2023 + 24 hours, 1-min step, 1-hr frame. Upper: TAT-C polygons; Lower: G5NR

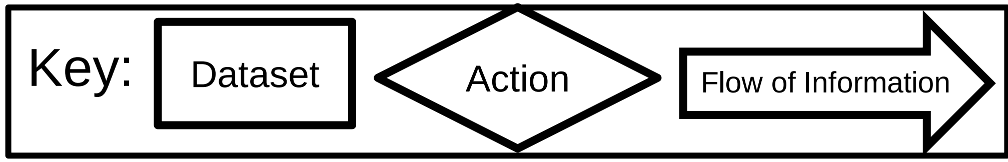


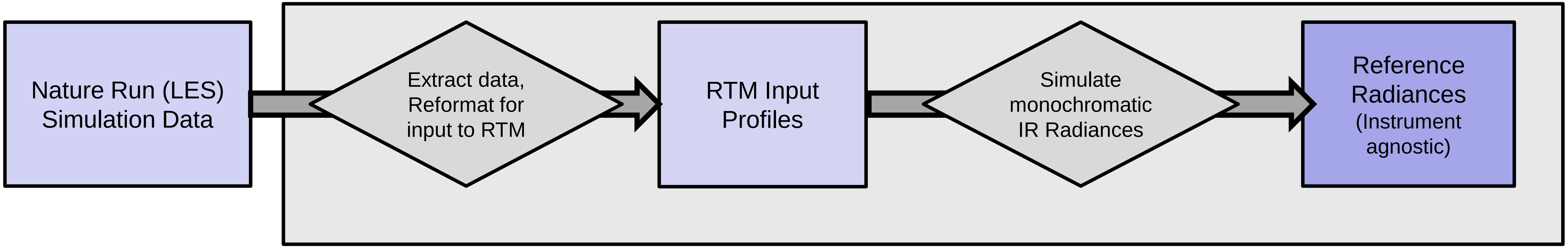
ParOSSE Workflow

Key: Dataset | Action | Flow of Information

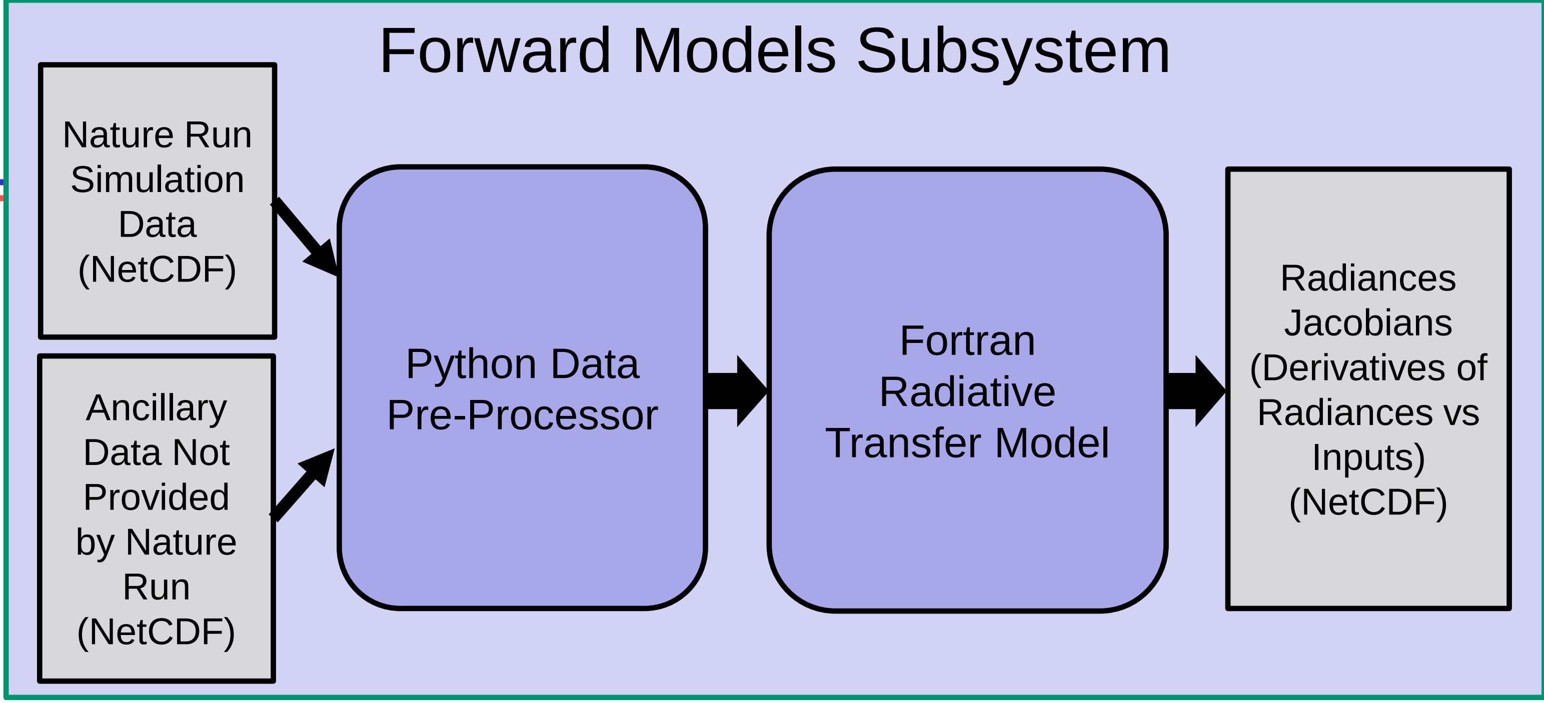


ParOSSE Workflow

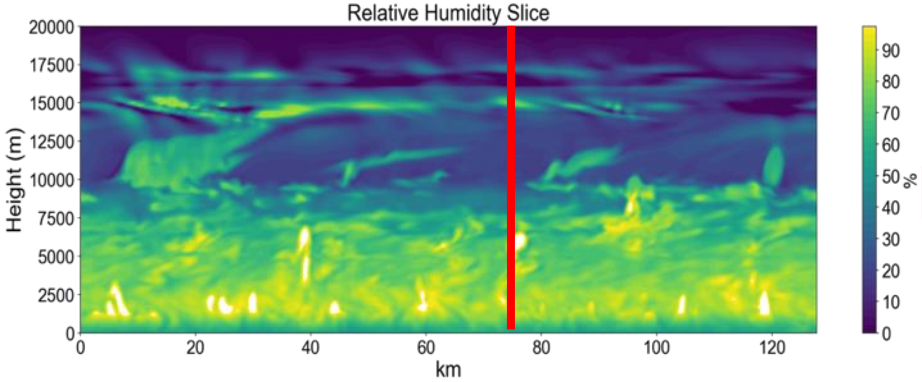




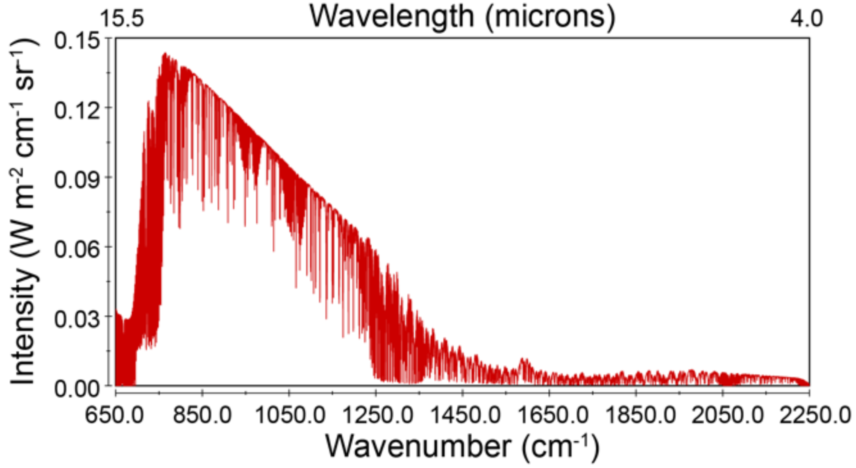
Forward Models Subsystem



- Pre-process nature run data
- Run physical (full complexity) radiative transfer model

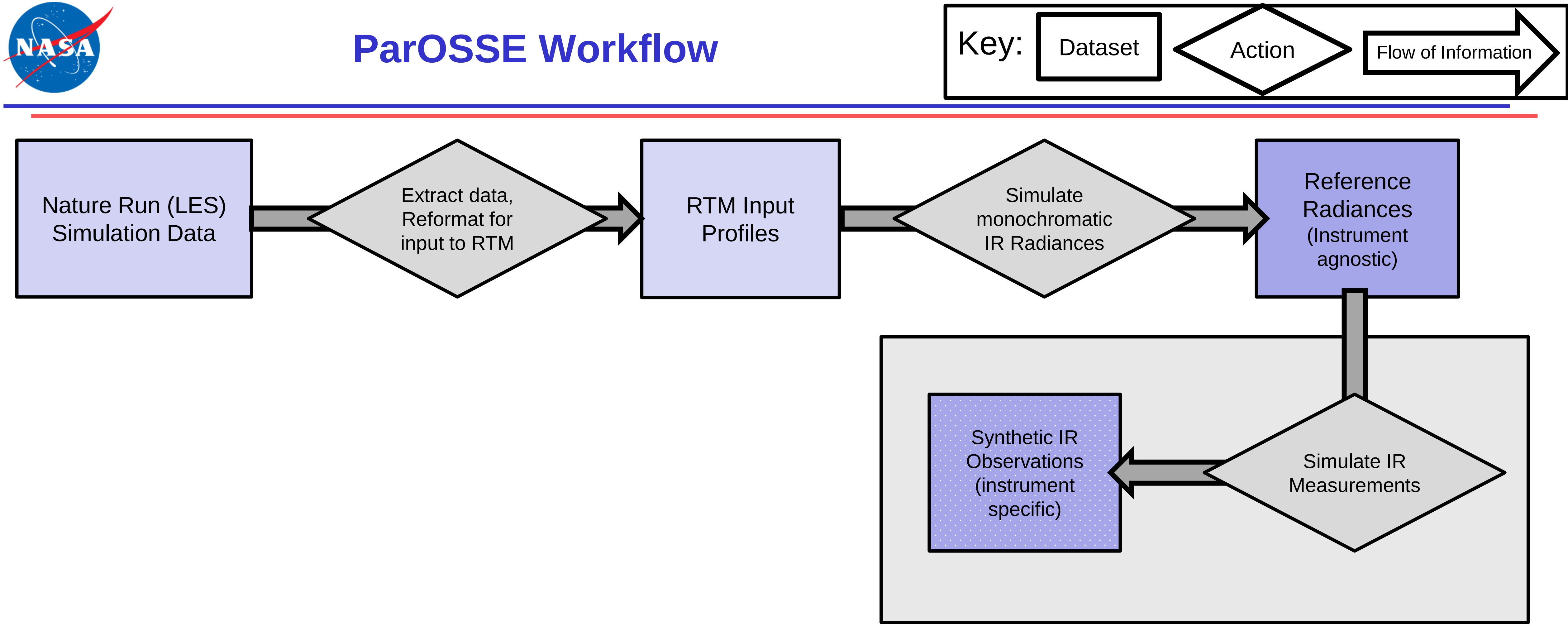


RT Model	Integration Time (s)	Integration Time With Jacobians
Full RT Model	1464	13824
Full RT Model 24 Cores	61	11491*



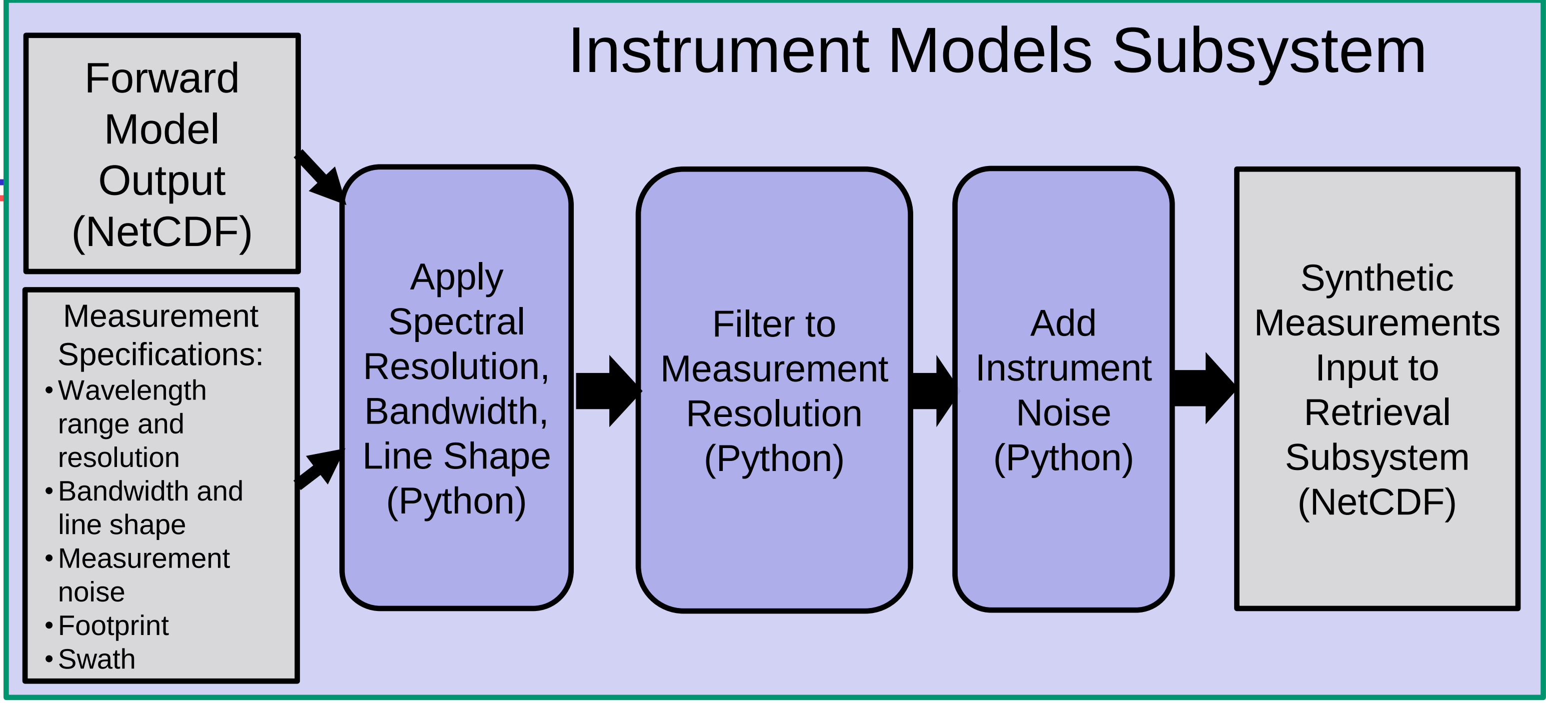
*Jacobian calculation not yet optimized

ParOSSE Workflow

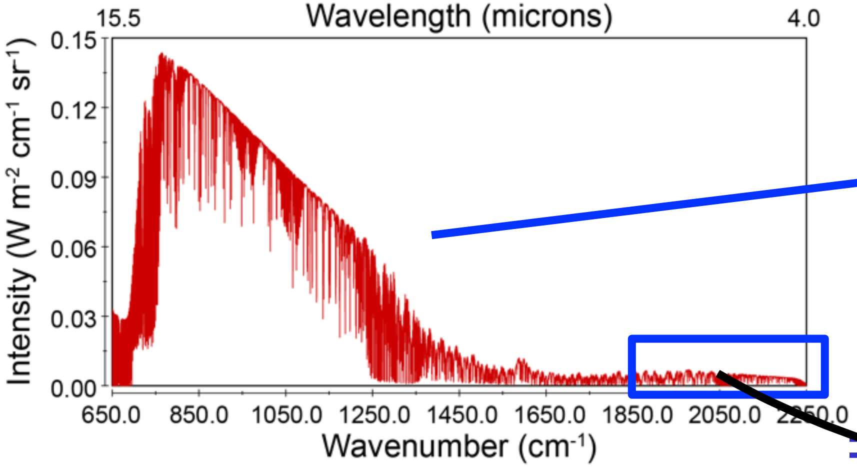


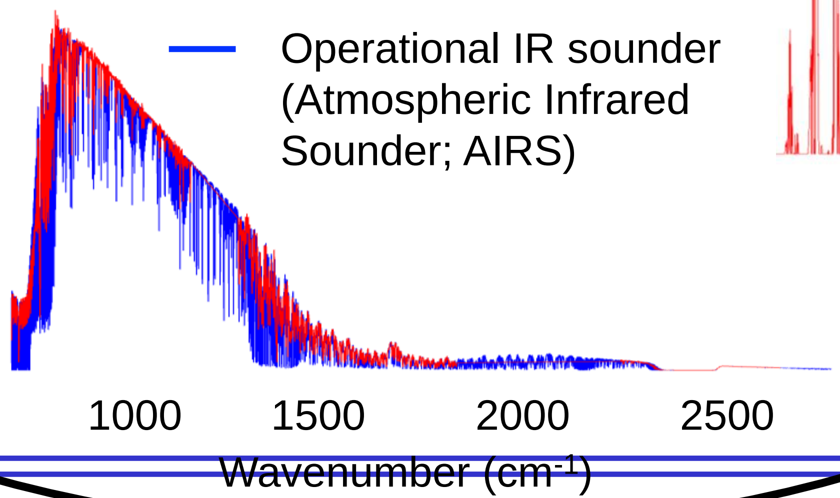
Instrument Models Subsystem

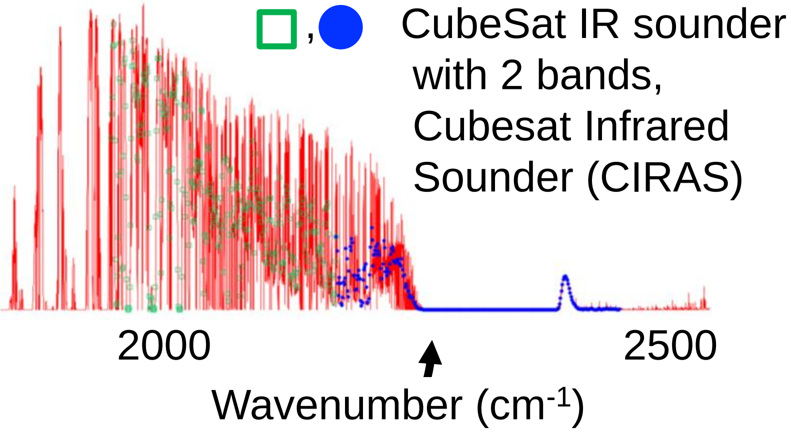
- Inputs full-resolution radiative transfer model output
- Applies measurement footprint, spectral range & resolution, and noise
- Outputs noisy observations consistent with what real on-orbit sensor is expected to produce



Number and resolution of spectral bands → vertical resolution







Instrument Models Subsystem

- Inputs full-resolution radiative transfer model output
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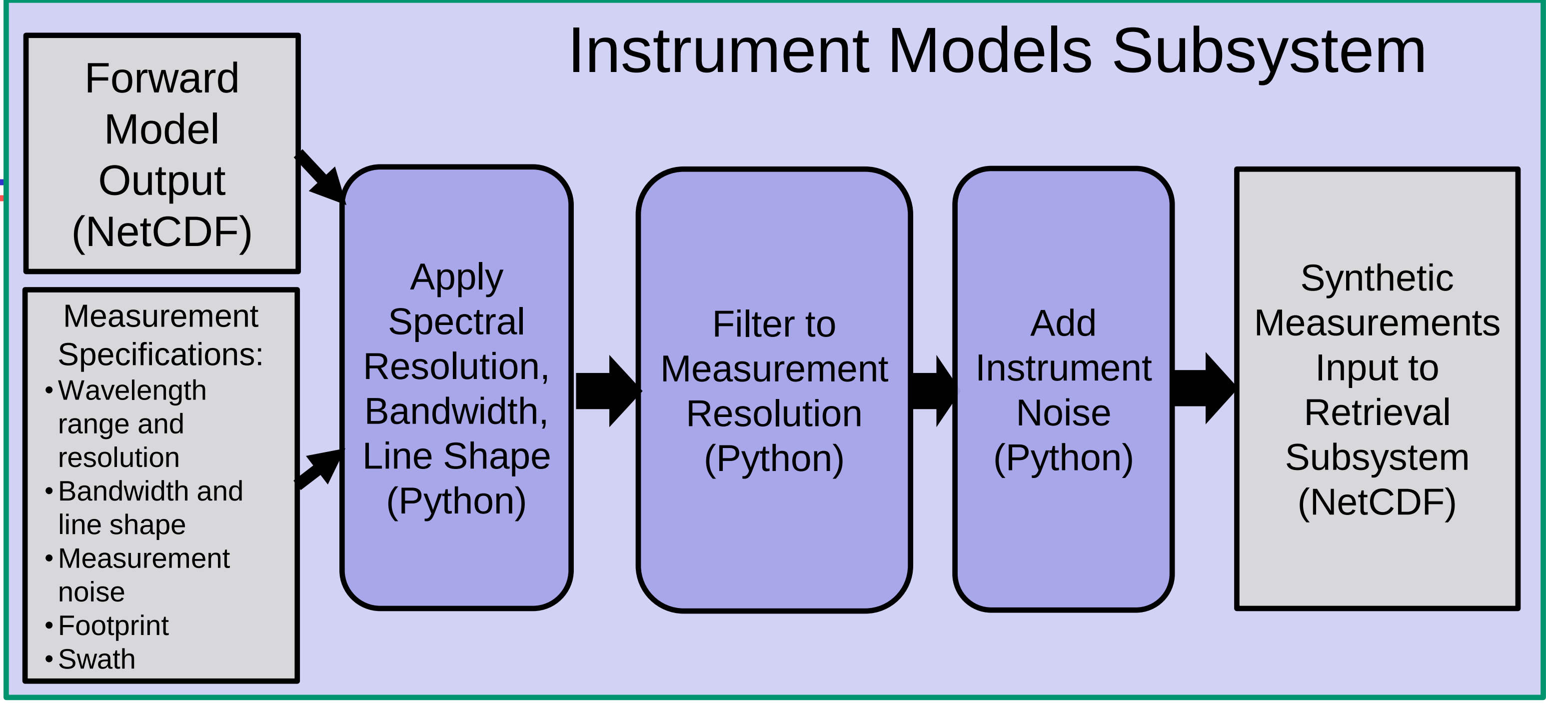
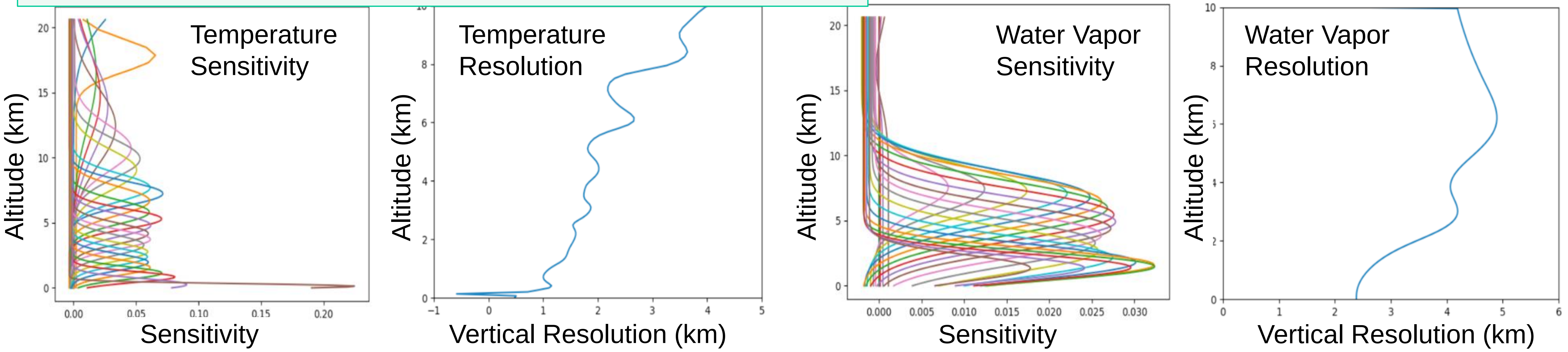
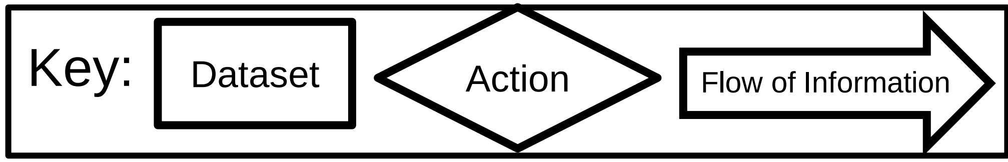
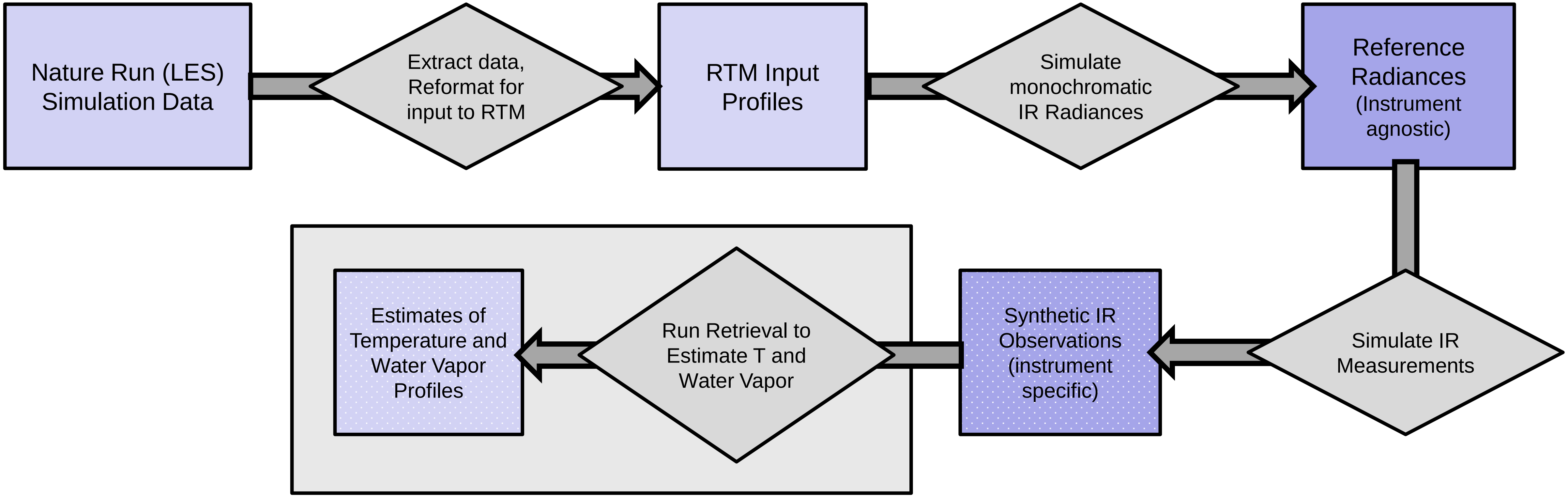


Number and resolution of spectral bands → vertical resolution



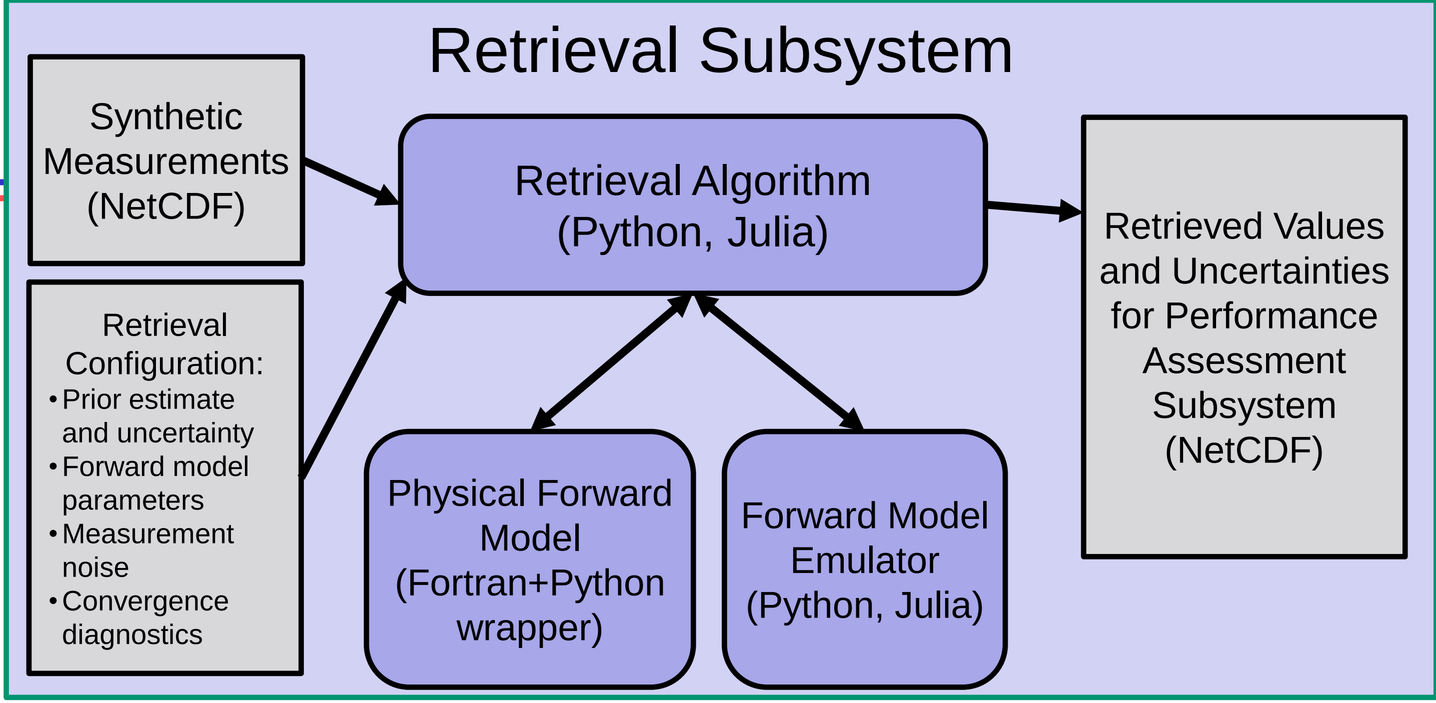
ParOSSE Workflow



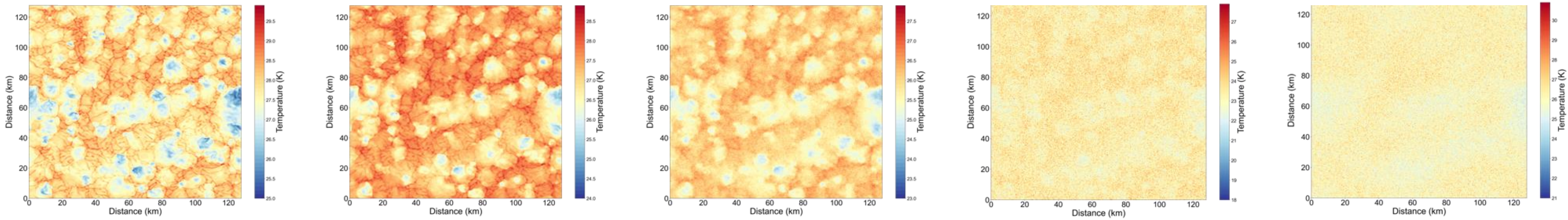


Retrievals Subsystem

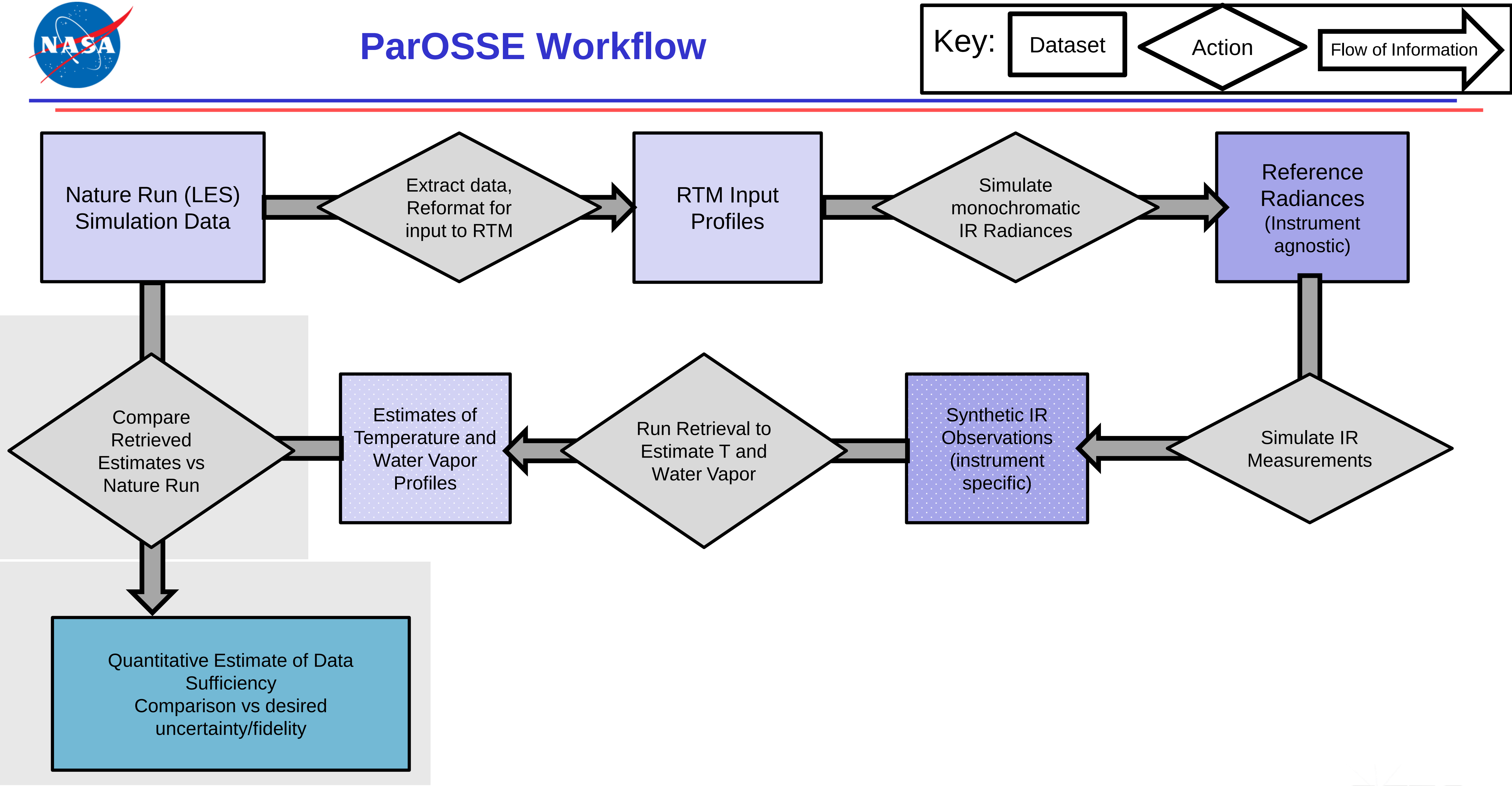
- Ingests synthetic observations
- Uses radiative transfer model to estimate geophysical variables from observations
- Outputs noisy geophysical variables consistent with a real-world retrieval



Nature Run (Reference)	Best Possible with Current Technology 500m dx, 500m dz	Best Feasible Solution (Medium Sat) 1000m dx, 1000m dz	Compact Sensor (Small/Cube Sat) 1000m dx, 2000m dz	Operational (e.g., AIRS) 13000m dx, 1000m dz



ParOSSE Workflow



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Accomplishments

- Configured and validated TAT-C refresh and data latency analysis against existing NOAA JPSS system
- Developed TAT-C method to calculate planar (multi-)polygon coverage regions suitable for clipping historical or nature run data; demonstrated with G5NR
- Established data interface between TAT-C and ParOSSE based on GeoJSON
- ParOSSE comparing retrieval estimates to nature run data from G5NR
- ParOSSE interfacing with CTRM for infrared and microwave instruments

Future Plans

- TAT-C to produce refresh and data latency estimates for future observing systems
  - Initial set (10s) of high-priority concepts informed by NSOSA study results
  - Expanded set (100s) including traditional and radical concepts including small sat constellations
  - Emphasize parallel/distributed processing to enable large tradespace consideration
- ParOSSE to complete tests of synthetic retrievals of thermodynamic profiles
- ParOSSE to produce synthetic retrievals for architectures in TAT-C tradespace
- Package TAT-C + ParOSSE as an ASPEN preprocessor for future use

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Accomplishments / Infusion / Collaboration

Accomplishments:

- ParOSSE aided in a quantitative analysis of measurement sufficiency for the ACCP designated observable study

Infusion / Collaboration:

- Adapting TAT-C+ParOSSE to aid in NOAA’s future mission design studies
- TAT-C+ParOSSE is being used as a core component of a Decadal Survey Incubation (DSI) Planetary Boundary Layer OSSE system
- ParOSSE is accelerating algorithm development for the INCUS EVM-3 mission
- The AOS mission continues to use ParOSSE in algorithm development
- ParOSSE is a component of an AIST ‘21 ACF project (PI: Arlindo da Silva)
- TAT-C is a component of a NIP '20 project (PI: Paul Grogan) and an AIST '21 NOS project (PI: Carrie Vuyovich)

Presentation Contents

- Background and Objectives
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- Publications - List of Acronyms

Publications

None yet to report.

Acronyms

ACCP: Aerosol and Cloud, Convection, and Precipitation

ACF: Analytic Collaborative Framework

AIST: Advance Information Systems Technology

AOS: Atmosphere Observing System

API: Application Programming Interface

ASPEN: Advanced Systems Performance Evaluation tool for NOAA

CRTM: Community Radiative Transfer Model

GEOS: Goddard Earth Observing System

G5NR: GEOS 5 Nature Run

IR: Infrared

JSON: JavaScript Object Notation

LES: Large Eddy Simulation

MW: Microwave

NIP: New Investigator Program

NOAA: National Oceanographic and Atmospheric Administration

NOS: New Observing Strategies

NSOSA: NOAA Satellite Observing System Architecture

SME: Subject Matter Expert

TAT-C: Tradespace Exploration Tool for Constellations

ParOSSE: Parallel Observing System Simulation Experiment

RTM: Radiative Transfer Model

New Observing Strategies Testbed (NOS-T) Design and Development

Paul T. Grogan (PI, Systems Engineering Research Center)

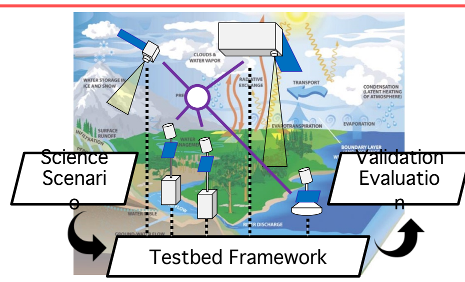
NOS Group Technical Review
Contract No. W15QKN-18-D-0040, Task Order W15QKN20F0551
July 12, 2023

Matthew LeVine, Brian Chell, Harrison Teele, Cameron Conway,
Project Alumni: Jerry Sellers, Hayden Daly, Matthew Brand, Leigha Capra,
Theodore Sherman, Alex Yucra Castaneda
(Systems Engineering Research Center)

New Observing Strategies Testbed (NOS-T) Design and Development

PI: Paul Grogan, Systems Engineering Research Center

Objective:
- Design and develop the NOS-T framework for disparate organizations to propose and participate in developing NOS software and information systems technology capabilities and services
  - Individually validate new NOS technologies
  - Debug and demonstrate novel NOS concepts
  - Compare competing technologies
  - Socialize NOS technologies and concepts
- Identify appropriate NOS-T governance model
- Identify appropriate NOS-T concept of operations



Approach:
- Enterprise system architecting processes
  - Identify and trace value streams for program objectives
  - Model-based systems engineering methods for traceability
- Loosely-coupled information system architecture
  - Achieve nonfunctional requirements such as modularity, extensibility, security, and scalability
  - Provide technical functions such as data distribution, time synchronization, and interoperability
- Engage with Earth Science community to support emerging NOS technologies and scenarios of interest
  - Adopt representative Earth Science use case
  - Demonstrate proposed NOS-T technology for community

Key Milestones:
- Framework Design v1.0: Nov. 8, 2020
  - Initial architecture/governance/operations
  - Development plan
- Framework Architecture v1.0: May 5, 2021
  - Refine requirements
  - Propose architecture
- Framework Development v1.0: Feb. 1, 2022
  - Define representative use case
  - Perform framework demonstration
  - Develop Interface Control Document
- Framework Development v1.1: Aug. 7, 2023

Entry TRL: 2 Current TRL: 4

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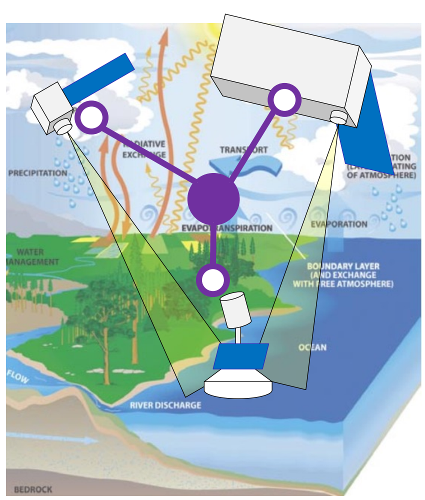
Problem Statement: New Observing Systems (NOS)

NOS encompasses distributed or decentralized observing systems that can:

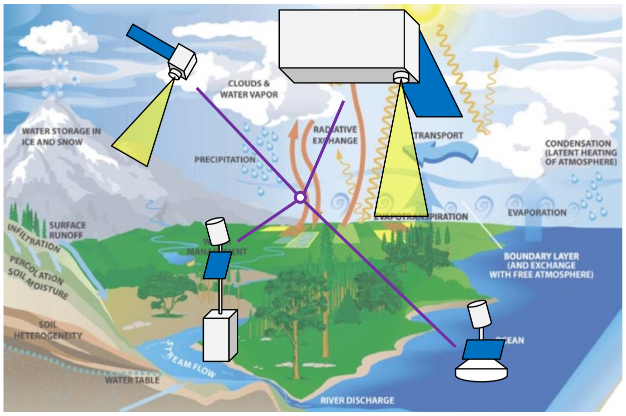
- Optimize measurement acquisition using diverse observing capabilities
- Observe phenomena from different spatial, temporal, and spectral vantage points
- Coordinate observations based on events, forecasts, or science models
- Leverage NASA and non-NASA assets and data



NOS Challenges:

- Compose both existing and future systems into a system-of-systems
- Develop collaborative agreements among partners
- Specify interaction protocols and information interfaces to coordinate operations
- Manage inter-organizational policies and procedures

Background: NOS Testbed (NOS-T)



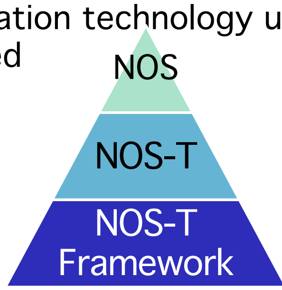
NOS-T provides a virtual testing environment to:

- Validate NOS technologies independently and as a system
- Demonstrate new distributed operational concepts
- Enable comparisons of competing technologies
- Socialize new technologies and concepts with the science community and reduce risk

NOS-T Framework Objectives

The NOS-T Framework provides technical/programmatic guidance to:

- Enable disparate organizations to propose and participate in developing NOS software and information technology using the Testbed



- NOS-T Framework components:
  - Governance and Concept of Operations
  - Technical Architecture and Interfaces
- Iterative development of prototypes to demonstrate NOS-T operation
  - Phase 1 (Aug. 2020 – Feb. 2022)
    - FireSat+ Test Case
    - Realtime Sensor Test Case
    - NOS "Flood" Pilot Case
    - Released version 1.0
  - Phase 2 (Mar. 2022 – Aug. 2023)
    - NOS-Live "Fire/Flood" Pilot Case
    - Extended test cases (ADCS, hardware, etc.)
    - Release version 1.1

NOS-T Framework: Technical Principles

Geographic distribution: user applications interconnect using standard network interfaces

Multi-party participation: user applications exchange limited information via standard messaging protocols

Security: encrypt transport data, provide fine-grain access control rules, monitor hosted infrastructure on authorized information systems

Modularity: loose coupling allows components to be added or updated without modifying the testbed

Extensibility: vary the number or capabilities of user applications to explore a wide range of test cases

Usability: allow members of the Earth science community to develop test cases and user applications without a substantial learning curve

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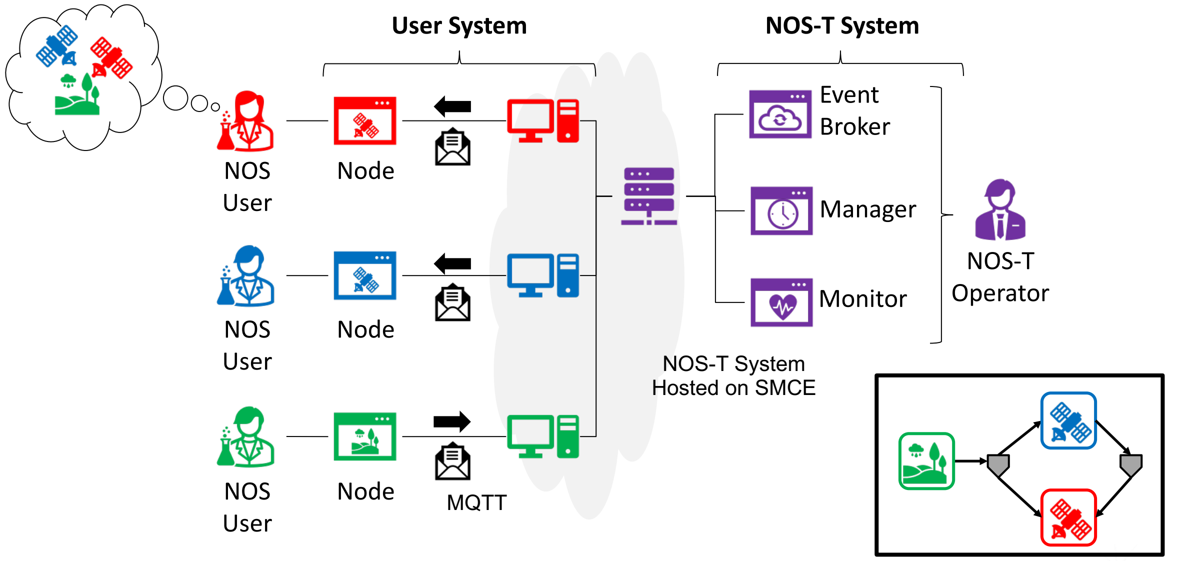
NOS Testbed (NOS-T) Concept and Architecture



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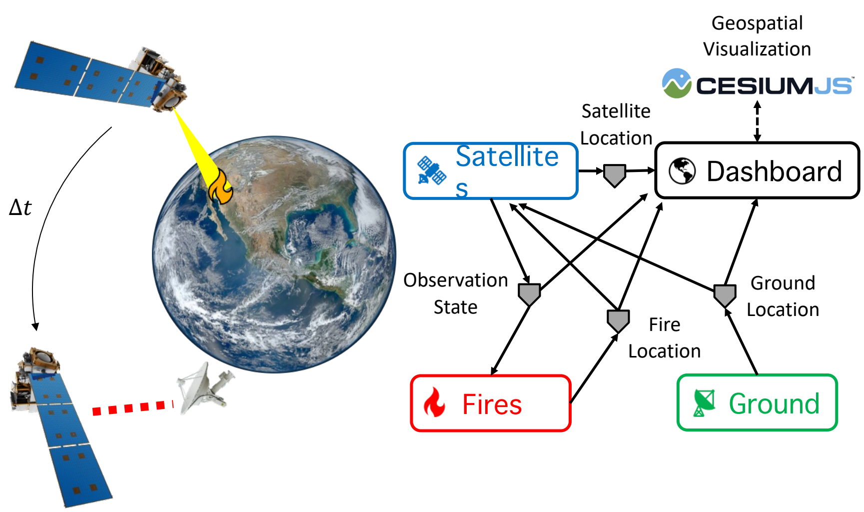
Test Case 1: Satellite Constellation

- Detect and report fire hazards in CONUS
- Initiate fires using 2020 Visible Infrared Imaging Radiometer Suite (VIIRS) data
- Observe fires using a three-satellite constellation
- Downlink observations to ground station
- Evaluate observation latency



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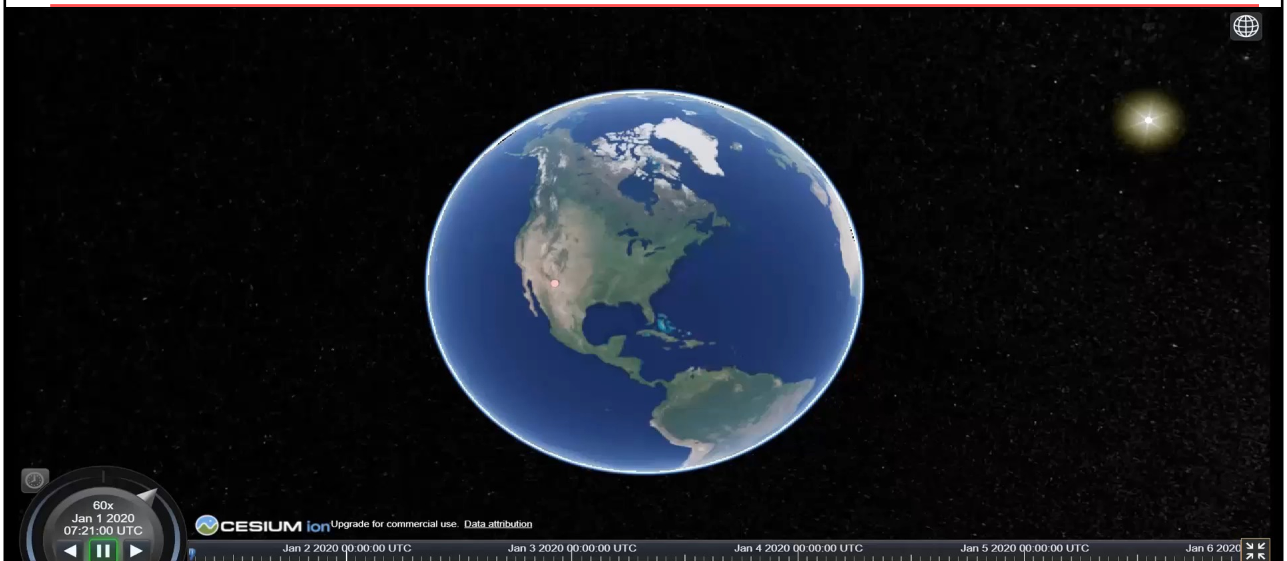
5-day (at 60x Speedup) Scenario; Playback Speed ~90x



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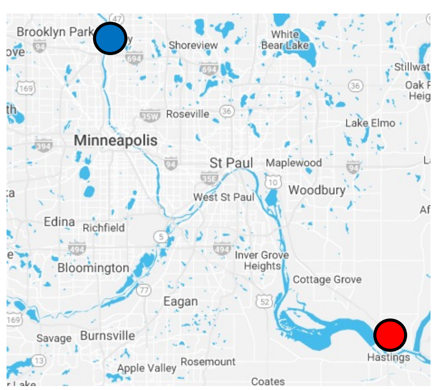
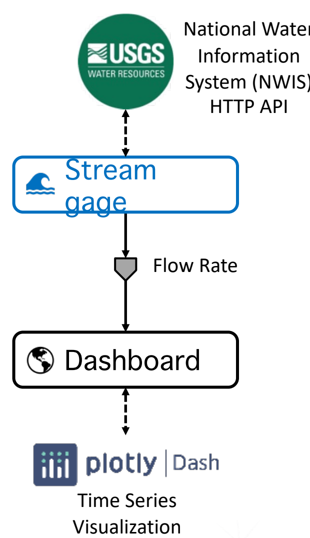
Test Case 2: Real-time Sensor Network

- Retrieve real-time stream gage data from the USGS National Water Information System (NWIS) HTTP API
- Display flow rates from two sensors on a dashboard – Mississippi River above and below Minneapolis/St. Paul
- Demonstrate ability to use real-time data for a test case





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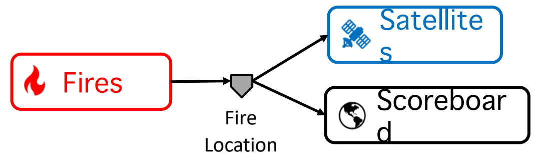
NOS-T Technical Interface

- Events are logical "glue" that couple observing system behavior
  - Modeled at a high level of abstraction: e.g., no physical link considerations
  - Assume applications have a persistent connection to the broker
- Each event type requires:
  - Hierarchical message topic (address)
  - Message payload structure (syntax)
- A data contract identifies:
  - Triggering logic for event publication
  - Subscriber response upon event receipt



- Example topic: **`nost/fires/location`**
  - **`nost`**: test case prefix
  - **`fires`**: application name
  - **`location`**: event label
- Example message payload (JSON encoding):

```
{
  'name': 'Fire',
  'properties': {
    'latitude': 40.742550415161055,
    'longitude': -74.02680374773608,
    'fireStart': '2021-08-10T12:00:00.000Z'
  }
}
```


NOS-T Operating Modes

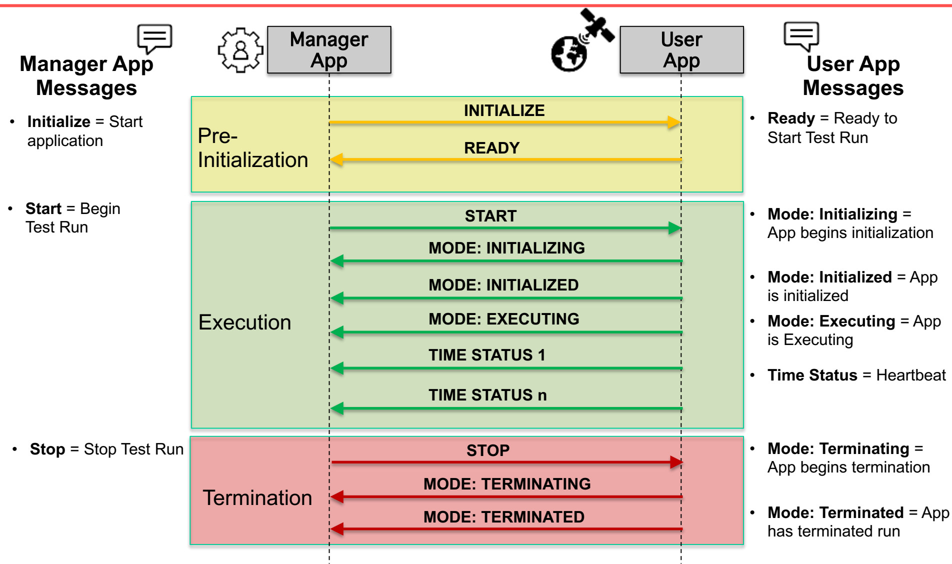
"Unmanaged" (i.e., Live)

- No central orchestration needed
- Applications publish and respond to events in real-time as needed

"Managed" (i.e., Simulation)

- Applications maintain an internal scenario clock synchronized to wall clock (real) time via a scale factor
  - Scale factor = 1: real-time
  - Scale factor > 1: faster-than-real-time
- *Manager* orchestrates test case execution using command messages
  - Initialize, Start, (Update), Stop
- All applications provide feedback using status messages
  - Time, Mode

Managed Application Interface



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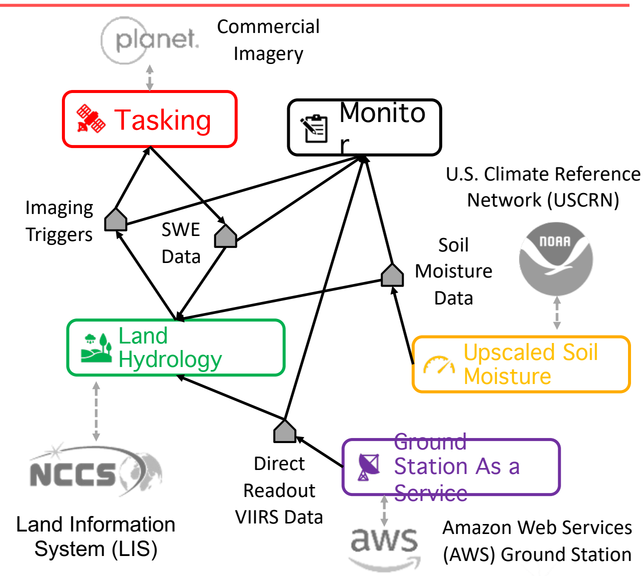
Test Case 3: Coordinated Observations (NOS "Flood")

- Collaborative pilot project (GSFC, LaRC, ARC, JPL, USC/MIT)
- Historical case from March 2019 Missouri River flood (Omaha, NE)
- Assimilate soil moisture and low-latency VIIRS data into Land Information System (LIS)
- Trigger requests for commercial Surface Water Extent (SWE) data



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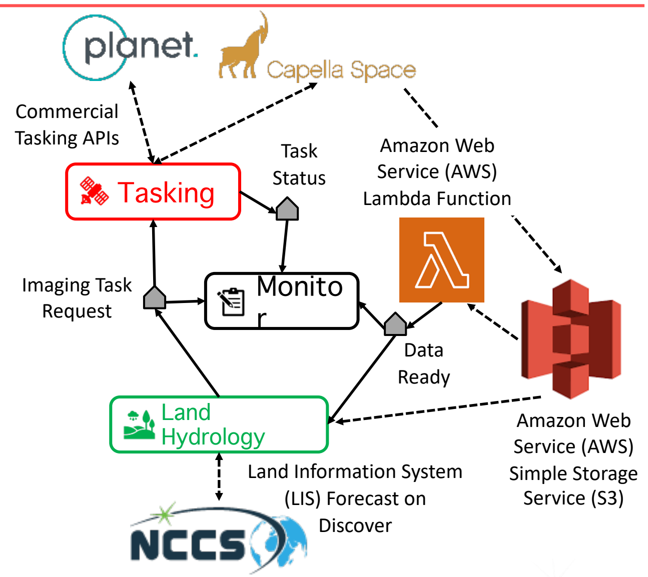
Test Case 4: Commercial Satellite Tasking (NOS-Live "Fire/Flood")

- Collaborative pilot project (UMD, GSFC, JPL, Capella/Planet)
- Forecast land hydrology for flood-prone burned areas and prioritize target areas
- Dynamically task commercial imaging spacecraft to retrieve Surface Water Extent (SWE) data
- Automatically assimilate data into next forecast run



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NOS-T Tools

- Reference NOS-T application implementations in the Python language
- Approved for public release under open-source BSD 3-clause license (Dec. 16, 2021, Reference FY22-005), initial release (v1.0) in Feb. 2022

Simulator: precision timing loop for time-managed applications

Application Template: wrapper for application execution with a time management loop

Managed Application: includes hooks to respond to manager commands during

Manager: orchestrates a managed test case execution

Logger: records (to file) all messages exchanged during a test case execution

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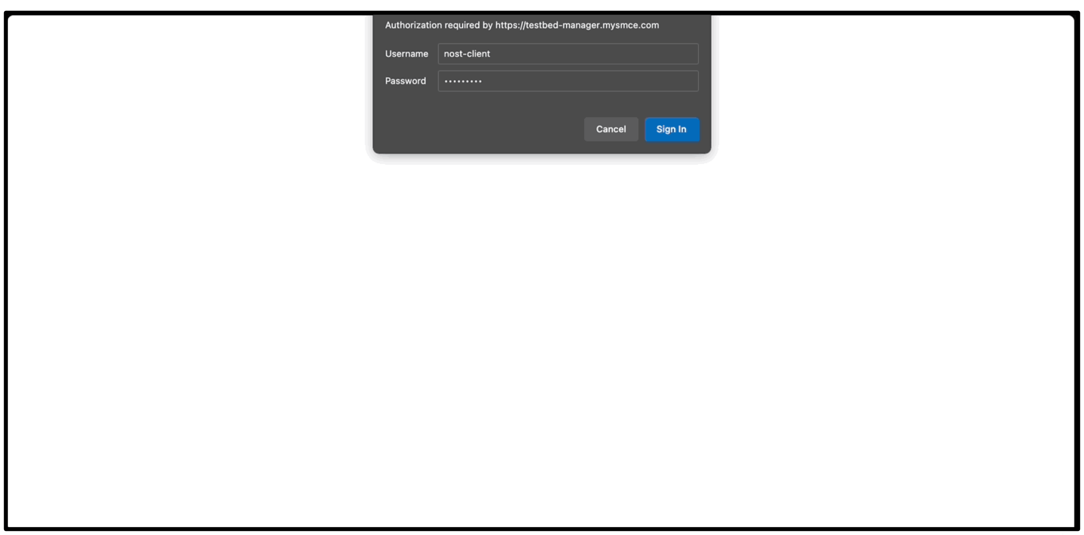
NOS-T Web-Based Monitor

Objective: provide a terminal alternative that utilizes UI web connections to various systems, thereby streamlining and enhancing the overall user experience.

- Key features:
  - Overview: Issues manager commands to initialize/start/stop a test case execution
  - Logs: Real-time access to records directly from the broker for troubleshooting
  - Test Script: Automate execution of manager commands
  - Settings: Configure preferences and parameters
- User Benefits:
  - Effortless monitoring of messages transmitted by the broker
  - Convenient UI to execute manager commands

To be included in version 1.1 release of NOST-Tools

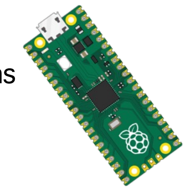
Web-based Monitor Demo



Hardware-in-the-Loop Test Case

Objective: verify NOS-T Framework applicability to hardware-in-the-loop test cases including stress-testing both hardware and software

Hardware Configuration:
- Raspberry Pi 3B+ → Publishes to MQTT & performs strenuous computations
- Raspberry Pico Module → 4x Picos subscribe to MQTT with varying topics



Methodology
- Implement various test cases to determine efficacy of NOS-T Tools
- Pico module and sensors subscribe to MQTT topics and react accordingly (hardware-to-hardware communication)

Problems Encountered
- Power-use optimization: MQTT subscription & MicroPython code draws considerable current for a simple breadboard power supply & 9V → More reliable power supply to be considered
- Some libraries not supported in MicroPython (RPi Picos) → calculations done on RPi 3B+

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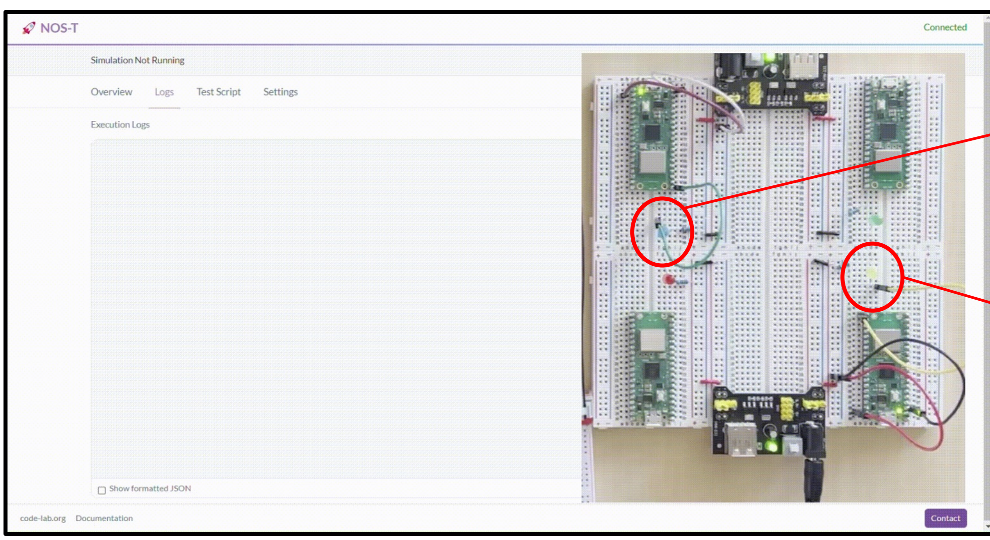
Pico Module Demo



AQUA in view and within range of any ground station

Suomi NPP in view and within range of any ground station

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Summary of Accomplishments

- NOS-T Framework enables participation by disparate organizations
  - Loosely-coupled structure via an event-driven architecture on lightweight MQTT protocol
  - Supports simulated and real-time scenario execution
  - NOS-T infrastructure operating SMCE nearly continuously for more than two years
  - 2 major multi-organization pilot test cases (NOS "Flood" and NOS-Live "Fire/Flood")
  - Demonstrated with variety of software (Python, Cesium.js, React.js) and hardware
- Completed initial release of NOS-T Framework
  - NOS-T Interface Control Document (v1.0, Feb. 2022)
  - Open-source release of NOS-T Tools library with examples
    - GitHub source code repository: https://github.com/code-lab-org/nost-tools
    - ReadTheDocs documentation: https://nost-tools.readthedocs.io/
  - Incremental updates added more examples and improved documentation

Future Plans

- Ongoing progress to close out January 2023 workshop actions:
  - Improve community documentation on open-source site: https://nost-tools.readthedocs.io
  - Provide guidance on "data contracts," common testbed services, debugging common issues, etc.
  - Relax the expectation of persistent system availability
  - Improve testbed authentication and authorization
  - Pursue limited hardware-in-the-loop demo
- Complete NOS-T Framework version 1.1 in August 2023
  - Interface Control Document and governance recommendations
  - Release NOS-T Tools version 1.1 with monitor and expanded examples
- Transition NOS-T capabilities to science test cases

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Infusions and Collaborations

- Infusion:
  - NOS-T technology used in NOS Pilot across SERC-GSFC-JPL-ARC-LaRC-USC
  - NOS-T technology used in NOS-Live Pilot across SERC-GSFC-JPL-UMD-Capella
  - NIP project: Co-simulation for Partnerships to Observe Convective Storm Systems (Grogan)
  - AIST-21 projects proposing NOS-T test cases during optional third year
  - Test Case for Blockchain Distributed Ledger for Space Resource Access Control (Yesha)
- Technology transfer:
  - NOS-T Tools open-source release (BSD license) completed in Jan 2022

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Publications

Conference Papers

P. T. Grogan, H. C. Daly, M. S. Brand, and J. J. Sellers, **"New Observing Strategies Testbed (NOS-T) architecture: Evaluating dynamic response to emergent events,"** in 2021 *IEEE International Geoscience and Remote Sensing Symposium*, Virtual, Online, Jul. 2021. doi: 10.1109/IGARSS47720.2021.9555131

P.T. Grogan, M. LeVine, B. Chell, L. Capra, and J.J. Sellers **"New Observing Strategies Testbed: Co-simulation for Earth science technology demonstration"**, *SISO Simulation Innovation Workshop*, Feb. 2022.

B. Chell, M. J. LeVine, L. Capra, J. J. Sellers, and P. T. Grogan, **"Conceptual design of space missions integrated with real-time, in situ sensors,"** in *Transdisciplinary Engineering 2022: The Future of Engineering*, B. R. Moser, P. Koomsap, and J. Stjepandic, Eds., Advances in Transdisciplinary Engineering, vol. 28, IOS Press, 2022, pp. 350–359. doi: 10.3233/ATDE220664. engrXiv: https://doi.org/10.31224/2408

M. J. LeVine, B. Chell, L. Capra, J. J. Sellers, and P. T. Grogan, **"Planning, implementing, and executing test campaigns with the New Observing Strategies Testbed (NOS-T): The FireSat+ example,"** in *2022 IEEE International Geoscience and Remote Sensing Symposium*, Kuala Lumpur, Malaysia, Jul. 2022. doi: 10.1109/IGARSS46834.2022.9883290

M. Seablom, J. Le Moigne, S. Kumar, B. Forman, and P. Grogan, **"Real-time applications of the NASA Earth Science "New Observing Strategy","** in *2022 IEEE International Geoscience and Remote Sensing Symposium*, Kuala Lumpur, Malaysia, Jul. 2022. doi: 10.1109/IGARSS46834.2022.9883850

B. Smith, S. Kumar, L. Nguyen, T. Chee, J. Mason, S. Chien, C. Frost, R. Akbar, M. Moghaddam, A. Getirana, L. Capra, and P. Grogan, **"Demonstrating a new flood observing strategy on the NOS Testbed,"** in *2022 IEEE International Geoscience and Remote Sensing Symposium*, Kuala Lumpur, Malaysia, Jul. 2022. doi: 10.1109/IGARSS46834.2022.9883411

M. J. LeVine, B. Chell, and P. T. Grogan, **"Leveraging a digital engineering testbed to explore mission resilience for new observing strategies,"** in AIAA SCITECH 2023 Forum, National Harbor, MD, Jan. 2023. doi: 10.2514/6.2023-0257

L. Capra, M. J. LeVine, and P. T. Grogan, **"Demonstration of a utility-based priority algorithm for filtering commercial satellite tasking requests,"** in AIAA SCITECH 2023 Forum, National Harbor, MD, Jan. 2023. doi: 10.2514/6.2023-1501

Journal Articles

B. Chell, M. LeVine, L. Capra, J.J. Sellers, and P.T. Grogan, **"New observing strategies testbed: A digital prototyping platform for distributed space missions,"** *Systems Engineering*, Early View. doi: https://doi.org/10.1002/sys.21672

Presentations

P.T. Grogan, "**New Observing Strategies Testbed (NOS-T) Design and Development**," *12th Annual SERC Sponsor Research Review*, Nov. 18, 2020.

P.T. Grogan, "**Co-Design and Co-Simulation Infrastructure for a New Observing Strategies Testbed**," eLightning Talk, *2020 AGU Fall Meeting*, Dec. 10, 2020.

P.T. Grogan, "**New Observing Strategies Testbed (NOS-T) Design and Development**," *2021 Earth Science Technology Forum*, Jun. 10, 2021.

P.T. Grogan, "**New Observing Strategies Testbed (NOS-T) Design and Development**," *13th Annual SERC Sponsor Research Review*, Nov. 3, 2021.

M.J. LeVine, "**New Observing Strategies Testbed (NOS-T) Design and Development**," *14th Annual SERC Sponsor Research Review*, Nov. 16, 2022.

P.T. Grogan, "**New Observing Strategies Testbed (NOS-T) Design and Development**," *2023 Earth Science Technology Forum*, Jun. 21, 2023.

Acronyms

ACL	Access Control List
ADCS	Attitude Determination and Control System
API	Application Programming Interface
CLI	Command Line Interface
FISMA	Federal Information Security Management Act
GUI	Graphical User Interface
HTTP	Hypertext Transfer Protocol
ICD	Interface Control Document
IoT	Internet of Things
IP	Internet Protocol
ITAR	International Traffic in Arms Regulations
JSON	JavaScript Object Notation
LAN	Local Area Network
MQTT	Message Queuing Telemetry Transport
NOS	New Observing Strategies
NOS-T	New Observing Strategies Testbed
NTP	Network Time Protocol
NWIS	National Water Information System
OS	Operating System
PI	Principal Investigator
RTI	Run-time Infrastructure
SERC	Systems Engineering Research Center
SMCE	Science Managed Cloud Environment
SMF	Solace Message Format
SOA	Service-Oriented Architecture
SSL	Secure Sockets Layer
TLS	Transport Layer Security
UARC	University-Affiliated Research Center
VPC	Virtual Private Cloud
WAN	Wide Area Network

A Path Towards Quantum-Computing-Assisted Earth Science Data Acquisition Tasking and Processing

PI: Shon Grabbe, NASA Ames Code TI
Co-I: Andrew Michaelis, NASA Ames Code TN
Co-I: Taejin Park, NASA Ames Code SGE
Co-I: Eleanor Rieffel, NASA Ames Code TI

AIST-21-0102 Annual Technical Review
July 12, 2023

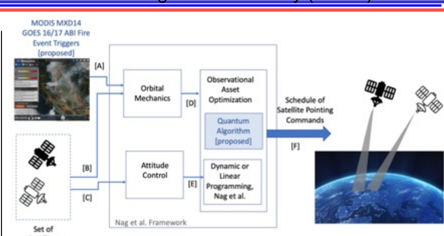
NASA Ames Earth Science Team Members: Hirofumi Hashimoto
NASA Quantum Artificial Intelligence Laboratory (QuAIL) Team Members:
Lucas Brady and Zoe Gonzalez Izquierdo
NASA Ames Program Analyst: Oscar Rivas

A Path Towards Quantum-Computing-Assisted Earth Science Data Acquisition Tasking and Processing

PI: Dr. Shon Grabbe, NASA Ames Quantum Artificial Intelligence Laboratory (QuAIL)

Objective

- Earth science research at NASA faces numerous computational challenges such as acquiring, analyzing, compressing, and interpreting the massive amounts of earth science data NASA collects
- Quantum computing has the potential to revolutionize computing, although it is currently in a low TRL stage
- The objective of our Early-Stage Technology (EST) effort is focused on the following Earth Science enabling activities: (1) identifying actionable wildfire event triggers and (2) optimizing data acquisition tasking
- This proposal will support NASA in being 'quantum-ready', develop valuable know-how on how and when to deploy quantum technologies on real, large-scale problems of interest to NASA's Earth Science Research Program



Modular framework proposed by Nag. et al (2018) and funded by AIST with our proposed MODIS MXD14 and GOES16/17 fire product triggers (top left) and a quantum algorithm for observational asset optimization (center, blue shaded box)

Approach

We present a two-pronged approach for supporting new observing systems design and observation to enable agile science investigation by

- Filter wildfire events into actionable triggers from Earth Science datasets
- Allocating Earth Science observational assets to collect observations so future datasets are complete

Co-Is/Partners: Andrew Michaelis, Dr. Taijin Park, Dr. Eleanor Rieffel, ARC

Key Milestones

• Initial database of fire events	11/22
• Initial benchmark problems	12/22
• Implement/test basic quantum algorithm	02/23
• Refined database of fire events	03/23
• Iterate design of quantum algorithm	07/23
• Analysis of quantum algorithm	09/23

TRL_{in} = 1 TRL_{curr} = 2

Team Members

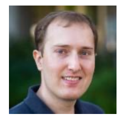
Hirofumi (Hiro) Hashimoto, Earth Scientist,
Role: GOES16/17 Advanced Baseline Imager (ABI) expert

Zoe Gonzalez Izquierdo, Research Scientist,
Role: quantum algorithm development and testing

Eleanor Rieffel, Co-I, Senior Research Scientist, QuAIL Lead, Role: Quantum computing lead

Andy Michaelis, Co-I, HPC Engineer/Earth Science support,
Role: High-performance computing and data management/munging support, general advisor

Taejin Park, Co-I, Earth Scientist,
Role: MODIS fire data production and improvement



Lucas Brady, Research Scientist,
Role: quantum algorithms development and testing

Shon Grabbe, PI, Research Scientist
Role: overall management and reporting and support quantum algorithm development and testing

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Background and Objectives

Technology and Science Gaps:
- Technology gap for identifying actionable event triggers from Earth Science datasets (wildfire focus)
- Technology gap for allocating the observational assets to collect observations so future datasets are more complete

Objectives:
- Coordinate a distributed set of sensing systems to maximize pertinent observations in space and time given a set of actionable event triggers, while minimizing any disruptions in the observing systems' expected day to day continuous acquisition requirements
- Support NASA in being 'quantum-ready', develop valuable know-how on how and when to deploy quantum technologies on real, large-scale problems of interest to NASA's Earth Science Research Program

Background and Objectives

How this project helps meet the R&A and Application science goals or cross cutting science areas your project supports:

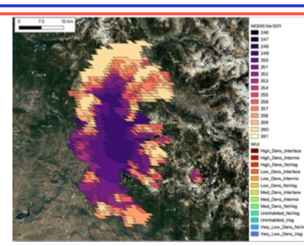
Science Area	How our project helps
Fires	Proposed work seeks to improve the frequency, quality, and timeliness of observations during fires
Disasters	The work has relevance in any area where anomalous events could require observing systems to focus on where the abnormal event occurred, study impacts, predict event evolution, and research any associated scientific processes.
Health and Air Quality	Improved observations can help inform research focused on air quality standards
Atmospheric Composition	Improving the frequency, quality and timeliness of observations can provide better inputs to research on the composition of Earth's atmosphere
Carbon Cycle	Helps improve inputs to studies dealing with the cycling of carbon in reservoirs and ecosystems
Climate Variability	Helps improve observational data sets used for climate variability studies

Presentation Contents

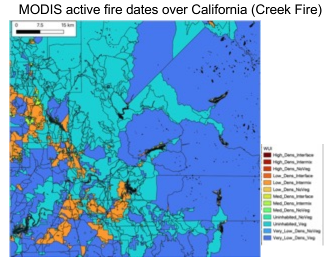
- Background and Objectives
- Technical and Science Advancements
- Summary of Accomplishments and Future Plans
- Actual or Potential Infusions and Collaborations
- Publications - List of Acronyms

Technical and Science Advancements

- Developing an actionable trigger library from historical and near-real time Earth Observations
  - Used existing fire products (MXD14) from Terra and Aqua MODIS sensors
  - FireTracks algorithm ingests MXD14 and creates start and end dates, and vectorized perimeters of historical fires
  - Vectorized historical fires and Wildland Urban Interface (WUI) data over California from 2020/07/19 through 2020/09/28 being used for initial quantum algorithm development and testing.
  - For near-real time actional wildfire triggers, leveraging current ongoing efforts in the NASA NEX group developing hyper-temporal earth observation datasets from operation GEO satellites



MODIS active fire dates over California (Creek Fire)



WUI classification over California

Sample WUI and active fire progression dates over California from both Terra and Aqua MODIS observations (MOD14A1 & MYD14A1).

"FireTracks" algorithm (https://github.com/dominiktraxl/firetracks)

Technical and Science Advancements

Work extends the model of [STO20] to a constellation of satellites.

1. Map problem to QUBO

(Quadratic Unconstrained Binary Optimization)

BINARY VARIABLES

$$x_{r,i,j} = \begin{cases} 1 & \text{if acquisition request } r \text{ captures the selection at imaging attempt } i \text{ by satellite } j \\ 0 & \text{otherwise} \end{cases}$$

COST FUNCTION

Minimize the total cost of the mission plan

$$-\sum_{r\in R}\sum_{i\in I_r}\sum_{j\in S} w_{r,i,j}x_{r,i,j}$$

PENALTY TERMS

- An acquisition attempt should be met at most once.
- Sufficient time to maneuver must be allowed between image acquisition attempts

2. Minimize cost function + penalties

[STO20] T. Stollenwerk, V. Michaud, E. Lobe, M. Picard, A. Basermann, T. Botter, Image Acquisition Planning for Earth Observation Satellites with a Quantum Annealer, IEEE Transactions on Aerospace and Electronic Systems, Vol. 57, No. 5, pp. 3250-3528 (2021) and arXiv:2006.09724 (2020)

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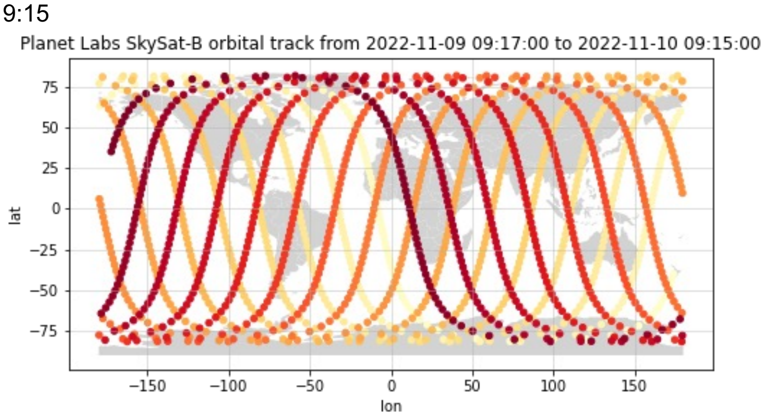
Summary of Current State

- Quantum algorithm to be demonstrated using one or more satellites in Low Earth Orbit (LEO)
  - Initial work to consider a single satellite followed by a constellation of satellites
- Initial testing has utilized Planet Lab's SkySat [SKY22a] satellites to provide representative orbital tracks
- Pitch and roll of SkySats will be varied for benchmark problem set development to explore the effects of varying the field of view (FOV)
- SkySat background [SKY22b]:
  - Constellation of 21 satellites with sub-meter resolution (72 cm) [L3Harris]
  - Approx. 80 cm long and weigh roughly 100-264 kg
  - Swath width: 5.5-8 km at nadir
  - Revisit time of 4-5 days with reference altitude of 500 km
- SkySat orbital tracks derived from NASA's Navigation and Ancillary Information facility (NAIF) SPICE (Spacecraft Planet Instrument C-matrix Events) framework [NAIF] using two-line elements (TLE) datasets

[SKY22a] Planet Labs SkySat [https://www.planet.com/products/hi-res-monitoring/]
[SKY22b] SkySat Instruments [https://earth.esa.int/eogateway/missions/skysat]
[L3Harris] https://www.l3harrisgeospatial.com/Data-Imagery/Satellite-Imagery/High-Resolution/SkySat
[NAIF] https://naif.jpl.nasa.gov/naif/toolkit.html

Summary of Current State

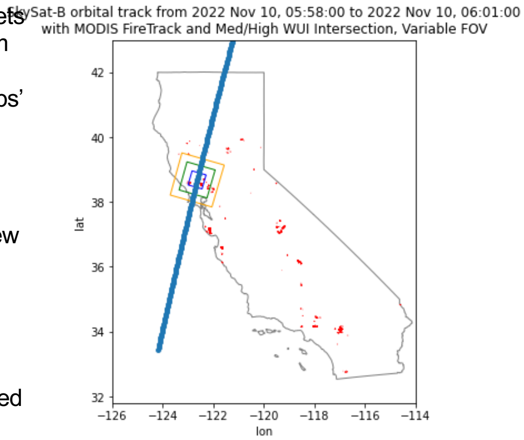
Sample SkySat-B orbital tracks from Nov. 9, 2022 @ 9:17 to Nov. 10, 2022 @ 9:15



Data points are orbital tracks in one-minute increments generated from SPICE using the TLE (two-line element) dataset for SkySat-B. Color coding used to show changes in time. Light yellow points are closer to Nov. 9, 2022 @ 9:17 and dark red points are closer to Nov. 10, 2022 @ 09:15

Summary of Current State

- For the initial benchmark problem sets being developed to test the quantum algorithm,
  - Orbital tracks for the Planet Labs' SkySat-B satellite on Nov. 10, 2022 used
  - Variations in the satellites pitch and roll abilities considering by varying the satellites field of view (FOV)
  - FOV values of 50x50km, 100x100km, and 150x150km considered
- Distortion associated with image acquisition off-nadir can be accounted for in the 'value' assigned to a potential image acquisition target
  - Acquisition targets closer to nadir can have higher values and less distortion, and vice versa



Data points are orbital tracks in in one-second increments for SkySat-B on Nov. 10, 2022. Red filled polygons are the intersection of MODIS FireTracks data from July 19 – Sept 28, 2020 with the WUI med/high data. Black, green, and orange rectangles are the notional field of view (FOV) centered about the position of SkySat-B on Nov. 10, 2022 at 5:59:44 with dimensions of 50x50km, 100x100km, and 150x150km, respectively.

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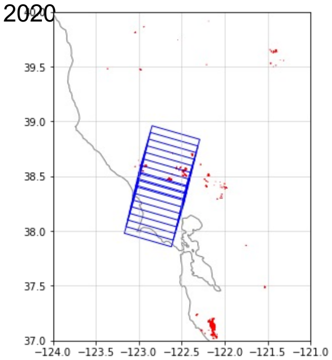
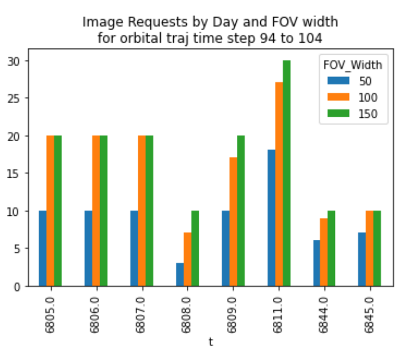
Summary of Current State

Sample image acquisition statistics for a 10 second snapshot of the SkySat-B satellite with a variable FOV starting starting at Nov. 10, 2022 at 5:59:34 with MODIS FireTracks data from Aug 19-23, Aug. 25, and Sept. 27-28, 2020



Blue rectangles are 50x50km FOV polygons drawn every one second along the SkySat-B orbital track starting at Nov. 10, 2022 @ 5:59:34. Red polygons are the intersection of the sample MODIS FireTracks data with WUI



Potential image acquisition opportunities along the SkySat-B orbital track starting on Nov. 10, 2022 @ 5:59:34 for MODIS FireTrack data on Aug. 19-23, 2020 (days 6805-6809), Aug. 25, 2020 (day 6811), and Sept. 27-28, 2020 (days 6844-6845). FOV dimensions of 50x50km, 100x100km, and 150x150km shown in blue, orange, and green respectively

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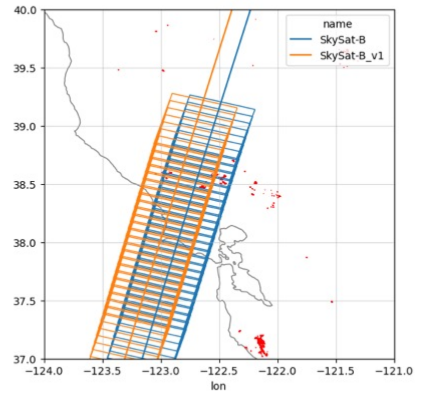
Summary of Current State

- Initial work extending the benchmark problem sets to include a constellation entails,
  - Use of original orbital tracks for the Planet Labs' SkySat-B satellite on Nov. 10, 2022.
  - Addition of replicated orbital tracks for 'SkySat-B_v1' -- offset by 0.5^{o} in latitude from the original orbital tracks.
  - Variations in the satellites pitch and roll abilities considering by varying the satellites field of view (FOV)
  - FOV values of 50x50km, 100x100km, and 150x150km considered
- Satellite constellation being developed to generate computationally challenging satellite scheduling problems, not necessarily realistic constellations



Lines are orbital tracks in in one-second increments for SkySat-B on Nov. 10, 2022 (blue line) and an artificial SkySat-B satellite offset 0.5 degrees in latitude (orange line). Red filled polygons are the intersection of MODIS FireTracks data from July 19 – Sept 28, 2020 with the WUI med/high data. Rectangles are the notional field of view (FOV) centered about the position of the satellites Nov. 10, 2022 at 5:59:44

Summary of Future Plans

Characterization of Wildfire Triggers

- Improve detected fire events to avoid cloud cover interruptions
- Continue efforts to overlay WUI on detected fire events to find more important fires.
- Share the produced individual fire information with collaborators to investigate historical fire spread and duration patterns.
- Host the produced individual fire information in an accessible repository

Refinement and testing of quantum algorithms for allocating observation assets

- Complete development of benchmark problems to include elements, such as:
- Refine problem aspects related to satellite maneuvering
- Refine and test quantum algorithm solvers
- Run all the algorithms on a larger range of appropriately chosen test cases to gauge relative performance

Develop manuscript once analysis of quantum algorithm is compled.

Presentation Contents

Actual or Potential Infusions, Collaborations, and Publications

Summary of actual or potential collaborations

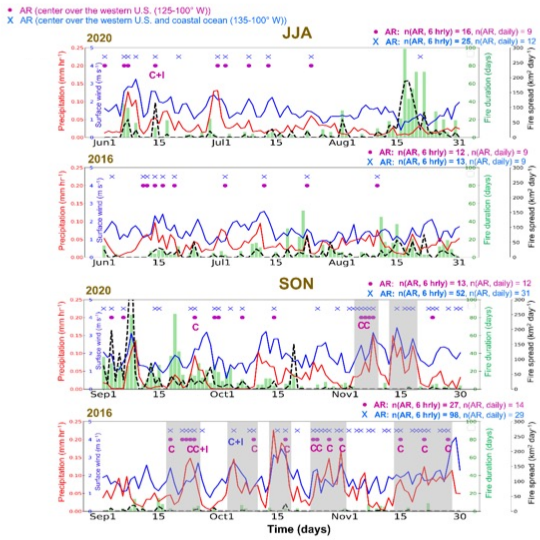
- Investigating fire spread and duration changes under varying atmospheric conditions (Collaboration with NASA ARC SGG)

Journal / Conference Papers

- Ryoo, J.M. and Park, T., 2023. Contrasting characteristics of atmospheric rivers and their impacts on 2016 and 2020 wildfire seasons over the western United States. Environmental Research Letters. https://doi.org/10.1088/1748-9326/acd948
- Ryoo, J.M. and Park, T., 2022, December. Characterizing Seasonal Atmospheric Rivers, Climate, and Wildfire Patterns over the Western United States. In AGU Fall Meeting Abstracts (Vol. 2022, pp. NH44F-01).

- *Plans to develop manuscript once analysis of quantum algorithm is complete*

Actual Collaboration



- Developed fire perimeters from FireTracks algorithm and MODIS data over the western U.S. were used to track fire duration and spread rate of individual fires.
- Collaborative investigation with the Atmospheric science branch examines how historical Atmospheric River (AR) and daily fire spread have interacted.
- Strong fire suppression with wet & windy ARs but promotion with dry & windy ARs

[Ryoo and Park, Contrasting characteristics of atmospheric rivers and their impacts on 2016 and 2020 wildfire seasons over the western United States, Environmental Research Letters (2023)

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List of Acronyms

ABI	Advanced Baseline Imager
AR	Atmospheric River
FOV	Field of View
GEO	Geostationary Orbit
JJA	June, July, August; hereafter Summer
NAIF	Navigation and Ancillary Information Facility
NEX	NASA Earth Exchange
QAOA	Quantum Approximate Optimization Algorithm
QuAIL	Quantum Artificial Intelligence Laboratory
QUBO	Quadratic Unconstrained Binary Optimization
R-QAOA	Recursive - Quantum Approximate Optimization Algorithm
SMAP	Soil Moisture Active Passive
SON	September, October, and November; hereafter Fall
SPICE	Spacecraft Planet Instrument C-matrix Events
WUI	Wildland-urban interface
MODIS	Moderate Resolution Imaging Spectroradiometer
VIIRS	Visible Infrared Imaging Radiometer Suite
FIRMS	Fire Information for Resource Management System (NASA)

UNIVERSITY OF MIAMI
INSTITUTE for DATA SCIENCE & COMPUTING

enabling DISCOVERY

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Blockchain Distributed Ledger for Space Resource Access Control

Dr. Yelena Yesha
Knight Foundation Endowed Chair of Data Science and AI
Director, IDSC AI + Machine Learning
IDSC Innovation Officer and Head, International Relations
Professor, Department of Computer Science, College of Arts and Science
Professor, Department of Radiology, Miller School of Medicine
Founding Director, NSF CARTA

IDSC Team
Stephen Dennis, Phuong Nguyen, Yusen Wu

MIAMI IDSC

Overall Goals

- Implement a permissioned blockchain network to enable zero-trust cybersecurity protection for data access and message exchange in the New Observing Strategies Testbed (NOS-T)
- Evaluate a publish-subscribe interface protocol to exchange messages among member applications as components of an Earth Observing (EO) system.
- Implement a secure instrument registration and access control overlay in NOS-T using permissioned blockchain.
- Collaborate with the NOS-T team for system integration
- Perform a test case execution either for an emergent event or PBL dynamics for at least two components of a decentralized EO system.

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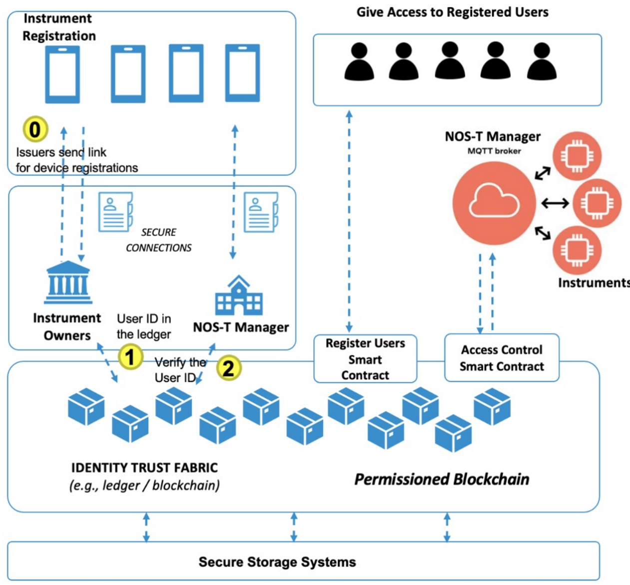
Architecture



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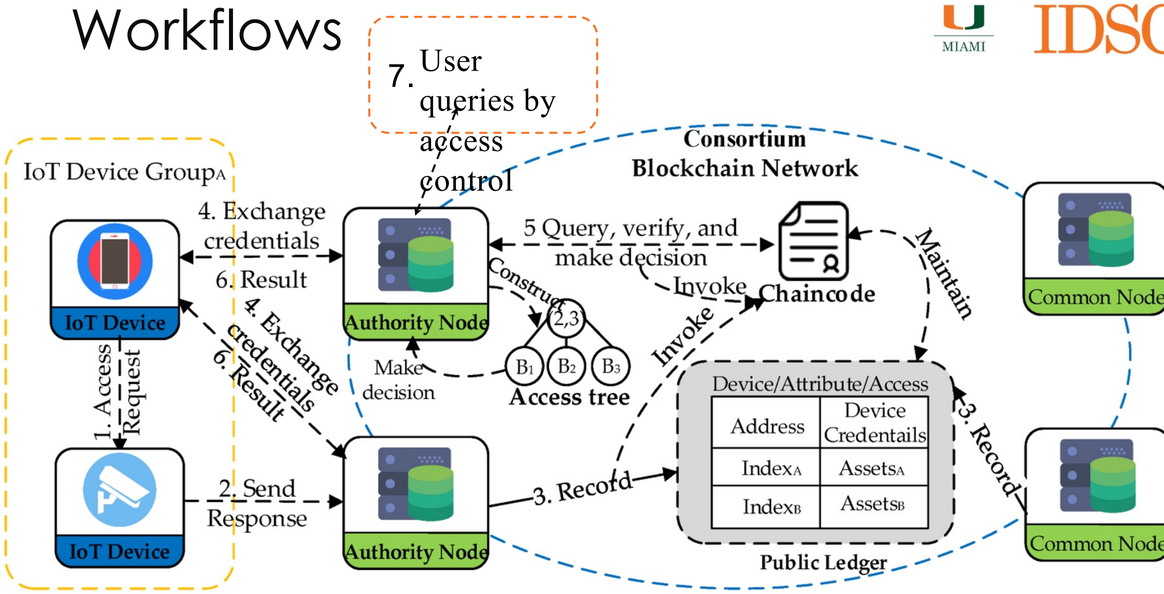
Workflows



Address	Device Credentails
IndexA	AssetsA
IndexB	AssetsB

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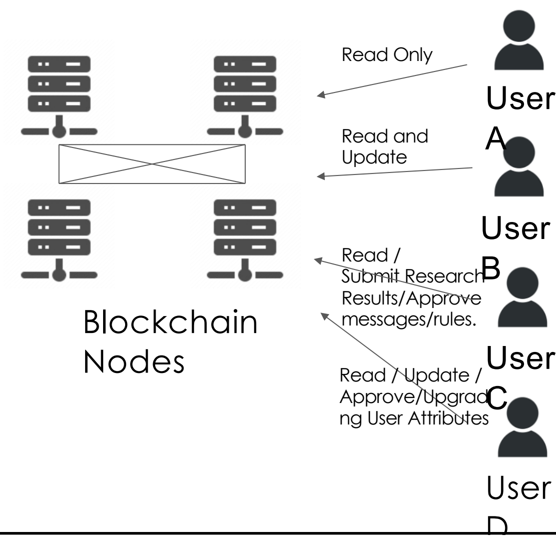
Role Based Access Control



Role-Attribute: *Guests*

Role-Attribute: *Regular Users/Apps*

Role-Attribute: *NOS-T Operators*

Role-Attribute: *NOS-T PIs/Researchers*

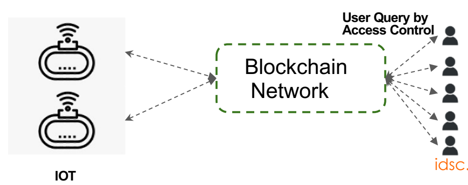
API Functions

API	VARIABLES
1. Instrument Registration	*Unique Instrument Identity*
2. User Registration	*User Email, Telephone Number…*
3. Provenance Tracking	*Blockchain Identifier (API #1)* *Datatype (instrument datatype name for the survey)* *Fields (list of fields entered)* *Datetime (moment in time for the transaction)*
4. Instrument Validation	*Blockchain Identifier (API #1)*
5. User Access Revocation	*Blockchain Identifier (API #1)* *User Identifier (API #2)*
6. Transaction history	*Blockchain Identifier (API #1)* *User Identifier (API #2)*

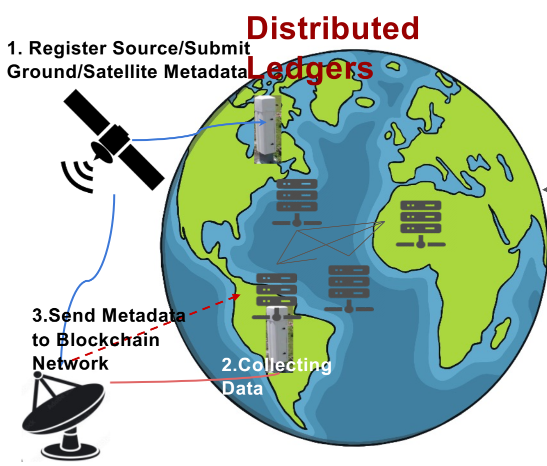
Use case: smoke events observe, forecast, and alert smoke from wildfires using ceilometer, satellite, model

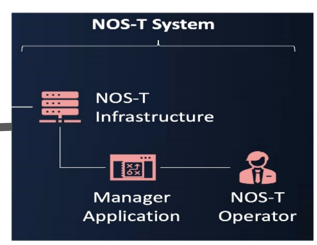
- From space, satellites (GOES-16) have features that detect smoke plumes from above, but when the smoke is concealed, or underneath the clouds, the challenge to observe smoke becomes difficult to impossible

- The ceilometer (CEIL), a ground instrument that measures cloud height,



Use Case: Smoke Events Caused by Wildfires





Example Mission Functions
- Environment: Models fire ignition and growth
- Ground Station: Models ground station operation
- Satellite: Models orbit propagation and detection
- Adjudicator: NOS-T Queries distributed ledger for metadata and access controls

Example Technical Functions
- *Register/Collect metadata from Instruments*
- *Send Metadata to Blockchain, Query By Device ID*
- *Access Controls and Integration with NOS-T MQTT*

Key Milestones

- Implement instrument registration 06/23
- Start a blockchain network 07/23
- Implement access control rules 09/23
- Register and test two instruments 12/23
- Integrate with NOS-T 02/24
- Perform a test case with NOS-T 03/24
- Evaluation the system performance 05/24

A New Snow Observing Strategy in Support of Hydrological Science and Applications

Carrie Vuyovich (PI, NASA GSFC)

Sujay Kumar (Co-I, NASA GSFC); Batuhan Osmanoglu (Co-I, NASA GSFC); Mark Carroll (Co-I, NASA GSFC); Paul Grogan (Co-I; Stevens Institute of Technology); Kwo-Sen Kuo (Co-I, Bayesics LLC); Michael Rilee (Co-I, Bayesics LLC); Ethan Gutmann (Co-I, NCAR)

AIST-21-2-0055 Annual Technical Review

12 July 2023

SOS Team Members: Bob Rosenberg (NASA GSFC), **Mike Bauer** (Bayesics LLC)**, Dai-Hai Ton That** (Bayesics LLC)**, Niklas Griessbaum** (Bayesics LLC), **Eunsang Cho**, (UMD, NASA GSFC), **Jaime Bardaji**, (Stevens Institute), **Josue Tapia** (Stevens Institute), **Ross Mower** (NCAR, University of Washington), **Anam Bayazid** (Stevens Institute)

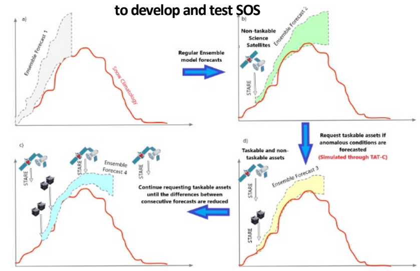
A New Snow Observing Strategy in Support of Hydrological Science and Applications

PI: Carrie Vuyovich / GSFC

Objective

- Design a Snow Observing Strategy (SOS), that responds to the dynamic nature of seasonal terrestrial snow and focuses on regions of interest in a timely, efficient manner
- Develop capability to support rapid analysis and ingestion of snow data from multiple sources
- Incorporate logic for designing and operating optimized snow observations in a distributed mission configuration
- Demonstrate the observing strategy for a relevant use case using the New Observing Strategies Testbed

Workflow of hypothetical experiment to develop and test SOS



Approach

Design new snow observing strategy:

1. Define snow observation metrics through a global snow evolution and coverage analysis
2. Simulate new space-based snow observations using TAT-C and introduce logic to evolve observations strategy seasonally
3. Harmonize geospatial data for snow with STARE and develop I/O integration with LIS
4. Develop a hypothetical experiment designed to demonstrate value of SOS to hydrological science questions and applications
5. Demonstrate SOS for relevant use cases

Co-Is/Partners: S. Kumar (GSFC), B. Osmanoglu (GSFC), M. Carroll (GSFC), P. Grogan (Stevens Institute), K. Kuo (Bayesics LLC), M. Rilee (Bayesics LLC), E. Gutmann (UCAR)

Key Milestones

- Global maps of monthly observational snow needs 02/23
- Prototype data ingestion into LIS 08/23
- SOS assets stored in TAT-C Knowledge Base 11/23
- Prototype observing strategy for relevant use case 05/24
- Validation in relevant environment (NOS-T, Year 3) 05/25

TRL_{in} = 3 $TRL_{current}$ = 4

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Background / Objectives

- Research and Applications science goals for the specific or cross cutting science area your project supports
  - **Water & Energy, Jared Entin**; **Disasters, Shanna McClain**; **Water & Food, Brad Doorn**
- This project will help address science questions related to water and energy and the impact of snow on related applications, such as water resource availability and disasters
- Understanding of how climate change will impact regional water management practices is a stated science goal in the most recent NASA Science Plan, *Science 2020-2024: A Vision for Scientific Excellence*. Well documented changes to the seasonal snowpack will affect prediction capability based on historical information.
- This work is well-aligned with NASA SnowEx campaign, a multi-year field and airborne campaign to test different remote sensing techniques in various landscapes and snow climates (Durand et al. 2019). Data collected during recent and upcoming campaigns can be used to validate the model results.
- SOS could be used to inform future snow mission on optimal orbital configuration, and temporal and spatial coverage to address science and application goals.
- SOS can also inform an optimal commercial satellite tasking approach for snow observations

Why do we need a snow observing strategy?

Seasonal snow is an ideal candidate for an optimized observational strategy that focuses on monitoring at the most critical times and areas to provide cost-effective and robust information.

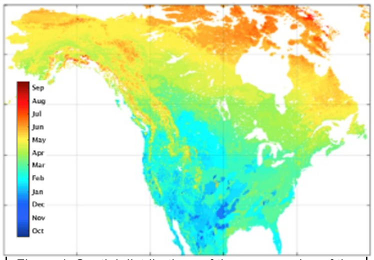


Figure 1: Spatial distributions of the average day of the year when the peak SWE occurs in North America, showing how it shifts in latitude and elevation throughout the season (adapted from Kim et al. 2021)

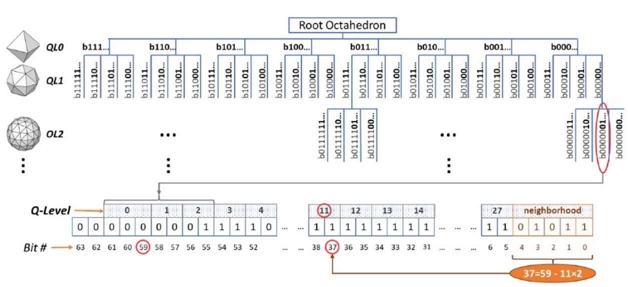
The goal of this proposed work is to design a Snow Observing Strategy (SOS), targeting observations (e.g. peak SWE and the onset of melt) with the greatest impact to hydrological metrics as they occur in different regions.

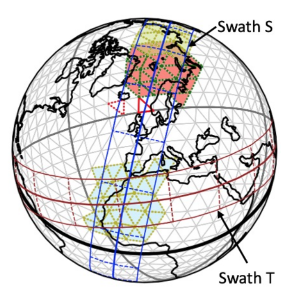
Hydrological science and application questions:

1. What is the optimal combination and timing of snow observations for constraining snow processes in hydrologic, ecologic and Earth System predictive models?
2. How do snow observation requirements evolve throughout the season to capture snow accumulation and melt processes?
3. What snow observations are needed for predicting and mitigating snow-related events and disasters?

SpatioTemporal Adaptive-Resolution Encoding (STARE)

- STARE is a highly efficient spatio-temporal encoding scheme that supports the combination of diverse data for integrative analysis
  - well suited to handle data related to phenomena with dynamic, temporally- and spatially-varying extents
  - flexible foundation for cross-dataset comparisons
  - provides a universal way to index geoscience data
  - minimizes costly data transfers
- STARE API is available and will be expanded to work with target applications, e.g. LIS

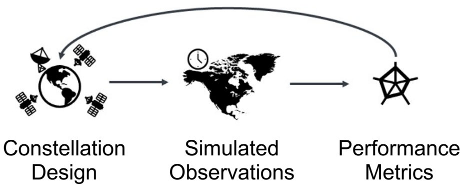


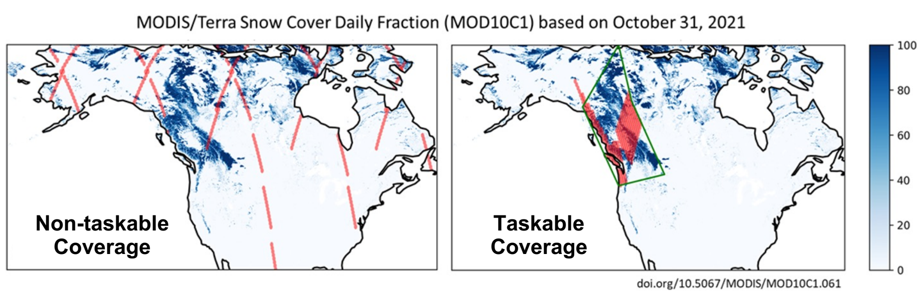


The bit pattern of STARE Hierarchical Triangular Mesh (HTM) spatial encoding

Tradespace Analysis Tool for Constellations (TAT-C)

- TAT-C is a space mission analysis tool for pre-Phase A concept development focused on constellation-style architectures
  - Model constellations
  - Simulate observations
  - Evaluate performance metrics
- Python library and parallel task-worker application





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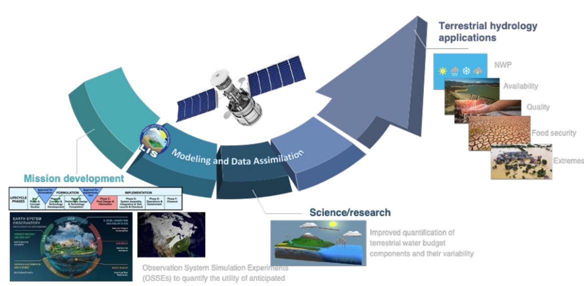
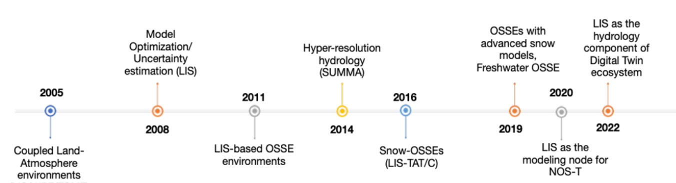
Land Information System (LIS; lis.gsfc.nasa.gov)

- A system to study land surface processes and land atmosphere interactions by using the “best available” observations to force and constrain model predictions.
- LIS capabilities span a broad spectrum of land hydrology research from mission development to applied science.
- Benefited by significant ESTO investments for the development of modeling and data assimilation capabilities.





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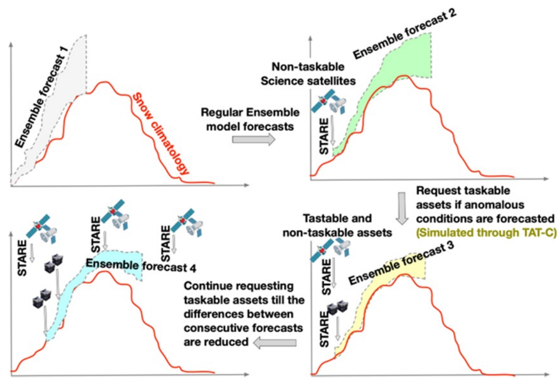
Objectives

Objectives:

The specific tasks of this proposed project are:

1. Develop spatial and temporal coverage metrics based on seasonality, snow cover statistics and event timing at continental to global scales.
2. Develop capability for rapid analysis and ingestion of snow data from multiple sources (STARE).
3. Incorporate logic for designing and operating optimized snow observations in a distributed mission configuration (TAT-C)
4. Assess the value of multiple coincident observations and tasking assets (from space, airborne and ground) for hydrological events with a hypothetical experiment in the NASA Land Information System (LIS)
5. Develop a systematic observation strategy recommendation for commercial sensors and a future snow satellite mission



Workflow of hypothetical experiment to develop and test SOS

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Global snow evolution & coverage analysis

1. Developed global snow climatology
   → **ERA5-Land** (10-km) gridded SWE product was used to develop a global 20-year (2002-2021) SWE climatology
   → Data were compared against other higher resolution products (University of Arizona, 4km res and Western US Reanalysis, 0.5km res) and found to provide reliable results
2. Define global snow metrics:
   → Identify **spatial and temporal coverage needs** based on **seasonality**, **snow cover statistics** and **event timing** at continental to global scales.

- Monthly maximum snow-covered area
- Monthly average snow-covered area
- Monthly maximum SWE
- Monthly Average SWE
- Peak SWE
  - Average Peak SWE date
  - Standard Deviation of Peak SWE
- Extreme events
  - 7-day Maximum **Accumulation** of SWE
  - 7-day Maximum **Ablation** of SWE

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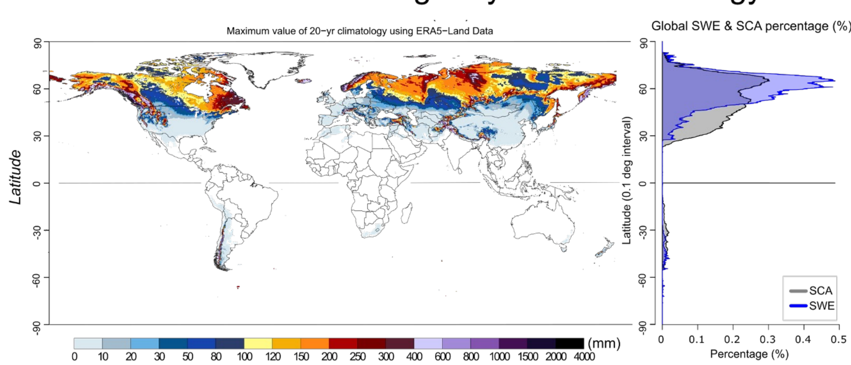
Global snow evolution & coverage analysis

Global SWE distribution using 20-yr SWE climatology



While global snow-covered areas (SCA) exist between 30-80 N, the majority of SWE exists above 45 N, and more than 50% of global SWE is above 60 N.

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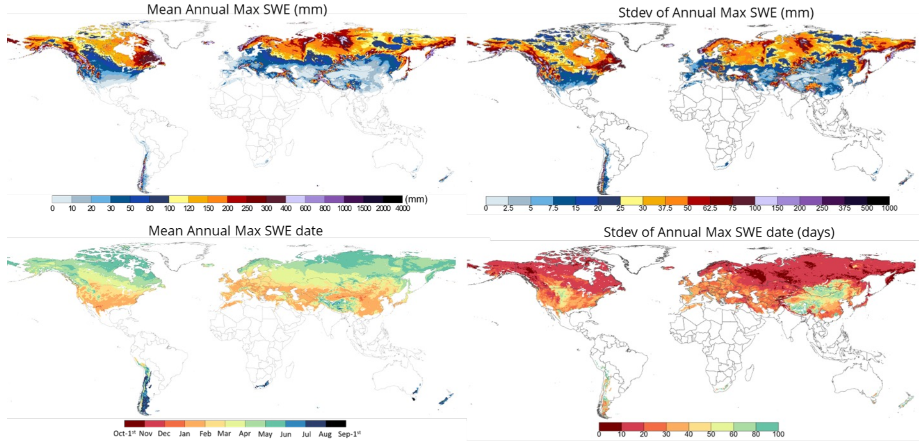
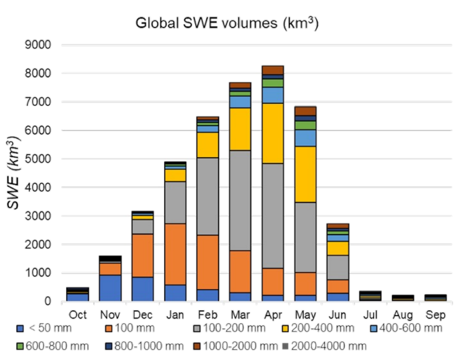
Global snow evolution & coverage analysis

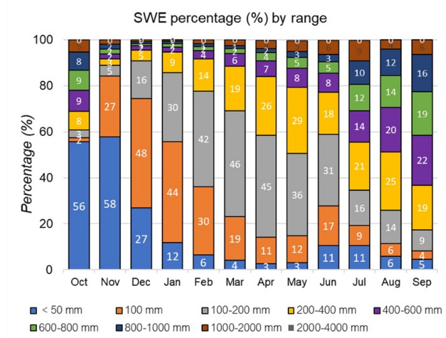
Annual Max SWE & Occurrence Date maps

*20 annual maximum ERA5-land SWE layers (10-km res; 2001 – 2020)



Global snow evolution & coverage analysis

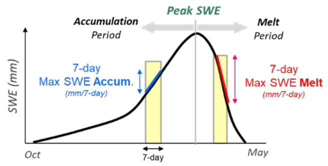




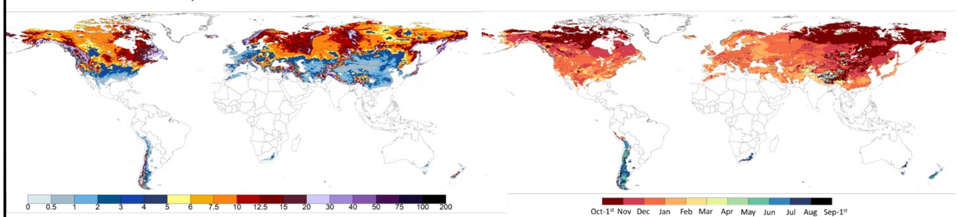
On Apr-1, **about 60%** of global SWE volumes is found in areas with **< 200 mm of SWE** and **85%** is in areas **< 400 mm**, suggesting that shallow-moderate SWE depths are important observational needs

Global snow evolution & coverage analysis

7-day Maximum SWE **Accumulation**



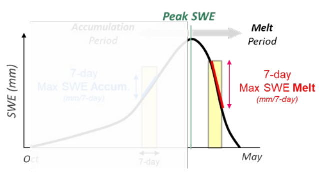
$$AccumSWE_{max,7d} = min(SWE_i - SWE_{i+7})$$



7-day maximum SWE accumulations occur up to 200 mm in **mountain** regions (e.g., Rockies, HMAs), The timings of the maximum accumulations are spatially less variable (e.g., Dec - Jan in CONUS).

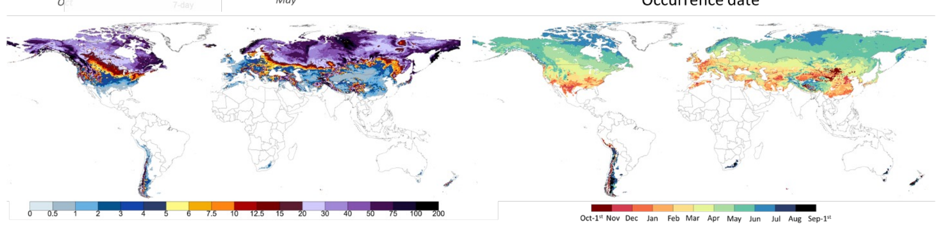
Global snow evolution & coverage analysis

7-day Maximum SWE **Melt**



$$MeltSWE_{max,7d} = max(SWE_i - SWE_{i+7})$$

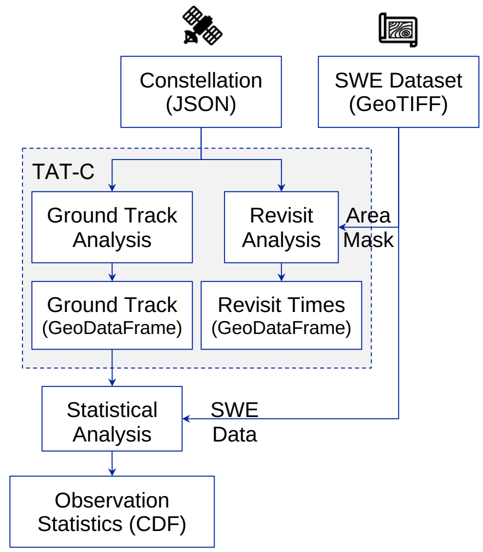
Occurrence date



The 7-d maximum SWE melt varies by **elevations** and **latitudes** but is generally largest at high latitudes. There are large spatial variations in maximum melt timing in low latitude areas (e.g., ephemeral snow)

TAT-C: Constellation Evaluation Tools

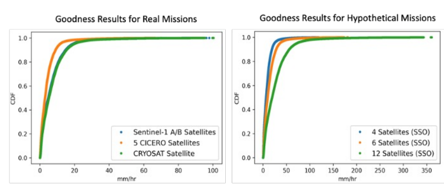
- TAT-C analysis workflow established to interface with SWE datasets
- **Inputs**:
  - Constellation: JSON with satellites, instruments, orbits
  - SWE dataset: GeoTIFF with selected SWE feature (e.g., maximum annual SWE averaged over 20 year ERA5-Land source)
- **Outputs**:
  - Ground track: spatial region observable by constellation
  - Revisit times: spatial distribution of mean time between observations
  - Observation statistics: distribution of SWE features observed vs. total

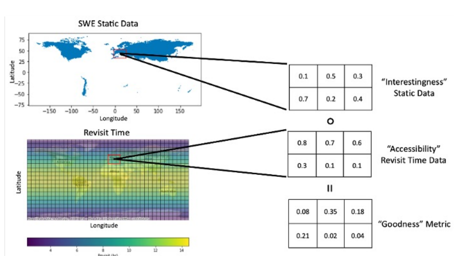


TAT-C for Static Mission Analysis

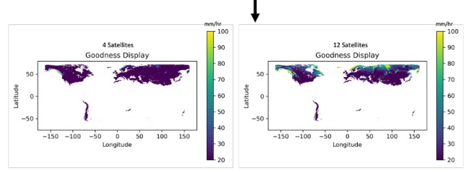
Metric Objective

- Develop a metric able to **evaluate performance of snow missions** by analyzing the "goodness" of the observations, keeping the SWE data static, and changing the mission architecture (number of satellites, orbits, swath width of sensors…)





We can also project these results in a map for visual aid

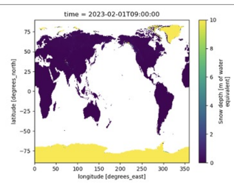


- The results show that, when dealing with static data, a **larger** satellite constellation will provide **better observations**.
- Having larger satellite constellations composed of small (lower-cost) satellites can produce better observations than big multi-functional satellites.
- Future work will consider implementing more **assets** to target observations on snowiest regions and developing and integrating time series to guide operational plans in **dynamic scenarios**.

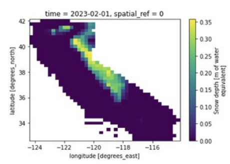
TAT-C for Dynamic Mission Analysis

Objective

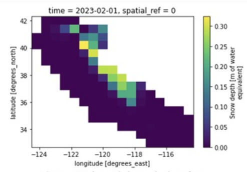
Use ERA5 reanalysis dataset to model and compare the spatial resolution differences between an optical sensor and Synthetic Aperture Radar (SAR) by plotting satellite ground tracks over the region of interest.



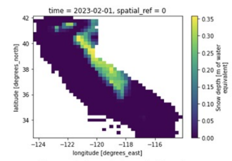
Visualization of ERA5 reanalysis dataset from February 01, 2023 at 09:00 hours



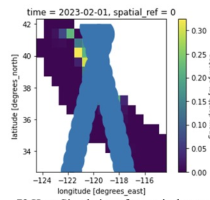
Used TAT-C to clip ERA5 dataset to the California shapefile



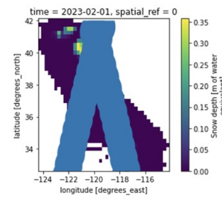
Converted spatial resolution for an optical sensor



Converted spatial resolution for a Synthetic Aperture Radar (SAR)



72 Hour Simulation of an optical sensor ground track over California



72 Hour Simulation of SAR ground track over California

- Based on the visualizations, it can be observed that SAR provides a higher spatial resolution over California in comparison to an Optical Sensor.
- Future work could include a cloud dataset in the analysis
- Extract numerical data from visualizations for quantitative measurements and compute the fraction of visible snow using numerical data

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Harmonize geospatial data for snow using STARE

STARE development focused on tool and method improvements to support working with SWE data sets, including the following.

- Methods for constructing STARE covers for common region-of-interest specifications including GeoPandas and Shapely polygons
- Improvements to STARE's temporal API, particularly the Pystare API
- Addition to STAREPandas dataframe functions for spatiotemporal queries of harmonized data stored in STARE Parallel Optimized Data Store (PODS)
- Test application of these functions to Extratropical Cyclone and precipitation events (see next slides)

Acknowledgment: Some of these results benefited from technological development work associated with SBIR 80NSSC22PA962, Spatiotemporally Aligned POSIX-Compliant Data Store for Event-based Analysis.

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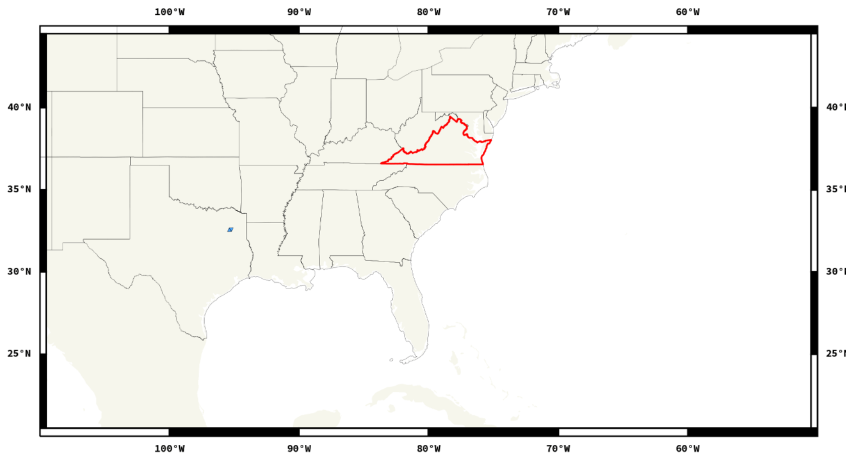
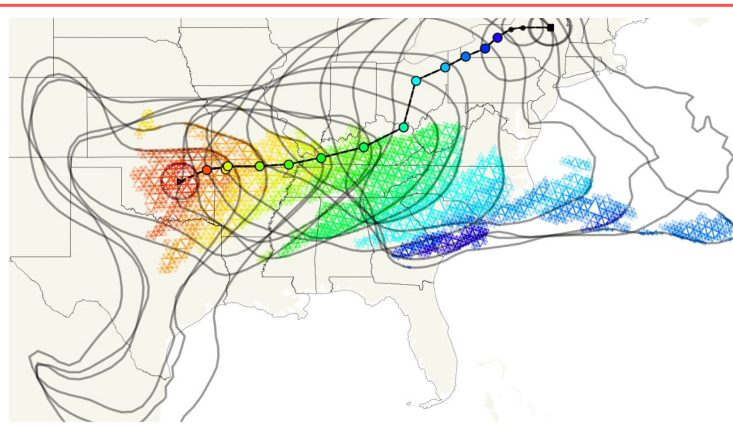
Harmonize geospatial data for snow using STARE



A precipitation event found using IMERG data (blue trixels) associated with an Extratropical Cyclone (filled contours). Both have been indexed using STARE, and the STARE covers at different times are shown.

Harmonize geospatial data for snow using STARE



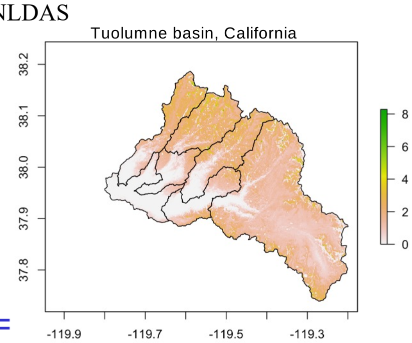
Precipitation event data (colored STARE trixels) connected to Extratropical Cyclone outlines showing the temporal evolution of the event.

The colored circles indicate the ETC centroid over the course of the event and are color-matched to the precipitation data.

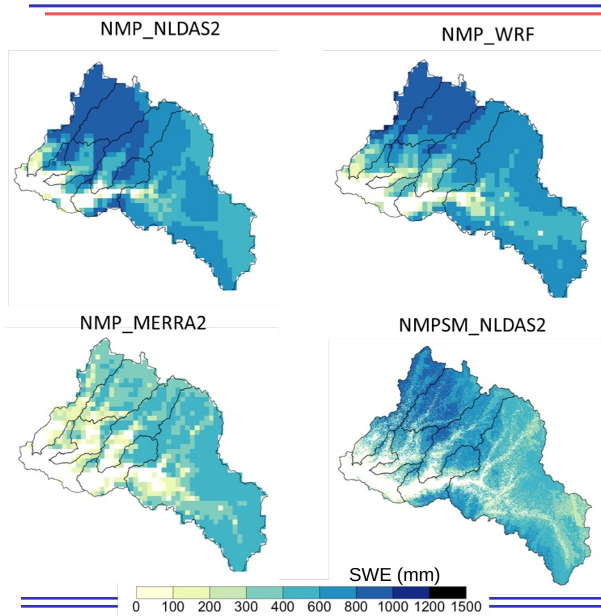
Hypothetical Experiment

Objective: A hypothetical experiment designed around real-world use cases to demonstrate how additional snow data could improve hydrological predictions.

Experimental Design:
- Domain: Tuolumne basin, California to test Observing System for drought/flood use case
- Time Period:
  - low snowpack winter of 2015
  - high snowpack in winter of 2017/2023
  - **Water Year: Sept 1 - Aug 31**
- Nature Run: SnowModel/Noah-MP with NLDAS
- Open Loop: Noah-MP with MERRA2
- Climatology: 1990 - 2023
- Resolution: 50m (NR), 1 km (OL)
- Forecast configuration: ESP



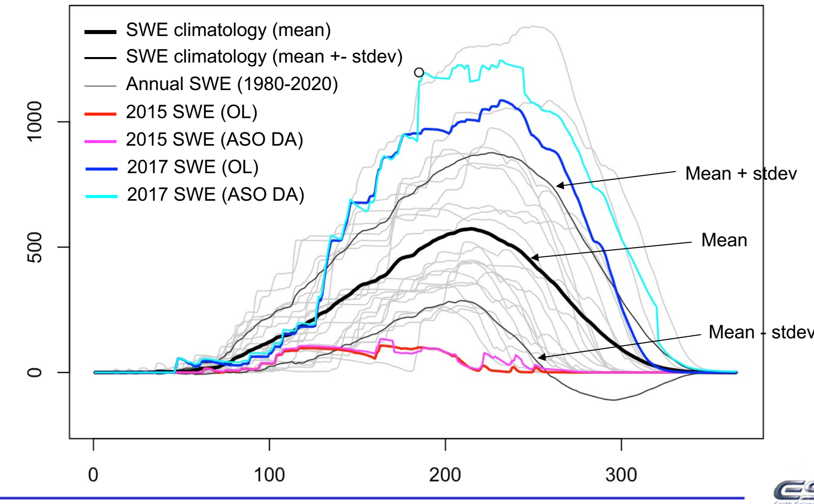
Hypothetical Experiment



Comparison of model runs with different forcing data

April 1 SWE shows different spatial patterns and magnitude depending on model configuration.

Hypothetical Experiment



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SOS Workflow

Observation	Metric
Frequency of expected snowfall events	Greater/less than average event frequency
Major rainfall/snowfall/ melt events	Event greater than 7-day maximum accumulation/melt for that period
SWE anomalies: values outside normal range	SWE greater/less than 75/25 percentile SWE for that date
Wet/melting snow	Earlier/later snowmelt

→

Triggers

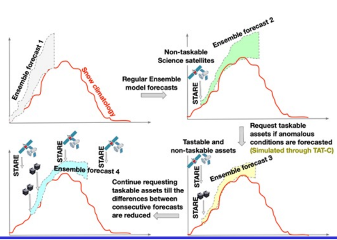
Satellite, airborne or ground obs to improve estimate accuracy and reduce bias

Assimilated Observations:
1. Existing non-taskable assets
   - AMSR2 SWE/melt products
   - MODIS/VIIRS snow cover
   - Sentinel-1 C-band snow depth/melt
   - NISAR SWE/Snow depth
2. Hypothetical future mission obs
3. Taskable assets
   - Airborne lidar snow depth
   - ICESat-2 snow depth
   - Planet, MAXAR, Blacksky stereo
   - X-band SWE estimates

→

Targeted Observables

Evaluate performance against observables:
- SWE
- snow melt
- discharge
- stage



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Presentation Contents

- Background and Objectives
- Technical and Science Advancements
- Summary of Accomplishments and Future Plans
- Actual or Potential Infusions and Collaborations
- Publications - List of Acronyms

Plan Forward

Coverage Analysis
- Integrated index to prioritize observational needs with local capacity

STARE:
- Index and harmonize select snow data sets to test dynamic event-based analysis
- Start STARE processing of SWE data sets on NCCS HEC and SMCE resources
- Design and develop LIS plugin for STARE

TAT-C:
- Develop a design-and-evaluation scheme for a dynamic snow observing strategy with temporally-evolving SWE data and observation opportunities
- Use STARE as a data model in TAT-C to model differences in spatial resolution

Hypothetical Experiment
- Assess value of assimilated observations on model uncertainty for Tuolumne test case
- Stand up hypothetical experiment over large domain to assess value for seasonal monitoring

Cloud computing
- Investigate the potential use of SMCE for project collaboration and development, leveraging existing advances e.g. EIS

Summary

Seasonal snow is spatially and temporally variable, evolving throughout the season, affecting different regions, elevations and latitudes at different times of the year.

- Seasonal snow patterns were identified to help prioritize critical observational needs and develop a snow observing strategy
- Merging multiple datasets together requires an efficient spatio-temporal encoding scheme to handle diverse data. We have been evaluating performance of different techniques & platforms
- TAT-C has been successfully interfaced with SWE data sets to produce preliminary mission evaluation measures
- Hypothetical experiment in Tuolumne triggers potential snow flood/drought use case for testing SOS

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Actual or Potential Infusions and Collaborations

Project Infusions & collaborations:

NASA THP SnowEx: Field and airborne campaign has helped quantify uncertainty in different snow remote sensing techniques, improve understanding of snow processes and characteristics, and develop multiple snow datasets, all of which can provide knowledge transfer to SOS.

AIST18-0045: “Preparing NASA for future Snow Missions: Integrating the Spatially explicit SnowModel in LIS” is developing and validating the capability to run SnowModel in LIS through a high resolution OSSE demonstration. This system will be used to run the hypothetical experiment.

AIST21, ESDT: “Reproducible Containers for Advancing Process-oriented Collaborative Analytics,” Tanu Malik, PI, of DePaul University. Their science use case involves precipitation features for process-oriented analysis. STARE developments certainly help both projects.

Presentation Contents

Publications/Presentations

- Cho et al 2022: Global snow water equivalent distribution analysis of observational needs, Oral Presentation, AGU Fall meeting December, 2022
- Bardaji et al 2023: Constellation Evaluation Tools for a New Snow Observing Strategy, Paper and Poster Presentation, IGARSS Conference, July 2023

Acronyms

List of Acronyms

- API Application programming interface
- CDF Cumulative distribution function
- CONUS Continental United States
- DEM Digital Elevation Model
- DS Decadal Survey
- ECMWF European Centre for Medium-Range Weather Forecasts
- ERA5 ECMWF Reanalysis 5th Generation
- FY Fiscal Year
- GPM Global Precipitation Mission
- GSFC Goddard Space Flight Center
- HEC High-End Computing
- HTM Hierarchical Triangular Mesh
- I/O Input/Output
- IMERG Integrated Multi-satellitE Retrievals for GPM
- km Kilometer
- LIS Land Information System
- MODIS Moderate Resolution Imaging Spectroradiometer
- NCAR National Center for Atmospheric Research
- NOS-T New Observing Strategies Testbed
- OSSE Observing System Simulation Experiment
- TAT-C Tradespace Analysis Toolkit for Constellations
- TRL Technical Readiness Level
- SCA Snow Covered Area
- SOS Snow Observing System
- STARE SpatioTemporal Adaptive-Resolution Encoding
- SWE Snow Water Equivalent
- UMD University of Maryland

Multi-path Fusion Machine Learning for New Observing System Design and Operation

James MacKinnon (PI, GSFC/587)
Mark Moussa (Co-I GSFC/587)
Matt Brandt (Co-I GSFC/587)
David Harding (Co-I, GSFC/618-Emeritus)
Mark Carroll (Co-I, GSFC/606)
Fred Huemmrich (Co-I/UMBC)
Valerie Thomas (Co-I/VT)
Randy Wynne (Collaborator/VT)
Daniel Donahoe (Grad student/VT)
Paige Williams (Grad student/VT)

AIST-18/21-0072 Annual Technical Review
July 12th, 2023

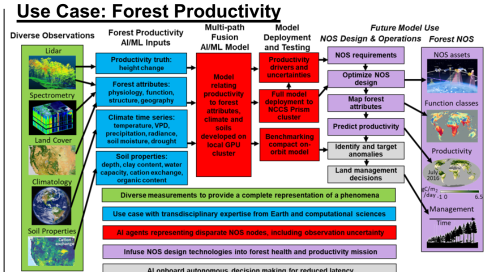
Multi-path Fusion Machine Learning for NOS Design and Operations
Proposal for AIST New Observing System

PI: James MacKinnon, NASA/GSFC

Objectives

- **Build machine learning (ML) analytic tools and computing environment capabilities for new observing system (NOS)** design and operations that utilize large amounts of diverse airborne and satellite observations
- **Demonstrate the capabilities based on a forest productivity use case**, by developing ML models that relate productivity to ecosystem, soil and geography properties and climatology and drought time series
- **Develop on-ground, maximum-accuracy models for NOS design purposes**, conducting sensitivity studies to guide sensor and mission requirements traceability
- **Provide light-weight model to GSFC groups doing benchmarking on flight-like hardware** in order to enable onboard decision making such as targeting or compressive sensing

Use Case: Forest Productivity



Approach

- **Develop curated, ML training datasets incorporating information from diverse sources**
  - At National Ecological Observatory Network (NEON) forested sites across the United States
  - Forest height change from lidar time series for truth labels
  - Spectrometry, lidar structure, climatology, drought, soil and geography parameters as training inputs
  - Training at two resolutions: 1m using high-resolution airborne data and upscaled to 30m emulating satellite observations
- **Train several types of multi-source deep learning models on these datasets to predict forest growth and loss and evaluate performance**
- **Deploy capability on NASA High-end Computing platform**

Key Milestones

- Machine Learning Model Prototype – Q3 PY1
- Full Training Dataset Completion - Q4 PY1
- Model Training including Hyperparameter Search – Q2 PY2
- Benchmark Model on PRISM & Flight-like Systems – Q3 PY2
- Final Reporting – Q4 PY2

Co-Is/Partners – D. Harding (GSFC), J. Ranson (GSFC), M. Moussa (GSFC), M. Brandt (GSFC), M. Carroll (GSFC), F. Huemmrich (UMBC), V. Thomas (VT), R. Wynne (VT)

TRL$_{in}$ = 3, TRL$_{out}$ = 5

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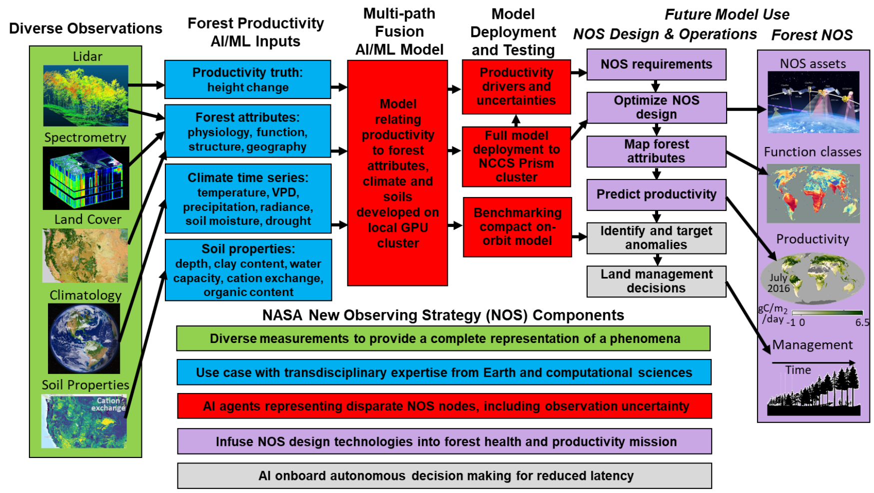
Background and Objectives

- By establishing a Machine Learning (ML) foundation for a forest productivity NOS design and operations**, our work will provide a capability that can be used to address two of the R&A Carbon Cycle and Ecosystems overarching questions**
  - How are ecosystems changing around the globe, and what mechanisms, processes, and feedbacks contribute to this change?
  - How do ecosystems, land cover, and biogeochemical cycles respond to and affect global environmental change?
- **Our work will also contribute to Applied Ecologic Forecasting objectives**
  - Promote the use of NASA Earth observations to monitor, analyze and forecast ecosystem changing in response to changing climates, extreme weather conditions and human activities
  - With a community of knowledgeable partners, develop resource management strategies, products and tools that benefit society
- Our ML infrastructure will be developed to operate on land remote sensing data sets applicable to questions in additional focus areas, including
  - Earth surface and interior
  - Water and energy
  - Disasters, such as **Wildfires**
  - Water and Food

Productivity NOS Concept



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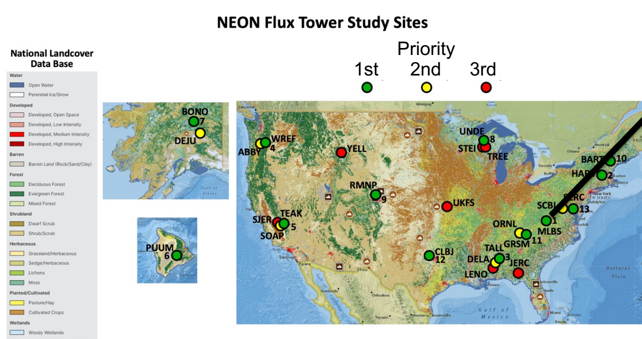
Technical and Science Advancements: Overview

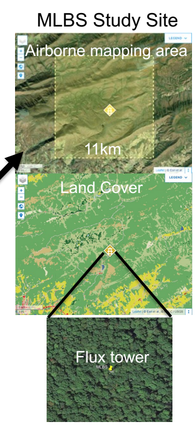
Three primary areas of advancement

- **Earth Science Dataset Creation**
  - Leveraged NSF's National Ecological Observatory Network (NEON), an already widely used source of data for scientists, **but not unified into single dataset**
  - Created a single co-registered Machine Learning ready dataset **comprised of 121 training parameters** relevant for forest productivity, derived from data accessed in NEON, NASA, NOAA, USDA and USFS repositories
- **Machine Learning Model Development**
  - Developed method for fusing these different sources of data together using **hierarchical neural networks (NN)**
  - Identified best possible NN layer types for each data source
- **ML-ops Process Advancement**
  - Applied "off-the-shelf" and open-source ML-ops tools to enable quick iteration and experimentation, necessary due to huge variety of input combinations
  - **MLFlow** used for experiment tracking and metric collation, and **Optuna** used for hyperparameter tuning

Technical and Science Advancements: Dataset Sources

- Created training datasets at the **26 NEON eddy covariance flux tower sites** located in forests across the United states, combining products from:
  - NEON multi-year high-resolution airborne lidar and hyperspectral imaging
  - NASA GMAO MERRA-2 climatology time series
  - NOAA NISDIS drought time series
  - USDA NATSGO soil properties
  - USFS LCMS land cover change
  - Due to its large size, it is stored on NCCS high performance computing resources, and will be accessible by both our AIST team members and other researchers interested in using the data





Technical and Science Advancements: Dataset Sources

Products	Parameters	Sources
Truth labels	Canopy height increase between flight years for productivity models Canopy height decrease between flight years for degradation models	NEON Airborne Observing Platform lidar mapping
Spectrometry training data	VNIR-SWIR spectral curves and their derivative Broad band albedo 20 derived vegetation composition and function indices Solar incidence and azimuth angles	NEON Airborne Observing Platform hyperspectral imaging
Lidar training data	Topography elevation, slope and azimuth Forest canopy roughness Derived canopy waveforms and height percentiles Canopy illumination patch classification Illumination patch frequency, size and connectivity	NEON Airborne Observing Platform lidar mapping
Climate training data	Daily time series of air and surface temperatures, vapor pressure deficit, precipitation, evaporation, solar irradiance and soil moisture	NASA Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2)
Drought training data	Five-day time series of Palmer Drought Severity and Z indices from extremely wet to extreme drought	NOAA National Integrated Drought Information System (NIDIS)
Soil training data	Depth, clay content, cation exchange capacity, water storage and organic matter	USDA Gridded National Soil Survey Geographic Database (gNATSGO)
Data rejection criteria	Probability of forest land use < 70%	USFS Landscape Change Monitoring System (LCMS)
	Cloud cover > 10% Cloud shadow on ground	NEON Airborne Observing Platform

- Canopy height increase and decrease truth labels are used as a stand-in for forest productivity and degradation, respectively, since these are hard to measure directly
- The predictive power of our numerous training parameters is not known, but we will be able to determine that based on quantified parameter importance in our ML models
- All products are re-gridded to 1-meter and 30-meter pixel sizes to represent potential airborne and orbital platforms respectively

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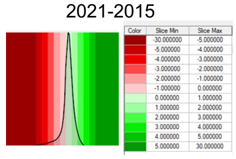
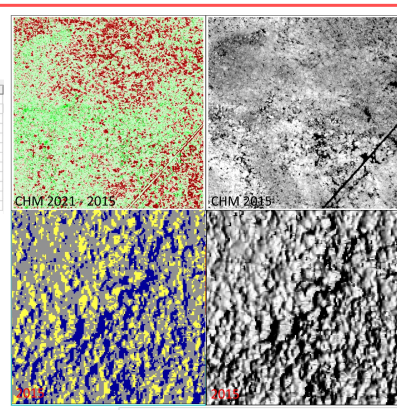
Technical and Science Advancements: Lidar Example

ML Truth Label
Canopy height change
2021-2015





ML Training Data
Canopy height
2015

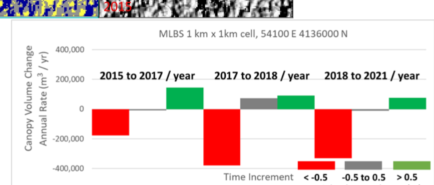
ML Training Data
Illumination classes
2015

Deep shadow	Intermediate illumination	Brightly sunlit
Less than mean – st dev	mean – st dev to mean + st dev	Less than mean + st dev

ML Training Data
Shaded relief
2015

Canopy volume change per year
Volume loss is due to ash borer infestation

We will predict both volume gain and loss with our model



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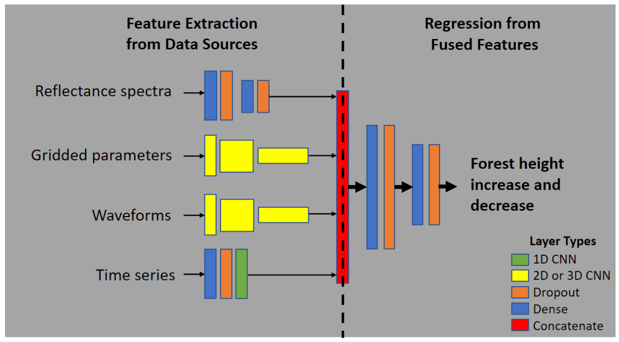
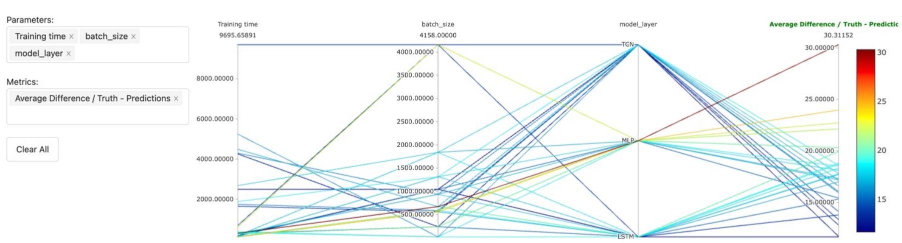
Technical and Science Advancements: Model Development



- This diagram shows an overview of our hierarchical model for canopy loss
  - Model architecture based on previous “Multi-Path” ML models flown on Tech demonstration missions, but much more complex with more “paths” and larger variety of layer types
  - Features are extracted by sub models tuned to a particular data source, e.g., 1D convolutions for pure spectral, 2D conv for pure spatial, and 3D conv for combined spectral/spatial (like an HSI data cube for example)

Technical and Science Advancements: ML-Ops Process Development

- Based on open-source tools MLFlow and Optuna with additional custom code
  - **MLFlow organizes training runs, and Optuna automates hyperparameter search**
- Includes TensorFlow style data generators capable of reading generic scientific data sources (versus the more typical raster image or single pixel methods)
  - Our sophisticated data generators take a simple configuration file and automatically create data stacks from the requested input sources
  - Additionally, the model is built up at runtime to match the input sources being fed to it, **meaning a single model class can instantiate all models in this effort**



Example metric generation from MLFlow

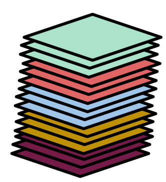
Presentation Contents

- Background and Objectives
- Technical and Science Advancements
- Summary of Accomplishments and Future Plans
- Actual or Potential Infusions and Collaborations
- Publications - List of Acronyms

Summary of Accomplishments and Future Plans

Current State

- **Dataset is currently in verification phase**
  - Tests are being run on a single site, MLBS, and involve manual inspection, model training, and metric generation
- **Keras data generator and runtime model builder are being further refined to work with this dataset**
  - Data generator must be able to handle an enormous number of possible combinations so weird edge cases are being found for before the "big" run
  - Runtime model builder only supports a subset of what we want it to support



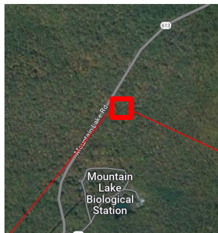
A fully wrangled stack has:
1. The full suite of multiscale stacks (sub-stacks)
2. in a consistent grid; the local UTM zone @ 20 meters
3. At a 1 km extent (a 50 x 50 grid of 20 meter pixels)

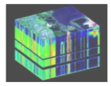
These stacks are spatially small, but they are deep

K + TensorFlow

Use of TensorFlow means easy compatibility
with several onboard processing platforms, enabling the possibility for these models to also be used in space

Summary of Accomplishments and Future Plans: Feature Engineering Example



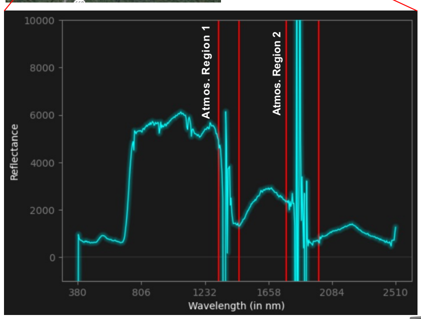


Original signature (for a single pixel)

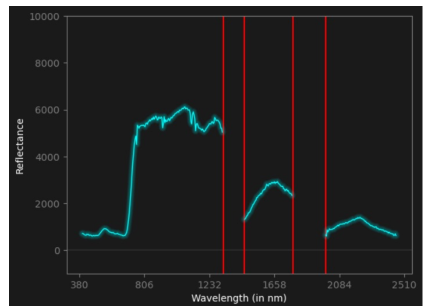
Preprocessing of our NEON hyperspectral dataset includes creating two data cubes:

I) Savitzky-Golay (Savgol) smoothed cube

II) Savgol smoothed with derivative

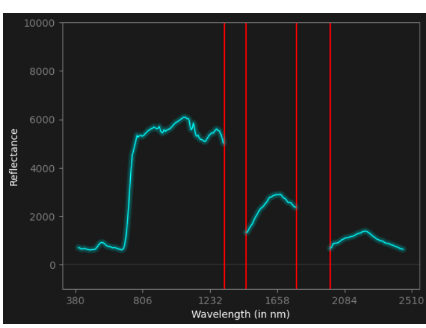


Original signature with bad-bands removed

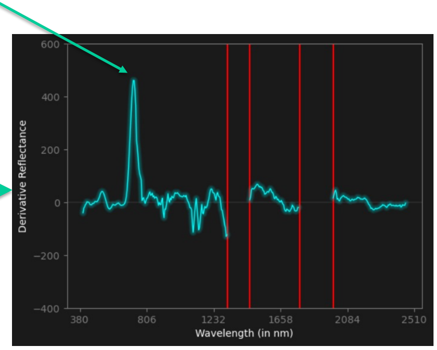


Summary of Accomplishments and Future Plans: Feature Engineering Continued

Savgol filtered data gives us prominent signal for red-edge, important for vegetation function determination due to its relationship with Chlorophyll content



Hyperspectral Cube 1: Savgol smoothed
(single pixel for remaining bands)



Hyperspectral Cube 2: Savgol smoothed *with derivative*
(single pixel for remaining bands)

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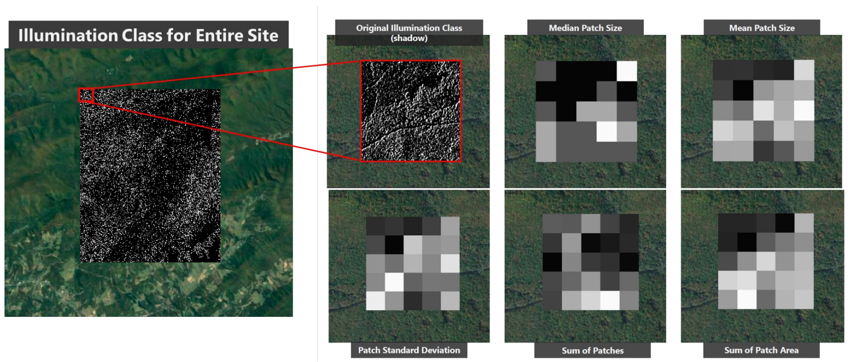
Summary of Accomplishments and Future Plans: Feature Engineering Continued

Information on forest patches were derived from illumination classes (shadow, intermediate, sunlit) and were generated for the entire site to document forest fragmentation using the GUIDOS Toolkit



Summary of Accomplishments and Future Plans

Progress on dataset, and priority rankings

Group Priority	Smoothed Spectra for 1st Year of the Canopy Height Change Time Interval	1m	30m
1	Visible: 400 - 670 nm	extracted	averaged
1	Red edge: 670 - 780 nm	extracted	averaged
1	Near infrared (NIR): 780 - 1320 nm	extracted	averaged
1	Shortwave infrared 1 (SWIR-1): 1460 - 1775 nm	extracted	averaged
1	Shortwave infrared 2 (SWIR-2): 1990 - 2455 nm	extracted	averaged

Group Priority	Spectra Derivative for 1st Year of the Canopy Height Change Time Interval	1m	30m
2	Visible: 400 - 670 nm	extracted	averaged
2	Red edge: 670 - 780 nm	extracted	averaged
2	Near infrared (NIR): 780 - 1320 nm	extracted	averaged
2	Shortwave infrared 1 (SWIR-1): 1460 - 1775 nm	extracted	averaged
2	Shortwave infrared 2 (SWIR-2): 1990 - 2455 nm	extracted	averaged

Group Priority	Sensor and Solar Angles for 1st Year of the Canopy Height Change Time Interval	1m	30m
	Sensor zenith angle	source data	averaged
	To-sensor azimuth angle	source data	averaged
3-5	Sun zenith angle	source data	averaged
3-5	To-sun azimuth angle	source data	averaged
3-5	BRDF angle between sensor and solar vectors	computed	averaged

Group Priority	Spectral Indices for 1st Year of the Canopy Height Change Time Interval	1m	30m
3	Photochemical Reflectance Index for Water Stress (PRIw)	computed	averaged
4	Photochemical Reflectance Index for Nitrogen Stress (PRIn)	computed	averaged
3	Normalized Difference Vegetation Index (NDVI)	computed	averaged
3	MERIS Terrestrial Chlorophyll Index (MTCI) Red edge	computed	averaged
3	Carotenoid Reflectance Index (CRI550)	computed	averaged
4	Carotenoid Reflectance Index (CRI700)	computed	averaged
4	Anthocyanin Reflectance Index (ARI)	computed	averaged
3	Water Band Index (WBI)	computed	averaged
4	Normalized Difference Water Index (NDWI)	computed	averaged
5	Near-infrared Reflectance of Vegetation (NIRv) NDVI*NIR	computed	averaged
5	Normalized Difference Nitrogen Index (NDNI)	computed	averaged
5	Normalized Difference Ligin Index (NDLI)	computed	averaged
5	Cellulose Absorption Index (CAI)	computed	averaged
5	Enhanced Vegetation Index (EVI)	computed	averaged
4	2-band Enhanced Vegetation Index (EVI2)	computed	averaged
5	Soil-adjusted Vegetation Index (SAVI)	computed	averaged
3	Leaf Area Index (LAI)	computed	averaged
4	Fraction of Photosynthetically Active Radiation (fPAR)	computed	averaged
3	Moisture Stress Index (MSI)	computed	averaged
4	Normalized Difference Infrared Index (NDII) canopy water	computed	averaged
5	Albedo	source data	averaged

Summary of Accomplishments and Future Plans

Progress on dataset, and priority rankings, part 2

Group Priority	Lidar Parameters for 1st Year of the Canopy Height Change Time Interval	1m	30m
6	Digital Terrain Model (DTM topography)	source data	averaged
6	DTM Slope (rise over run)	source data	averaged
6	DTM Aspect (direction)	source data	averaged
	Digital Surface Model (DSM highest surface)	source data	averaged
7	Canopy Rugosity (DSM highest surface st. dev.)	computed	averaged
7	Canopy Height Model (DSM - DTM)	computed	averaged
7	Shaded Relief Model (SRM) 3x3 pixels, 45° zenith, 135° azimuth	computed	averaged
TBA	98th height percentile of CASALS waveform simulation	resampled	computed
TBA	50th height percentile of CASALS waveform simulation	resampled	computed

Group Priority	Lidar Simulated Waveforms for 1st Year of the Canopy Height Change Time Interval	1m	30m
TBA	GSFC implementation of U of DE point cloud code	TBA	TBA

Group Priority	NATSGO Soil Parameters	1m	30m
6	Clay content 0-25cm	resampled	source data
6	Cation exchange capacity at pH 7 0-25cm	resampled	source data
TBA	Plant available water storage 0-50cm	resampled	source data
6	Soil Organic Matter	resampled	source data
TBA	Bedrock depth	resampled	source data

Group Priority			Illumination Classification and Patch Attributes for 1st Year of the Canopy Height Change Time Interval	1m	30m
Sunlit	Inter-mediate	Shadow			
TBA	TBA	TBA	Three-class SRM brightness classification	classified	n.a.
TBA	TBA	TBA	Fraction of pixels in a classification	n.a.	computed
TBA	TBA	TBA	Computed using Guidos Toolbox patch analysis software for 90m x 90m cells	resampled	resampled
TBA	TBA	TBA	Number of patch objects	resampled	resampled
TBA	TBA	TBA	Pixel fraction (class pixels / total pixels)	resampled	resampled
TBA	TBA	TBA	Median patch size	resampled	resampled
TBA	TBA	TBA	Average patch size	resampled	resampled
TBA	TBA	TBA	Standard deviation of patch size	resampled	resampled
TBA	TBA	TBA	Number of pixels in small cores	resampled	resampled
TBA	TBA	TBA	Number of pixels in medium cores	resampled	resampled
TBA	TBA	TBA	Number of pixels in large cores	resampled	resampled
TBA	TBA	TBA	Number of pixels in islets	resampled	resampled
TBA	TBA	TBA	Number of pixels in perforations	resampled	resampled
TBA	TBA	TBA	Number of pixels in edges	resampled	resampled
TBA	TBA	TBA	Number of pixels in loops	resampled	resampled
TBA	TBA	TBA	Number of pixels in bridges	resampled	resampled
TBA	TBA	TBA	Number of pixels in branches	resampled	resampled
TBA	TBA	TBA	Number of pixels in cores of all sizes	resampled	resampled

Summary of Accomplishments and Future Plans: Risks

The paramount risk is the suitability of the data set. This can be split into three aspects

- We are assuming our dataset is sufficiently accurate, but it is so large and complex that verification of the entire dataset's accuracy is outside the scope of our resources
  - Risk mitigations:
    - Understand the accuracy verifications done by the data providers
    - Conduct our own verification at our initial development site, MLBS
- Input dimensionality too high – We are merging a large amount of disparate data types; we must be careful how we structure the hierarchy. **This is core to the entire project; if this kind of massive fusion can be wrangled it will be a significant benefit across many fields.**
  - Risk mitigation:
    - First develop and test ML models applied to training parameters with the same structure (i.e., single path) to identify parameters with high predictive significance, before merging those disparate data in a multi-path model
- Our goal is to predict forest dynamics in the future, specifically productivity and degradation. The truth labels, lidar canopy height increase and decrease, are surrogates for productivity and degradation. Our labels are a remotely sensed product, and may not be fully represent the forest dynamics of interest.
  - Risk mitigation:
    - Compare our height change results to gross primary productivity established by NEON at the flux towers

Summary of Accomplishments and Future Plans

- Future Plans
  - Finalize ML-Ops approach
    - Finish data generator, and runtime model builder
  - Train series of models on our dataset
    - Several candidate groups of input sources are planned to be testing, we have assigned priority to them but it's possible in testing we will find combinations better than we predict
  - Analyze trained models to determine which inputs most relevant to predictions
    - We will use a combination of sensitivity studies and SHAP (SHapley Additive exPlanations) metrics to determine the best combinations
  - Start Open-source process for our code and data

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Actual or Potential Infusions and Collaborations

- Provide a summary of actual or potential infusions
  - A primary goal of this effort is that of Technology Transfer, we have a fully fleshed out open-source plan that will include both release of data products and model code
    - Data products will be available on NCCS due to size of dataset but will be available to anyone with access, meaning if a team has a different idea for a model, they would still be able to leverage our dataset
    - Code will be available on the official NASA Github page
      - We have experience open sourcing code
      - This project code also integrates well into existing open-source projects like MLFlow due to the way we set up our ML-ops process

- Provide a summary of actual or potential collaborations
  - Concurrent Artificially-intelligent Spectrometry and Adaptive Lidar System (CASALS)
    - We work closely with the CASALS development team. Our ML-based system can aid in requirements definition, design and operations of a future CASALS mission.
  - Surface Topography and Vegetation (STV) Incubation
    - The STV Incubation team will be conducting Observing System Simulation Experiments (OSSEs). Our system potentially can be a component of those OSSEs. We keep the STV study team lead informed about our work.

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Publications and Presentations

- **ACCEPTED: Multi-path Fusion: A Hierarchical Machine Learning Approach For Combining Diverse Data Sets For A Forest Monitoring New Observing System – Presenting at IGARSS 2023 next week**

IGARSS **16 - 21 July, 2023**

- **ACCEPTED: Predicting Forest Productivity and Degradation Using Multi-Path Fusion Machine Learning to Optimally Combine Lidar, Hyperspectral, Climatology and Soil Data Sources – Presenting at Silvilaser 2023 in September**

List of Acronyms

- CASALS - Concurrent Artificially-intelligent Spectrometry and Adaptive Lidar System
- GMAO – Global Modeling and Assimilation Office
- HSI – HyperSpectral Imager
- IGARSS – International Geoscience and Remote Sensing Symposium
- LCMS – Landscape Change Monitoring System
- MERRA-2 – Modern-Era Retrospective analysis for Research and Applications, Version 2
- ML – Machine Learning
- ML-Ops – Machine Learning Operations
- NATSGO – National Soil Survey Geographic Database
- NCCS – NASA Center for Climate Simulation
- NEON – National Ecological Observatory Network
- NISDIS – National Environmental Satellite, Data, and Information Service
- NOAA – National Oceanic and Atmospheric Administration
- NOS – New observing system
- NSF – National Science Foundation
- NTR – NASA Technology Report
- SHAP – SHapley Additive exPlanations
- SWIR – Short Wave Infrared
- UMBC – University of Maryland Baltimore County
- USDA – United States Department of Agriculture
- USFS – United States Forest Service
- UTM – Universal Transverse Mercator
- VNIR – Visual and Near Infrared
- VT – Virginia Tech

3D-CHESS: Decentralized, Distributed, Dynamic, and Context-aware Heterogeneous Sensor Systems

AIST-21-0089 Annual Technical Review
July 12, 2023

PI: Daniel Selva (Texas A&M University)
Co-Is: George Allen (Virginia Tech), Huilin Gao (Texas A&M University), Ankur Mehta (UCLA), Yizhou Sun (UCLA), Vinay Ravindra (ARC/BAERI), Cedric David (JPL)
Students: Alan Aguilar, Ben Gorr, Chrissi Erwin, Molly Stroud, Vivian Cheng, Zida Wu, Wooyeong Cho

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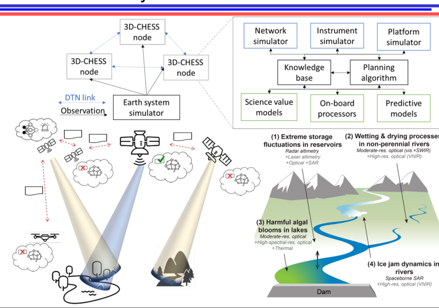
3D-CHESS: Decentralized, Distributed, Dynamic, and Context-aware HEterogeneous Sensor Systems

PI: Daniel Selva, Texas A&M University

Objective

- Demonstrate proof of concept (TRL 3) for a **context-aware** Earth observing sensor web of interconnected space, air and ground nodes.
- Context awareness: ability for the nodes to gather, exchange, and reason about contextual information (e.g., state of the observable, state and **capabilities** of itself and of other nodes in the network and how those relate to the task request and mission objectives).
- Demonstrate the technology and assess the value of contextual information in a multi-sensor **in-land hydrologic and ecologic monitoring system** with four inter-dependent mission objectives: studying intermittent rivers and sediment transport, and monitoring floods and algal blooms



Approach

- Knowledge graph reasoning using UKGE algorithm allows nodes to determine if they can perform a task
- Decentralized planning using modified CCBBA algorithm
- Platform/Instrument/Network simulators using existing tools (PyOrbit, InstruPy) provide realistic engineering constraints to planning algorithms
- Simple science models provide reasonable science-driven estimates of scientific/societal value of observations to planning algorithms
- Multi-agent simulation to benchmark 3D-CHESS against status quo and intermediate "transition" architectures

Co-Is/Partners: George Allen (VT); Huilin Gao (TAMU); Ankur Mehta, Yizhou Sun (UCLA); Vinay Ravindra (ARC); Cedric David (JPL).

Key Milestones

✓Kick-off	08/22
✓System architecture/interfaces defined	11/22
✓Initial integration and verification complete	03/23
✓Initial results in basic case study (TRL 2)	04/23
❑Feasibility, performance, and value of technology characterized in 2 single-mission scenarios	09/23
❑Multi-mission use case demonstrated (TRL 3)	11/23

TRL_{in} = 1-2 $TRL_{current}$ = 2

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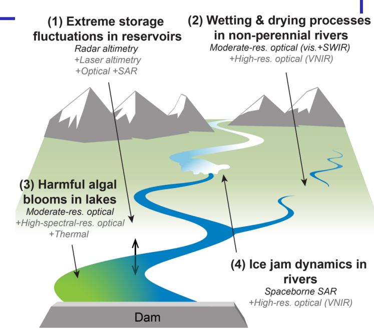
Background/Objectives

Overarching Goal: To provide **proof of concept** (TRL 3) for a **context-aware** network of **heterogeneous** sensors, in the context of an **inland water ecosystem monitoring** mission

- Inland water bodies can dramatically change states within minutes to hours.
  - These changes are increasingly extreme and difficult to predict due to climate change.
- Need for high spatial, temporal, and/or spectral resolutions, from **heterogeneous** sensors.
- To monitor and respond to a dynamic environment, significantly more **autonomy** is needed in the Earth observing systems.
- Autonomy requires **context awareness** and **decentralized** coordination.



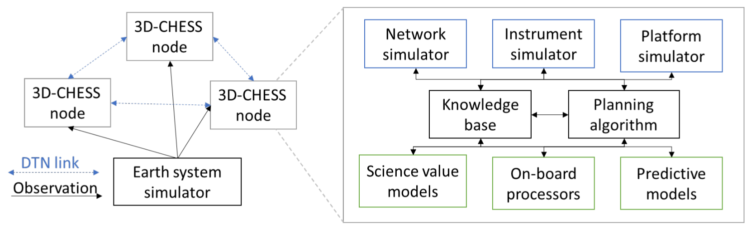
	State of practice	State of research	3D-CHESS
Context information used for planning	Own state	Own state **Earth system state (from own measurements)**	Own state **and capabilities** Earth system state (from own and others' measurements) **Others' states and capabilities**
Sensors and platforms	Homogeneous	Homogeneous or **Heterogeneous**	**Heterogeneous**
Mission	Single Static Objective	Single **Dynamic** Objective	**Multiple** Dynamic Objectives
Planning strategy	Centralized	Centralized or **Decentralized** with predefined functions	**Decentralized**

Relevant to Objective O1: Enable new observation measurements and new observing systems design and operations through intelligent, timely, dynamic, and coordinated distributed sensing.

Relevant missions: SWOT, NISAR, Delta-X, SMASH

Background / Objectives

- **Enabling technologies**: Knowledge graph reasoning algorithms (UniKER/UKGE) and decentralized consensus-based task allocation algorithms (MACCBBA).
- **Approach**: Multi-agent simulation (message-driven) where each node consists of
  - Engineering module (platform, sensors, and network simulators)
  - Science module (science value models, on-board processors, predictive models)
  - Planning module (knowledge-based reasoning, planning/scheduling)
- **Objectives**: Use multi-agent simulator to assess feasibility, scalability and value of the 3D-CHESS concept vs various benchmarks in the context of the relevance scenario
  - Assess feasibility of the proposed technology
  - Quantify the value of implementing 3D-CHESS compared to the status quo
  - Study "transition" architectures (somewhere btw. 3D-CHESS and status quo)
  - Study "federated" architectures (nodes owned & operated by different agencies)



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Example Mission: Study of Algal Blooms

- **Science Question**: What fraction of Harmful Algal Blooms occur due to nutrients from farmlands vs weather conditions?
- Basic model:
  - Algal bloom ➔ Rapid increase in Chlorophyll-A (Chl-A)
  - High temperature ➔ Algal bloom
  - Low water level/circulation ➔ Algal bloom
  - Floods ➔ Algal bloom
- **Goal**: Obtain co-observations of water quality, quantity and temperature during algal blooms, particularly during onset
  - Relevant spatio-temporal scales: tens of meters, ~6-12 hours
- Sensor network:
  - Water level sensors in certain lakes
  - Satellites with VNIR and or TIR sensors
  - Satellites with altimetry sensors

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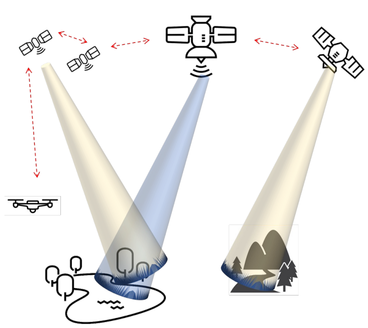
3D-CHESS: Concept of operations
Step 1 – Default mission; on-board data processing



Each node in the system conducts its **nominal mission**, following a **default plan** (e.g., provide global coordinated observations of inland water quantity and quality.)

Nodes can be in space, air, or ground, and they can perform one or more functions (observation, data processing, communication)

Nodes with **data processing** capabilities process the data on board in real time and look for Events of Interest (e.g., algal blooms).

Example on board data processing in VNIR satellite agent:
- Obtain Chl-A from VNIR radiances applying algorithm from Buma and Lee (Remote Sens. 2020, 12(15), 2437)
- Compare Chl-A and Chl-A growth rate with site-specific historical threshold to detect events of interest (Ho et al. 2019, Nature 574 667–670)

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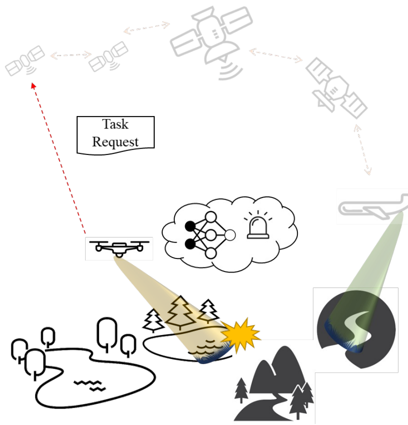
ConOps Step 2 – Detect Events of Interest and Generate Task Requests



A node in the network detects (or predicts) an **event of interest** (e.g., an algal blooms, a flood) at a certain location.

It sends a **Task Request** to the network (broadcast)

Event of Interest: Potential Algal bloom at {lat,lon}. Severity: 7/10

Task Request: Measure water level and temperature at *{lat,lon}* with Δx < 100m [within 6 hours]

Severity score calculated based on fraction of lake area affected. Could also include growth rate and lake use.

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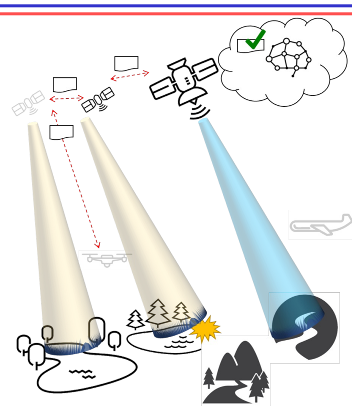
ConOps Step 3 – Node Capability Reasoning



Nodes receive the task request and use contextual information in their knowledge base and the UniKER reasoning algorithm to autonomously determine if they can perform this task.

This requires knowledge about
- Own state, own capabilities
- Relations between task and own capabilities
  - Reason across data product levels (e.g., Level 1← Level 2←Level 3)

Task: Measure water temperature at *{lat,lon}* with Δx < 100m [within 30 min]

Capability: Observe *{lat,lon}* in TIR with Δx < 100m [within 30 min]

```
TaskRequest(Water_Temperature)
CanBeObtainedFrom(Water_Temperature, TIR_Radiance)
CanMeasure(TIRSat-1, TIR_Radiance)
➔ CanPerformTask(TirSat-1)
```

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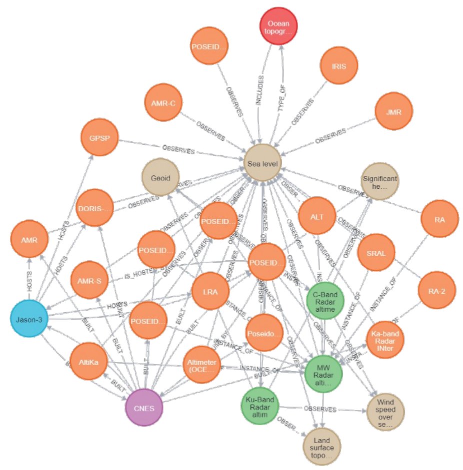
Knowledge Graph

- KG types of entities and relations loosely based on **Semantic Sensor Network** ontology
  - BUILT, BUILT_BY, HOSTS, INCLUDES, INSTANCE_OF, IS_HOSTED_BY, OBSERVES, TYPE_OF
- Data mined from **CEOS database** and **IEEE TGARSS** abstracts
- A **confidence score** is assigned to each triplet mined from IEEE TGARSS to capture epistemic uncertainty
  - Based on Spacy's Named Entity Recognition probs.
- Example triplets:
  - **Observes**(POSEIDON-3B Altimeter, Sea level, 1.0)
  - **Instance_of**(POSEIDON-3B Altimeter, Ku-band radar altimeter, 1.0)
  - Observes(SEVIRI, Vegetation, 0.46)
- Implemented in **Neo4j**
  - 3,536 nodes; 15,193 relations



UKGE: Embedding Uncertain Knowledge Graphs

Uncertain KGs

Hosts (TirSat-1 , TIR Sensor) 1.00
Observes(TIR Sensor, TIR Radiance) 1.00
DerivedFrom (Water Temperature, TIR Radiance) 0.86
RequiredBy (Task Request 1, Water Temperature) 0.75

Observes (TIR Sensor, Water Temperature) ? 0.73

Embedding learning

TIR Sensor

Observes

Water Temp

+

Logical Rule

OBSERVES(Sensor, ObservableProperty) <- INSTANCE_OF(Sensor, SensorType) ^ OBSERVES(SensorType, ObservableProperty)

Predict unseen triples

satellite= TirSat-1
sensor = TIR Sensor
L1 observation = TIR Radiance
L2 parameter = Water Temperature

Mission = "Monitor Algal Blooms"

CanPerformTask(satellite, mission) ⇐ Hosts(satellite, sensor) ∧ Observes(sensor, L1 observation) ∧ DerivedFrom (L1 observation, L2 property) ^ RequiredBy(L2 property, mission)

Probabilistic Soft Logic (PSL)

canPerformTask (TirSat-1, "Monitor Algal Blooms") 0.59

Loss function for training: $\mathcal{J} = \sum_{l \in \mathcal{L}^+} |f(l) - s_l|^2 + \sum_{l \in \mathcal{L}^-} \sum_{\gamma \in \Gamma_l} |\psi_\gamma(f(l))|^2$

MSE btw predicted and true confidence scores

Distance to rule satisfaction for unobserved triples

$l_1 \wedge l_2 = \max\{0, I(l_1) + I(l_2) - 1\}$
$l_1 \vee l_2 = \min\{1, I(l_1) + I(l_2)\}$
$\neg l_1 = 1 - I(l_1)$

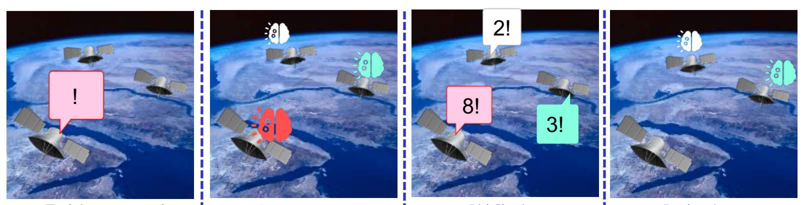
Current results: MSE=0.04 over test set (10% of triples)

ConOps Step 4 – Decentralized coordination

Nodes that determine they can perform the task, they enter a decentralized planning phase based on an **asynchronous consensus-based task allocation** algorithm similar to the well-known CBBA algorithm.

Nodes iterate between two phases: They generate bids for bundles of tasks based on a **science-driven** utility function that considers the tasks' priority scores and the agent's expected measurement performance for those tasks. Engineering costs (e.g., energy) are also considered.

Then they share their bids. If their local information needs to be updated, they do so and go back to generating new bids until consensus is achieved. Once converged, the nodes update their plans.



Task is announced | *Bid Generation* | *Bid Sharing* | *Replanning*

Computing Bids using Science-Driven Utility Functions

- Agent bids are calculated based on a utility function that considers both the of the inherent science value of the task (i.e., severity S of the event of interest), the measurement performance P, and the engineering cost to perform the task E

$$U = S * P - E$$

- Measurement performance calculated applying the VASSAR method (AIAA JSR 51.5 (2014): 1505-1521) where requirements come from a Science and Applications Traceability Matrix
- Example:

Science Objectives	Scientific Measurement Requirements												Science Objective Priority
	VNIR Spatial	VNIR Temporal	VNIR Spectral	VSWIR Swath	VSWIR SNR	TIR Spatial	TIR Temporal	Alt Spatial	Alt Temporal	Coincidence Type	Decorrelation Time	Data Product Duration	
Understand the impact of temperature on algal bloom formation	30 m/100 m	1 day/3 days	Hyperspectral/Multispectral	320 km/10 km	600/100	100 m/300 m	1 day/3 days			VNIR/TIR	1 day	5 days	Highest
Understand the local impact of temperature on algal bloom lifecycle	10 m/30 m	1 day/3 days	Hyperspectral/Multispectral	320 km/10 km	600/100	10 m/30 m	1 day/3 days			VNIR/TIR	1 hour	30 days	Medium
Understand the impact of lake level fluctuations on algal bloom formation	30 m/100 m	1 day/3 days	Hyperspectral/Multispectral	320 km/10 km	600/100			3 cm/10 cm	1 day/3 days	VNIR/Alt	1 hour/1 day	5 days	Highest
Characterize the algal bloom lifecycle	10 m/30 m	4 hours/1 day	Hyperspectral/Multispectral	320 km/10 km	600/100					N/A	N/A	30 days	Highest

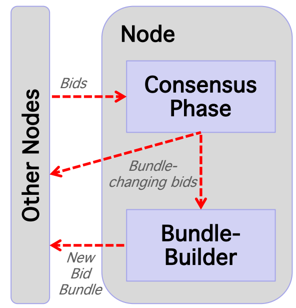
Modified Asynchronous Coupled-Constraint Consensus-Based Bundle Algorithm (MACCBBA)

Standard CBBA has 2 main shortcomings for our application:
- Assumes continuous and zero-latency communications
- Cannot handle complex task dependencies and coalitions

Solution: Async CBBA + Modified CCBBA (Syst Eng 21.5 (2018): 432-454.) → MACCBA

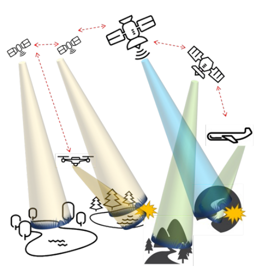
Complex Task Dependencies
- Complex dependencies include multiple geophysical parameters, simultaneous co-observations within decorrelation time, day/night/weather constraints, observation geometry constraints
- Nodes can only bid on tasks if they satisfy all requirements and time constraints (pre-filter based on reasoning)
- If not, they may form **coalitions** with other nodes and perform a **joint bid**

Asynchronous Bid Sharing
- Consensus phase and bundle-building phase occur asynchronously
- Listener (Consensus phase) only informs bundle-builder of incoming bundles when they may impact the current bundle
- Bundle-building phase only replans when new information is received from the listener
- Nodes only share information when the listener deems it critical or when the bundle-builder creates a new bundle



Asynchronous MCCBBA

ConOps Step 5 – Update plans; keep going

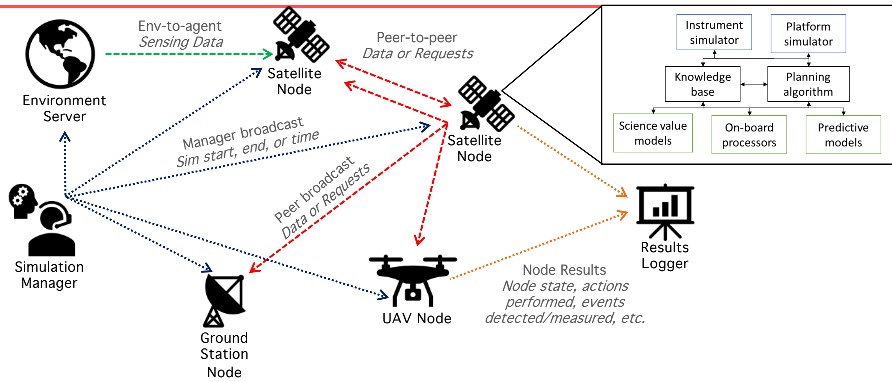


The pertinent nodes respond to the task request and the relevant images are taken and sent to the ground and/or the node that generated the task request.

The network continues to operate in this way. Nodes are added or removed from the network over time. Node states and the Earth system state change over time.

Nodes capabilities and relations between capabilities and tasks may also change slowly over time (e.g., new science discoveries!)

3D-CHESS Simulation Tool Overview



- 3D-CHESS Nodes modeled as agents that exchange messages to coordinate
  - Point-to-point (REQ/REP ports) for peer-to-peer communications
  - Publish-subscribe (PUB/SUB ports) for broadcasting messages
- Environment modeled as a server to be accessed by nodes
  - Simulates Earth system AND agent state (e.g., position, velocity, comms accesses, coverage metrics)
  - Nodes “sense” the environment by requesting data from the environment server
- Simulation Manager manages synchronization and time
  - Time management can be Real-time, Accelerated real-time, or Event-driven.
- Agents push results to Results Logger

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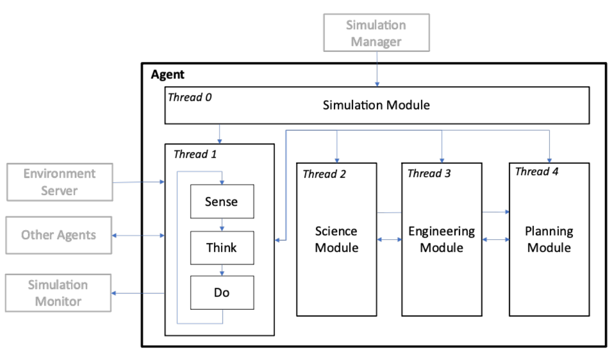
Agent Node Architecture



- Message-Driven Internal Modules
  - Intra-agent modules modeled as concurrent asynchronous processes
  - Communicate by sending messages into asynchronous message queues

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Engineering module - Spacecraft Subsystems

- **Command and Data Handling**
  - Saves images from payload to memory
  - Monitors remaining storage capacity to check for future overflows
- **Guidance and Navigation**
  - Gets position and velocity information from Environment, plus eclipse information
- **Electric Power Subsystem**
  - Tracks which submodules are "on" and provides power
  - Monitors battery level and sends warnings when below a certain threshold
- **Payload**
  - Gets images from Environment based on current orbit position and spacecraft attitude
  - Sends images to Command and Data Handling
- **Communications**
  - RX/TX requests from other agents, checking access windows
- **Attitude Determination and Control**
  - Slews spacecraft to proper angle to collect measurements based on a max slew rate and power consumption

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Scenario setup

- 262 lakes from GREALM + 1,000 lakes from HydroLakes
- Compared 6 configurations
  - A. **New** satellites, steer off nadir to see all lakes (**steerable**), and respond to events of interest (**responsive**)
  - B. **New** satellites, steerable, not responsive
  - C. **Existing** satellites, steerable, responsive
  - D. **Existing** satellites, steerable, not responsive
  - E. **New** satellites, not steerable, not responsive
  - F. **Existing** satellites, not steerable, not responsive (**status quo)**
- 8 Existing sats:
  - Landsat, Sentinel-2A/B, SWOT, Sentinel-6A/B, CryoSat-2, Jason-3
- 10 New satellites:
- 4 altimeters (2 planes of 2 satellites)
  - 6 imagers (3 planes of 2 satellites): 2 VNIR only, 2 VNIR+TIR, 2 TIR only
- Responsiveness based on completely decentralized strategy instead of MACCBBA (very limited coordination)
- Parameters
  - Agility of 1 deg/s
  - 30 days simulation time
  - 4-hour decorrelation time

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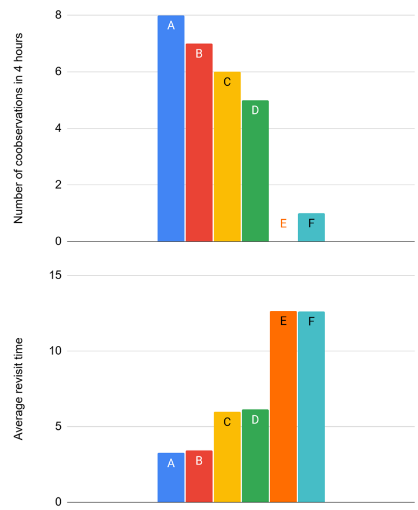
Preliminary Results

- Value metric is number of unique co-observations of water level + temp + Chl-A during algal blooms within 4 hours decorrelation time
- Responsiveness adds value for both new satellites (A>B) and existing satellites (C>D)
- New satellites (A & B) are better than existing satellites (C & D)
- All steerable cases (A-D) greatly outperform the nadir cases (E, F)
- New satellites steerable and responsive (A) is the best configuration with 8 unique co-obs and 3.25h avg revisit time



Presentation Contents

Accomplishments so far

- Developed the **MACCBBA algorithm** for decentralized task allocation in sensor webs with complex tasks
- Developed first version of the **3D-CHESS multi-agent simulation tool** that can be used to simulate a variety of sensor webs including space, air, and ground platforms
- Obtained initial performance results for **2 mission scenarios** that demonstrate sensor webs with satellites and ground sensors
  - Mission 1: Total Suspended Sediments and water levels
  - Mission 2: Algal blooms
- Currently developing scenario 3
  - Intermittent rivers
  - Incorporates UAVs

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Major Next steps

- Extensive simulation studies for feasibility, performance characterization, scalability, etc.
  - Scenario 1: Total suspended sediments + floods
  - Scenario 2: Algal blooms
  - Scenario 3: Intermittent rivers
- Extension to multi-mission (i.e., more autonomy)
  - Autonomous specification of task requests and configuration of planners (e.g., model selection, utility functions) from initial mission specification and knowledge graph
- If there is time:
  - Plan integration with NOS-T
  - Test coordination approach based on Decentralized Kalman filter that provides a rigorous way of accounting for uncertainty

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Presentation Contents

- Background and Objectives
- Technical and Science Advancements
- Summary of Accomplishments and Plans Forward
- Actual or Potential Infusions and Collaborations
- Publications - List of Acronyms

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Actual or Potential Infusions and Collaborations

- Used modules of EOSim (OrbitPy, InstruPy) developed in AIST **TAT-C project**
- Planning integration with AIST **NOS-T project**
- Plan on releasing 3D-CHESS tool open source
- Studying infusion into DOD programs
- 3D-CHESS Capstone project at Texas A&M University

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Presentation Contents

- Background and Objectives
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Publications

2 conference papers:

1. B. Gorr, A. Aguilar, Z. Wu, W. Cho, K. Cheng, M. Stroud, V. Ravindra, C. David, H. Gao, Y. Sun, A. Mehta, G. Allen, D. Selva. Multi-Instrument Flood Monitoring With A Distributed, Decentralized, Dynamic And Context-Aware Satellite Sensor Web. In 2023 IEEE International Geoscience And Remote Sensing Symposium (IGARSS).

2. A. Aguilar, B. Gorr, D. Selva, Z. Wu, W. Cho, K. Cheng, A. Mehta, M. Stroud, G. Allen, V. Ravindra, C. David, H. Gao, Y. Sun. Decentralized Market-based Measurement Assignment Strategy for Simultaneous Earth Observations for Distributed Heterogeneous Satellite Systems. In 2023 IEEE International Geoscience And Remote Sensing Symposium (IGARSS).

1 poster:

Selva et al. Simulating A Context-aware Heterogeneous Sensor System for Monitoring Inland Waters and Ecosystems with 3D-CHESS. *AGU Fall Meeting 2022*, Chicago IL.

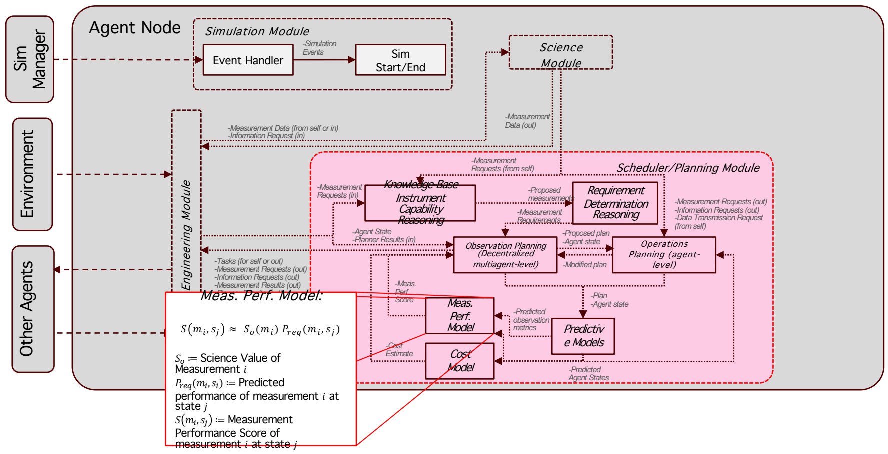
Acronyms

List of Acronyms

- 3D-CHESS — Decentralized, Distributed, Dynamic, and Context-aware Heterogeneous Sensor Systems
- DARPA — Defense Advanced Research Projects Agency
- KG — Knowledge Graph
- MACCBBA — Modified Asynchronous Coupled-constraints Consensus Bundle-Based Algorithm
- NISAR — NASA-ISRO SAR Mission
- NOS-T — New Observing Strategies Testbed
- RAPID — Routing Application for Parallel computatIon of Discharge
- SAR — Synthetic Aperture Radar
- SWOT — Surface Water and Ocean Topography mission
- TAMU — Texas A&M University
- TIR — Thermal Infrared
- TRL — Technology Readiness Level
- UCLA — University of California Los Angeles
- UniKER — Unified framework combining Knowledge graph Embeddings and logical Rules
- UKGE — Uncertain Knowledge Graph Embeddings
- VASSAR — Value Assessment of System Architectures using Rules
- VNIR — Visible and Near Infrared

BACKUP SLIDES

Scheduler Module



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Agent node architecture
Science Module

Objective: Schedule measurement requests according to the agent's measurement capabilities and state

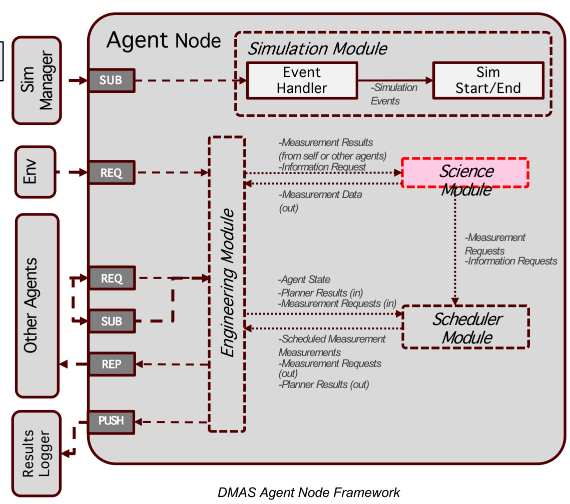
Desired Capabilities:

Consider Agent capabilities
- Use Knowledge-Base to inform whether the agent can perform a measurement

Consider agent's current and future state
- Use engineering module for current state
- Predict agent state as proposed scheduled actions are being performed

Schedule measurements as to maximize scientific value and minimize cost
- Quantify the predicted scientific value of a measurement and schedule accordingly
- Contain some sort of cost model that weighs down the value of measurements. Can be tied to the engineering cost of performing measurements

Publish and receive results to and from other agent if scheduling algorithm require collaboration with other agents



DMAS Agent Node Framework

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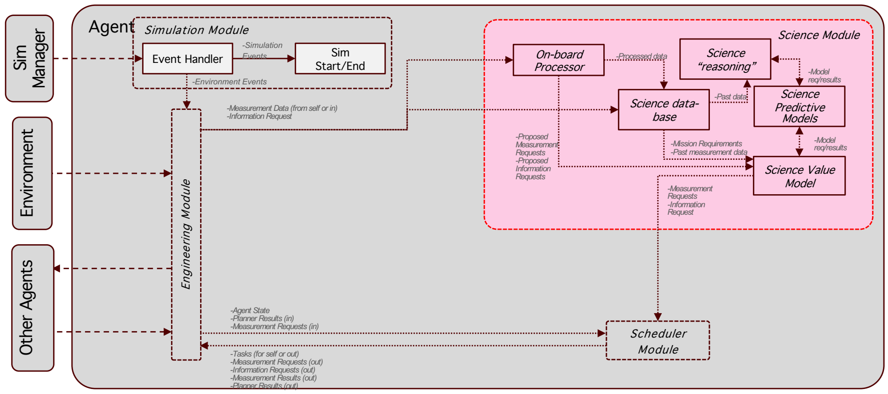
Science Module



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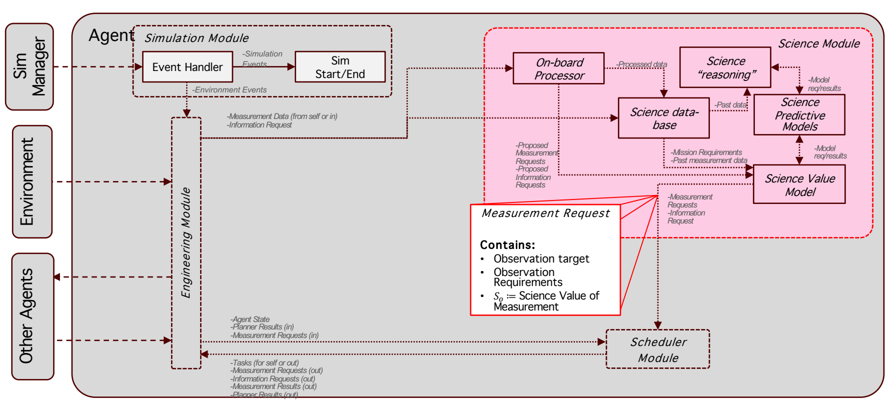
Science Module



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Agent Node architecture
Engineering Module

Objective: Simulate the agent's internal state and provide realistic behavior and capabilities based on its components and operations

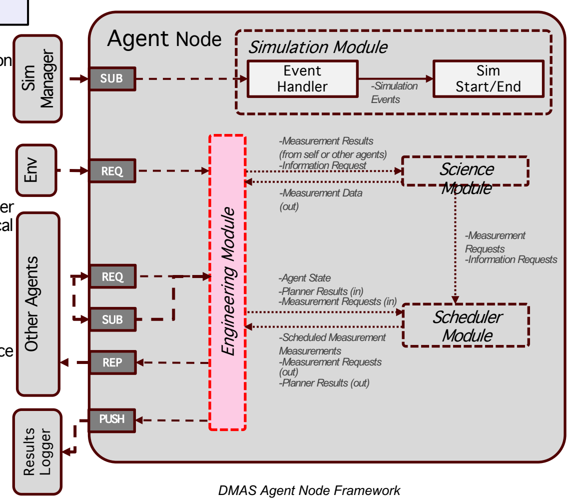
Desired Capabilities:

Agent State Tracking
- Sense and track agent's external state (position, velocity, attitude, and eclipse)
- Track agent's internal state (power and data generation, storage, and consumption, component status, etc.)
- React to environment events
  - i.e., turn off solar panels if eclipse event occurs

Scheduler Action Performance and Rejection
- Receive and perform instructions from scheduler
- Revert actions or even turn off agent if a critical state is reached
  - i.e., interrupt a measurement if power consumption from instruments exceeds generation

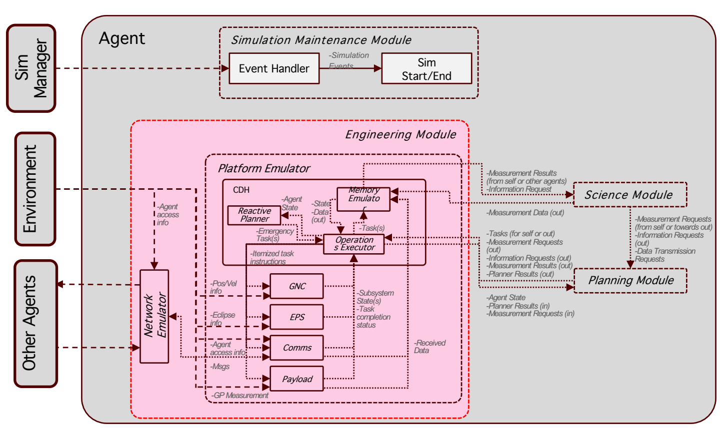
Instrument Simulation
- Sense the environment
- Provide realistic measurement results to science module

Network Simulator
- Send and receive messages from/to other agents
- Capture network delays
  - Due to transmission latency and data-rate
  - Due to buffer saturation



DMAS Agent Node Framework

Agent Node architecture
Engineering Module



Engineering Module - Initial Implementation :

Platform Emulator
Simulates the agent's on-board subsystems

Command and Data Handling (CDH)
- Receive commands to perform from planner
- Track and manage agent's internal memory state
- React to the platform's critical or failure states

Guidance Navigation and Control (GNC)
- Sense and track agent's position and velocity vector
- Sense and track agent's eclipse state

Electrical Power Subsystem (EPS)
- Track power generation/consumption

Comms
- Emulate transceiver buffers
- Discards messages that cannot fit in buffers

Payload
- Requests measurement information to the environment
- Provides CDH with simulated instrument results from an observation

Network Emulator
Simulate latency due to range latency or channel data-rate

Agent node architecture
Scheduler Module

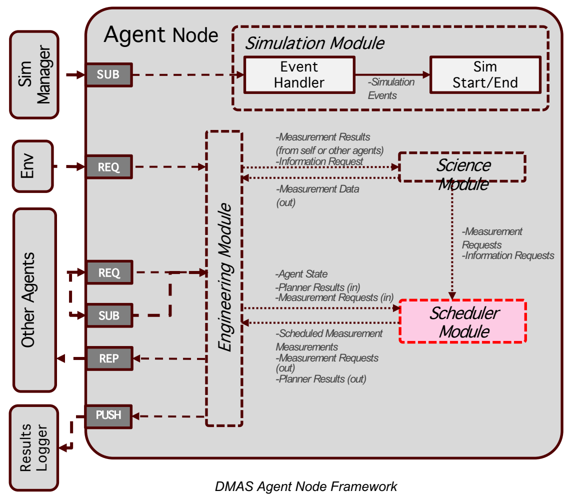
Objective: Simulate the agent's internal state and provide realistic behavior and capabilities based on its components and operations

Desired Capabilities:

On-board Data Processing
- Process raw data being sensed by the agent's instrument
- Process raw data sent from other agents who may lack processing capabilities

Create measurement requests for areas of interest
- Create a data-base with measurements from parent agent or from other agents
- Use data-base to detect areas of interest based on processed data
- Use predictive models to infer possible future events in areas of interest
- Request missing data as a measurement request or an information request to parent agent or to other agents if results would complete predictive model and if prediction would be worth the effort

Quantify Scientific Value of a Measurement
- Use predictive models, data-base, and (or) mission requirements to infer the scientific benefit of a potential measurement being considered by the scheduler



DMAS Agent Node Framework

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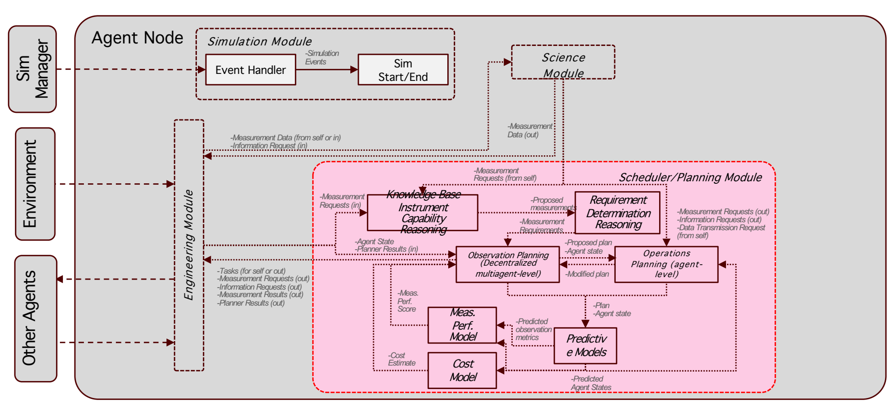
Scheduler Module



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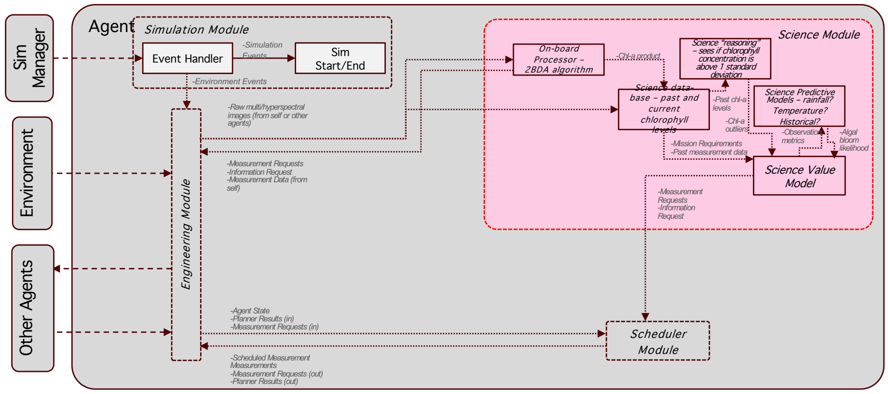
Science Module – Chl example

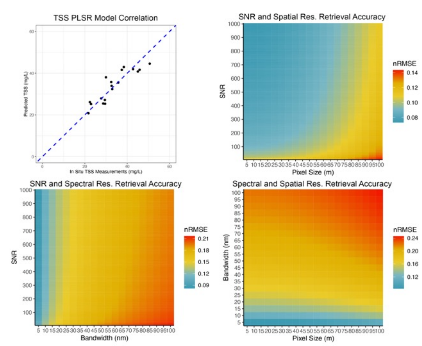


Science module – Example science value model

Science return function has multiple terms capturing data quantity and quality as a function of SNR and spatial/spectral/temporal resolution

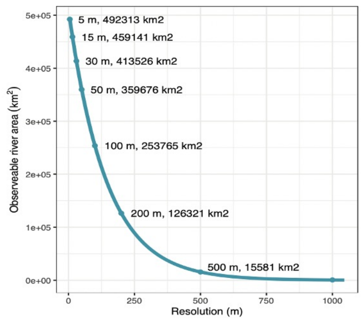
$$u = \beta_1 u_1 + (\beta_2 u_2 + \beta_3 u_3)$$

- Proxy for **data quality** is total suspended sediment retrieval accuracy
- Dependency of TSS retrieval accuracy on **SNR, spatial and spectral resolution** was found through data degradation study using AVIRIS data
  - $u_1 = a \log SNR - b\Delta x^2 - c \log \Delta\lambda + d$
  - a = 3.59 x 10^{-2}, b = 1.12 x 10^{-5}, c = 0.163, d = 0.978

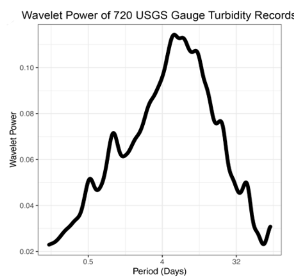


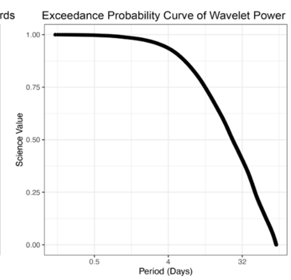
Science models – Data Quantity

- Dependence of **data quantity** on **spatial resolution** is found from the fraction of global rivers that are larger than Δx (GWRL database)
  - $u_2 = a_1 \exp\{b_1 \Delta x + c_1\}$
  - $a_1 = 1.97 \times 10^{-6}$, $b_1 = -0.007$, $c_1 = 13.14$
- Dependence of **data quantity** on **revisit time** Δt is found from a wavelet analysis on 720 turbidity gauge records

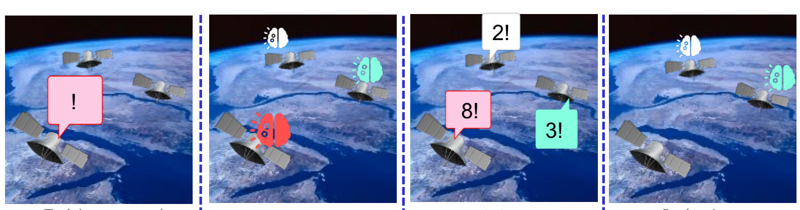


$u_3 =$





Planning Module – Decentralized Planning



Task is announced *Bid Generation* *Bid Sharing* *Replanning*

Decentralized Planning based on Consensus-Based Bundle Algorithm (CBBA)

- Decentralized market-based planning approach
- Nodes bid on measurement tasks using a **science-driven** utility function
- Nodes iterate between two phases
  - Bundle-building phase
    - Bids are generated based on a node's expected performance using their most recent task and bid information
    - Bids are saved in a bundle of a predefined length
  - Consensus phase
    - Agents broadcast their bid bundle and listen for other agents' bids
    - If differences are found with the incoming bids, an agent will re-enter the bundle-building phase and re-plan using the newly acquired information
    - If not, consensus is inferred to have been reached
- Winning bids represent final task assignment

UKGE Results over CEOSDB

- **Input**:
  - Knowledge Graph (mined from **CEOS database**)
  - Rules
    - i.e., OBSERVES(Sensor, ObservableProperty) <- INSTANCE_OF(Sensor, SensorType) ^ OBSERVES(SensorType, ObservableProperty)
- **Task**:
  - 21,194 triples divided in 80% training, 10% validation, 10% test (2120)
  - Predict confidence scores of unseen triples in the test set
- **Evaluation Metric:**
  - Mean Squared Error (MSE) between predicted vs actual confidence score of the triples.

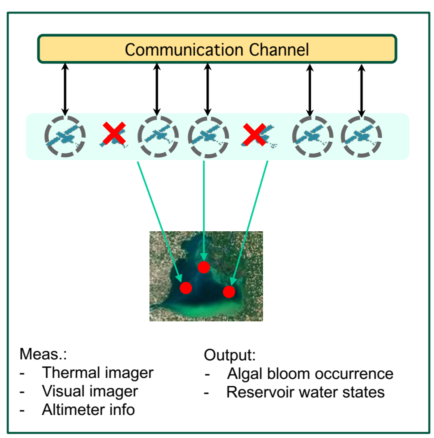
Using embedding only	Using embedding + rules
0.050327	0.041043

Decentralized input and state estimation of Satellite Sensor Network

Two components:

1. ***Decentralized Kalman Filter***
   - Simultaneously estimate the unknown input (algal bloom) and states (water level and quality) in a decentralized manner.
2. ***Sensor Planner***
   - Find a subset of sensors to achieve optimal estimation given costs of using different sensors/platforms.

- ***Advantages:***
  - Rigorous estimation of covariance
  - Seamlessly adapts to different types of agents



Decentralized input and state estimation of Satellite Sensor Network

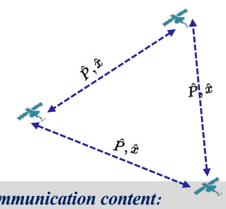
Decentralized input and state estimation of Satellite Sensor Network

Step 1: Find a subset of sensors based on the prior costs

$$y^* = \underset{y}{\operatorname{argmin}} \operatorname{Tr}\left(\tilde{P}\right)$$ ← Goal: minimize variance of each sensor

$$\text{s.t } c^\top y \leqq \beta$$ ← constraint: total computation cost

$$y = \left[y^1, y^2, \cdots, y^r\right]^\top \quad y^i \in \{0, 1\}$$



Communication content:
- $\hat{d}_j$: individual input estimation
- x_j: individual state estimation
- P_j: individual covariance estimation

Step 2: Decentralized estimation with communication

1. Input estimation of each node

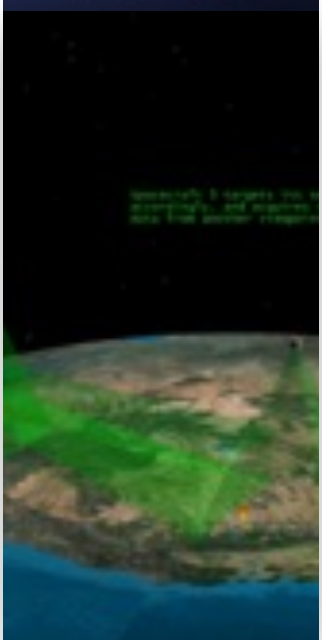
$$d_i = \sum_j^N \omega_j d_j$$

2. State estimation of each node

own prediction

$$\bar{x}_i = \bar{P}_i^{-1}\left[\hat{P}_i^{-1} \cdot \hat{x}_i + \sum_j^N \left[\bar{P}_j^{-1}\bar{x}_j - \hat{P}_j \cdot \hat{x}_j\right] + \sum_j \left[\bar{P}_j^{-1} - \hat{P}_j^{-1}\right] Bd_i + Bd_i\right.$$

state — state compensation through communication — Input compensation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