

An aerial photograph of a landscape featuring a large body of water on the left, a sandy beach curving along the shore, and a dense forest of green trees on the right. A small building with a red roof is visible in the lower right quadrant. The image is partially obscured by a green overlay on the left side.

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SMARTER DATA FOR A STRONGER PLANET

Advances in deep learning spectral models for mission-agnostic cloud detection

Arthur Vandenhoeke – 13th November 2024, Workshop on International Cooperation in Spaceborne Imaging Spectroscopy

Challenges

Recent progress in Earth Observation

- Satellite technology (Sensors, HW, SW)
- Ground network infrastructure

→ Shift towards **small, affordable** and **disposable** satellites.

Increasing demands for hyperspectral data providers

- Disaster response
- Environmental monitoring
- Security & Surveillance

High spatial /
spectral res
images

x

Limited bandwidth
for downlink
transmissions

x

Small
operational costs



Reduce the amount of data that needs to be sent to Earth by **processing hyperspectral images in orbit**.

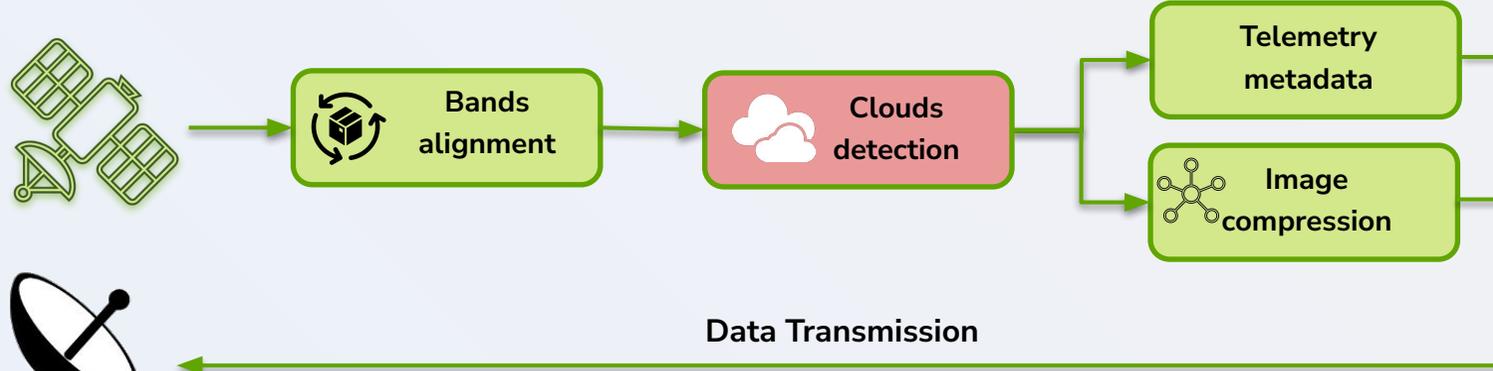
HF1A - South African Coast
10 October 2024 08:23:09 UTC



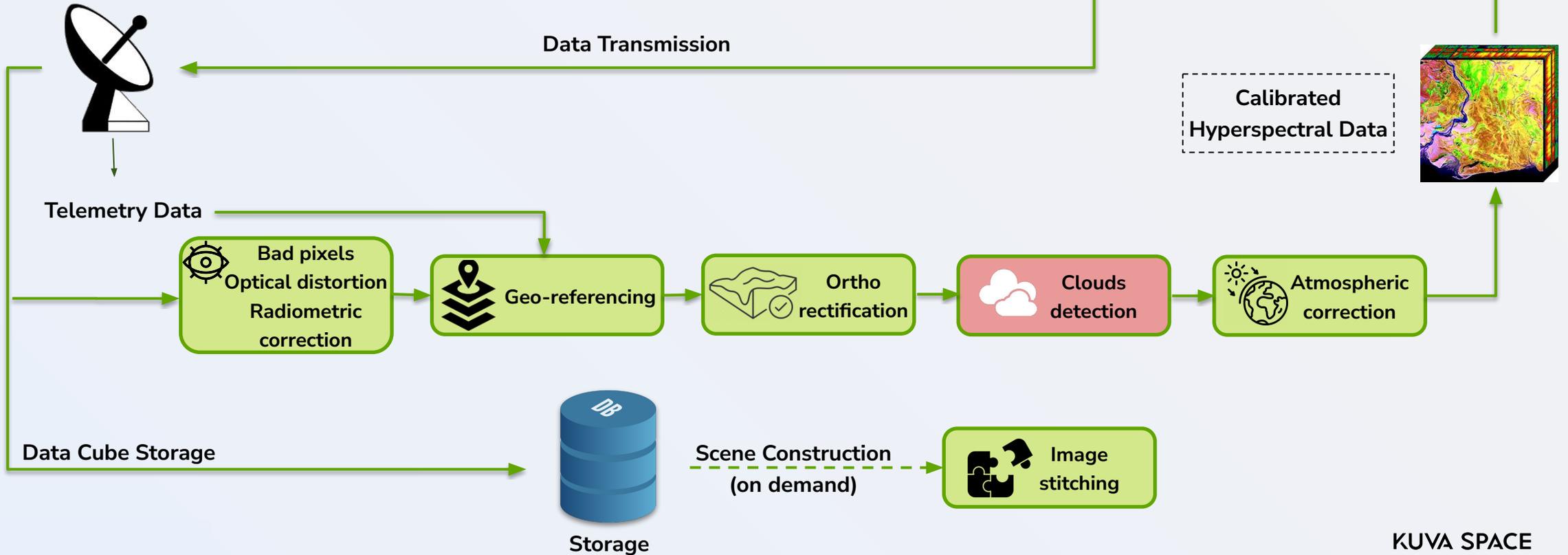
Data Processing chain

From satellite acquisition to hyperspectral product

On-Sat processing



On-ground processing



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SMARTER DATA FOR A STRONGER PLANET

On-orbit cloud detection

Approach

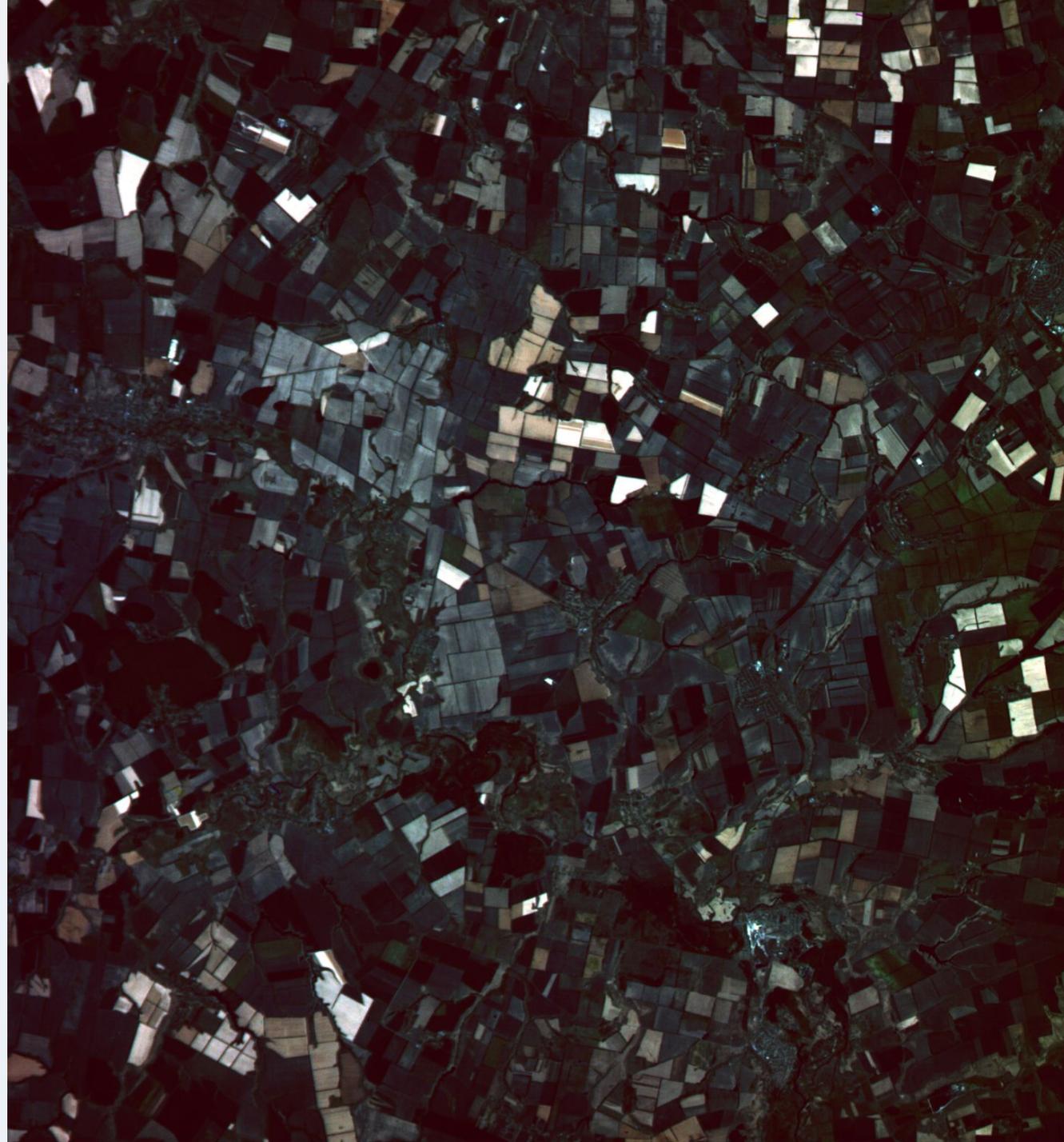
Limitations of Vision Transformers for Hyperspectral Imaging:

- Data Requirements: Extensive, high-quality labeled datasets
- High Computational Load: Large number of parameters
- Large Model Size: Tens-Hundreds of MBs >> uplink capacity
- Latency Constraints: Hinder near-real-time operations

Lite Vision Transformer with **Enhanced Self-Attention** †

- Reduced wavelengths (RGB-NIR only);
- Small inference latency (s to ms);
- Small number of parameters;
- Periodic fine-tuning & uplink;
- Maximum 2MB (= Max 1M parameters using float16);
- > 90% F1-Score on binary class.

† Yang, Chenglin et al. "Lite Vision Transformer with Enhanced Self-Attention." 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (2021):



On-orbit EO pipeline

Model Training

- Datasets
 - [L8-Biome](#) (clear / thin / thick / shadow - VIS-NIR-SWIR)
 - [95-Cloud](#) (cloud / no cloud - VNIR)
- Aggressive augmentation are key to generalization
 - Geometric augmentations (flipping, affine transformations)
 - Radiometric augmentations (brightness, gamma, blurring)

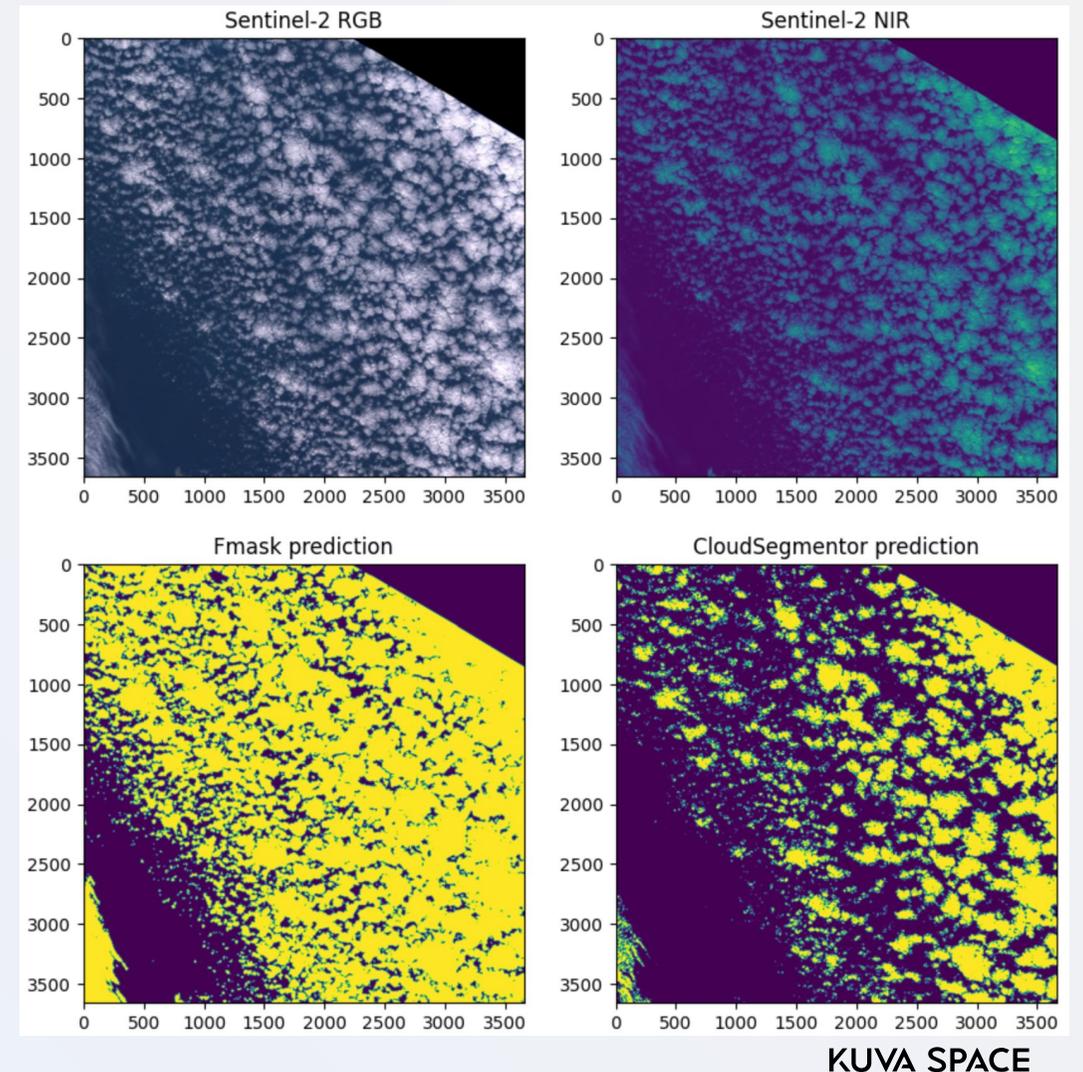
Model Evaluation

- Benchmark LVT across various sensors:
 - PRISMA [HSI] → Qualitative Inspection (WIP)
 - Sentinel-2 [MSI] → Comparison against FMASK
- LVT reaches **90.28% F1-Score** on binary classification (test set)
- Inference speed on 384 x 384 x 4 image = 2ms on NVIDIA 3090

Early results suggest our model have the capacity to **work even across different sensor technologies and satellites** despite have been developed just with Landsat imagery.

On-board deployment

The incorporation of GPU will be investigated in a recently secured project with Copernicus Security Services.



Benchmarking inference



Raspberry Pi 3B (Cortex A-53) - Hyperfield-1

- Ubuntu 22.04.3 LTS
- PyTorch 2.1.1
- Image size (4, 384, 384)
- Inference latency: **5.43 s / image**

NVIDIA Jetson AGX Orin Dev Kit - Hyperfield-2

- Ubuntu 22.04 at 30W power mode
- Jetpack 6.1 SDK with L4T PyTorch Image
- Inference latency: **32 ms / image** (4 x 384 x 384)
- = **431ms / HF-1 image** (64 x 4 x 256 x 256)



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SMARTER DATA FOR A STRONGER PLANET

On-ground cloud detection

On-ground Cloud Detection

Training Workflow

Model Selection

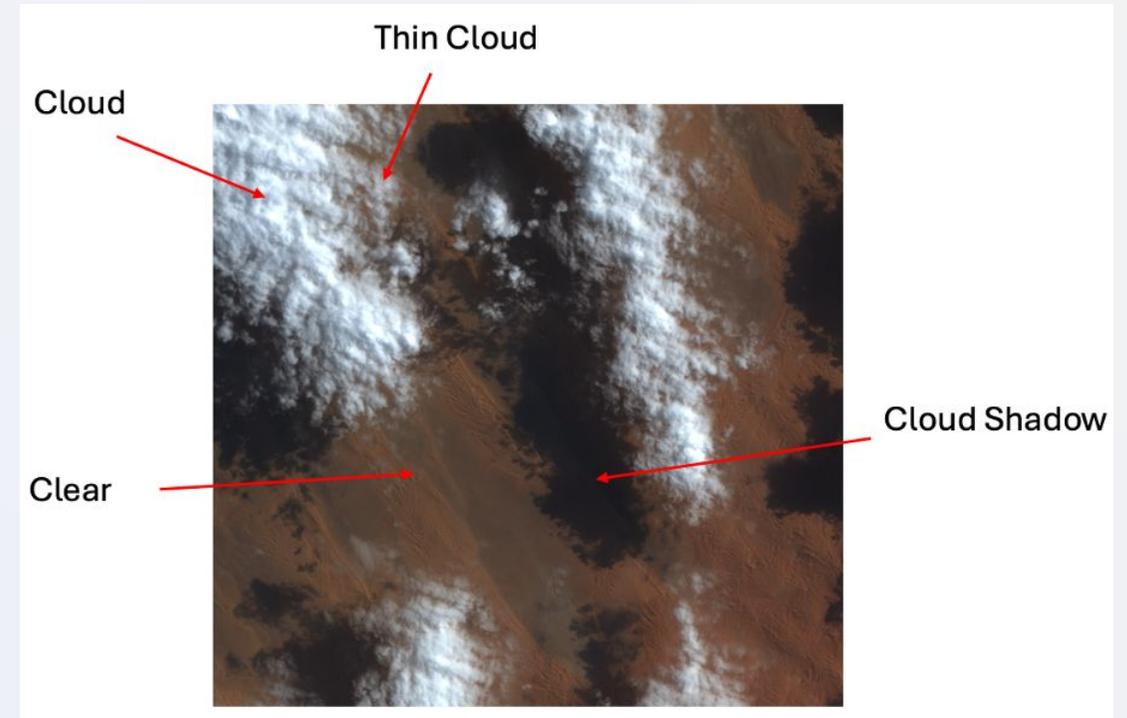
- Vision Transformer with patch_size = 4 and emb_dim = 192
- Keep model size down to 5.5M parameters (tiny)

Model Training

- Datasets: [L8-Biome](#) (clear / thin / thick / shadow - VIS-NIR-SWIR)
- Cosine learning rate scheduler with linear warmup
- Same augmentations as on-orbit cloud detection
 - Geometric augmentations (flipping, affine transformations)
 - Radiometric augmentations (brightness, gamma, blurring)

Iterative Fine-Tuning

- L8-Biome contains inconsistencies (especially cloud shadows)
- Vision Transformers are data-hungry (need >> 96 L8 images)
- Use L8-Biome to train v1 then use v1 as pre-annotator
- Encord annotation platform to manually fin-tune annotations
- Gradual increase of data set to **600 annotated PRISMA images**

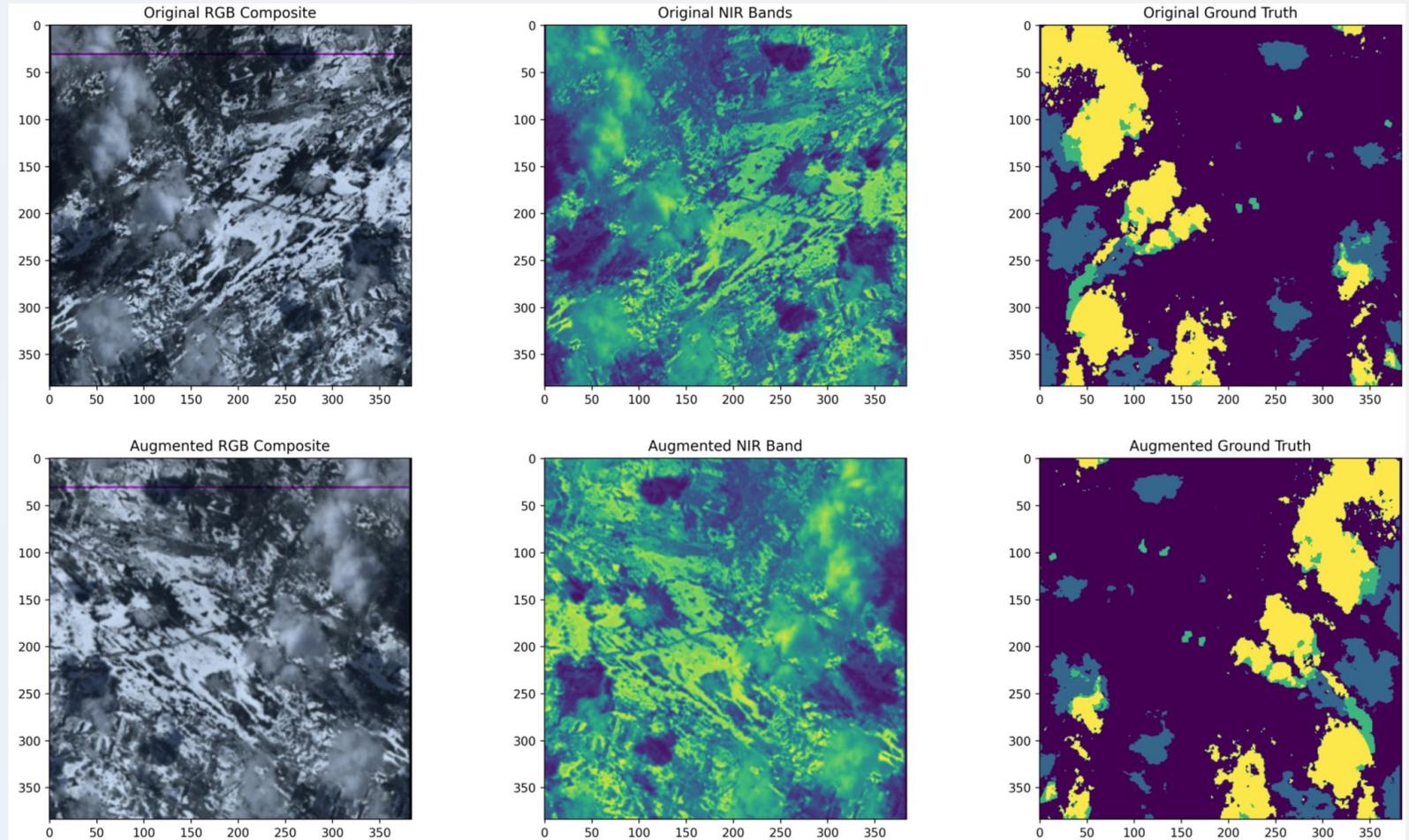


Ontology definition in L8-Biome and Encord annotation platform

On-ground Cloud Detection

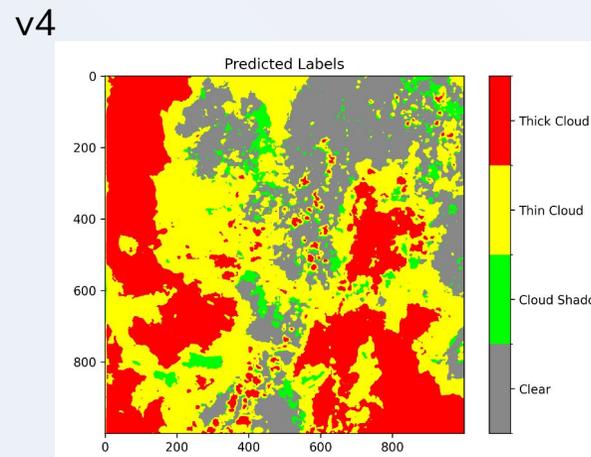
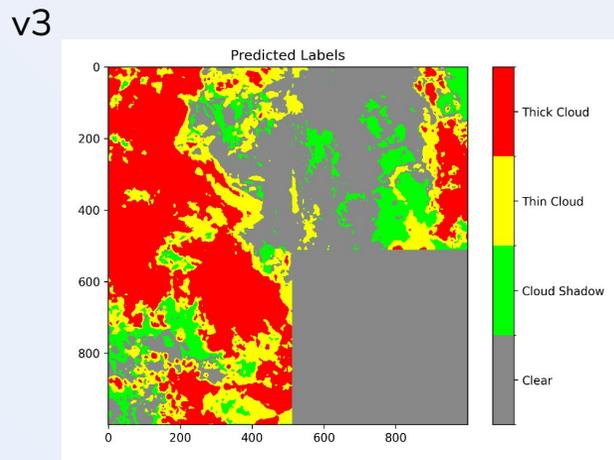
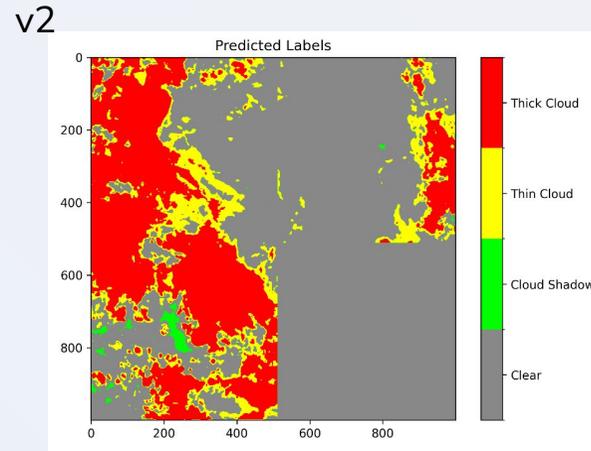
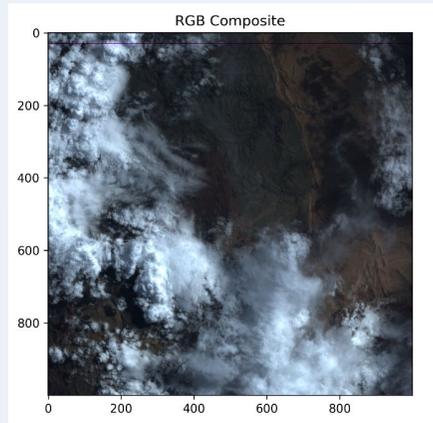
Manual PRISMA image annotations

- Sample of **PRISMA image** and its manual expert annotation (top).
 - Yellow = Thick Cloud
 - Green = Thin Cloud
 - Light Blue = Cloud Shadow
 - Dark Blue = Clear
- Bottom row = the cropped and blurred augmentation of the selected sample.
- Carefully chosen set of PRISMA images to overcome the known limitations of the L8-Biome data set.



On-ground Cloud Detection

Iterative fine-tuning

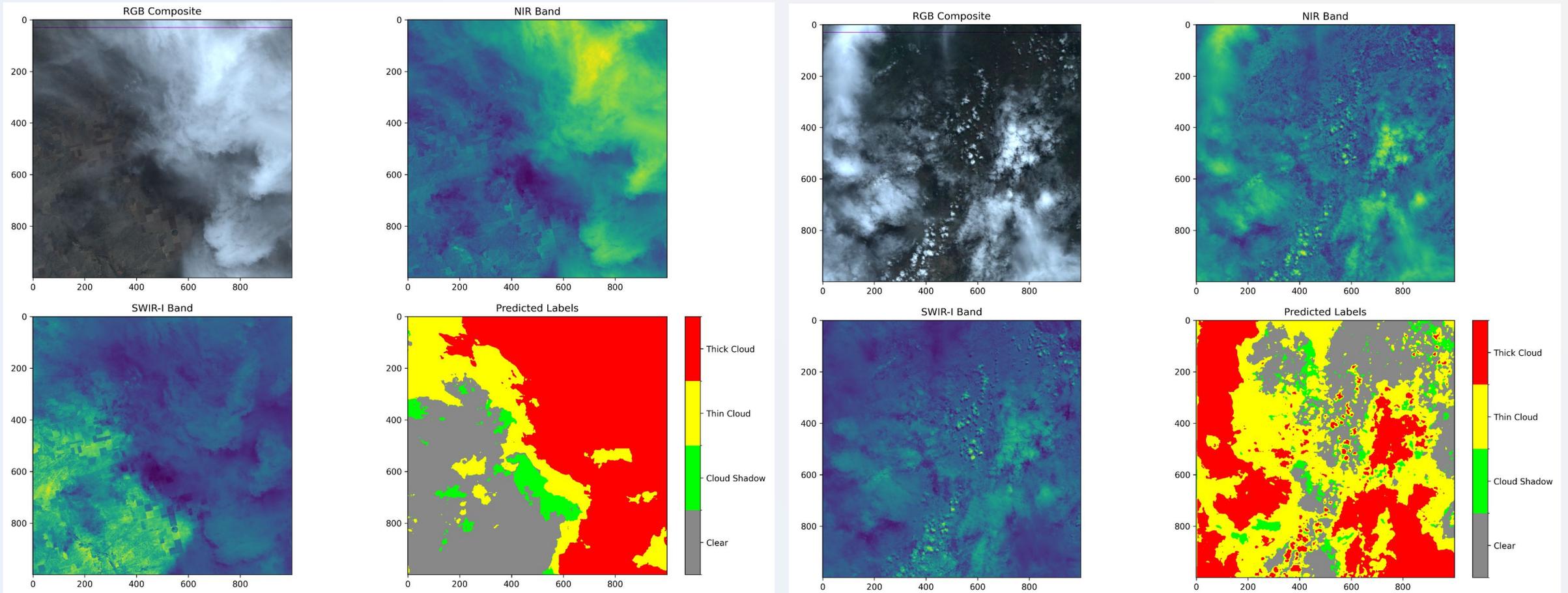


Epoch Number	ViT version	# PRISMA images	F1-Score (%)
271	v1	N/A	92.78
374	v2	250	94.02
593	v3	500	94.22
600	v4	600	94.45

Classification metrics across fine-tuning runs

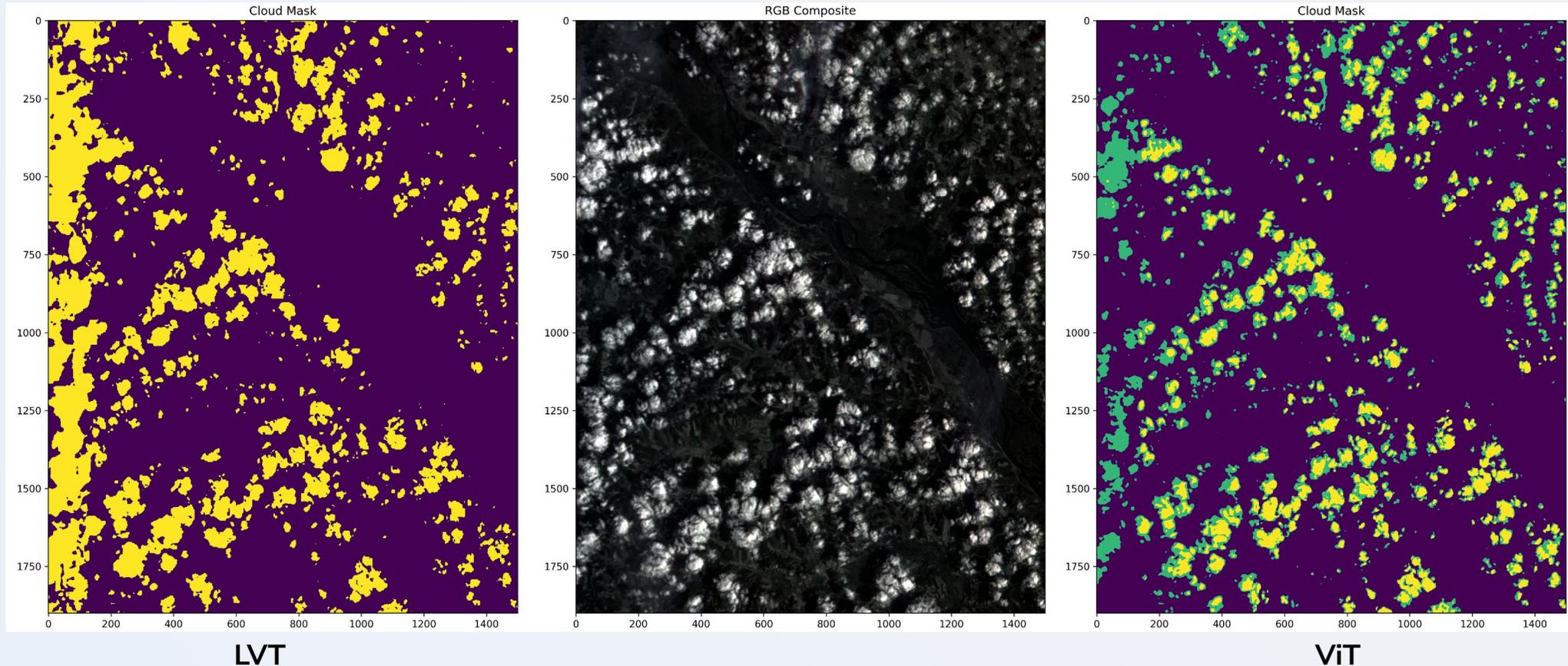
On-ground Cloud Detection

Inference on PRISMA imagery



On-ground Cloud Detection

Application to raw HF-1A imagery (uncalibrated DN)

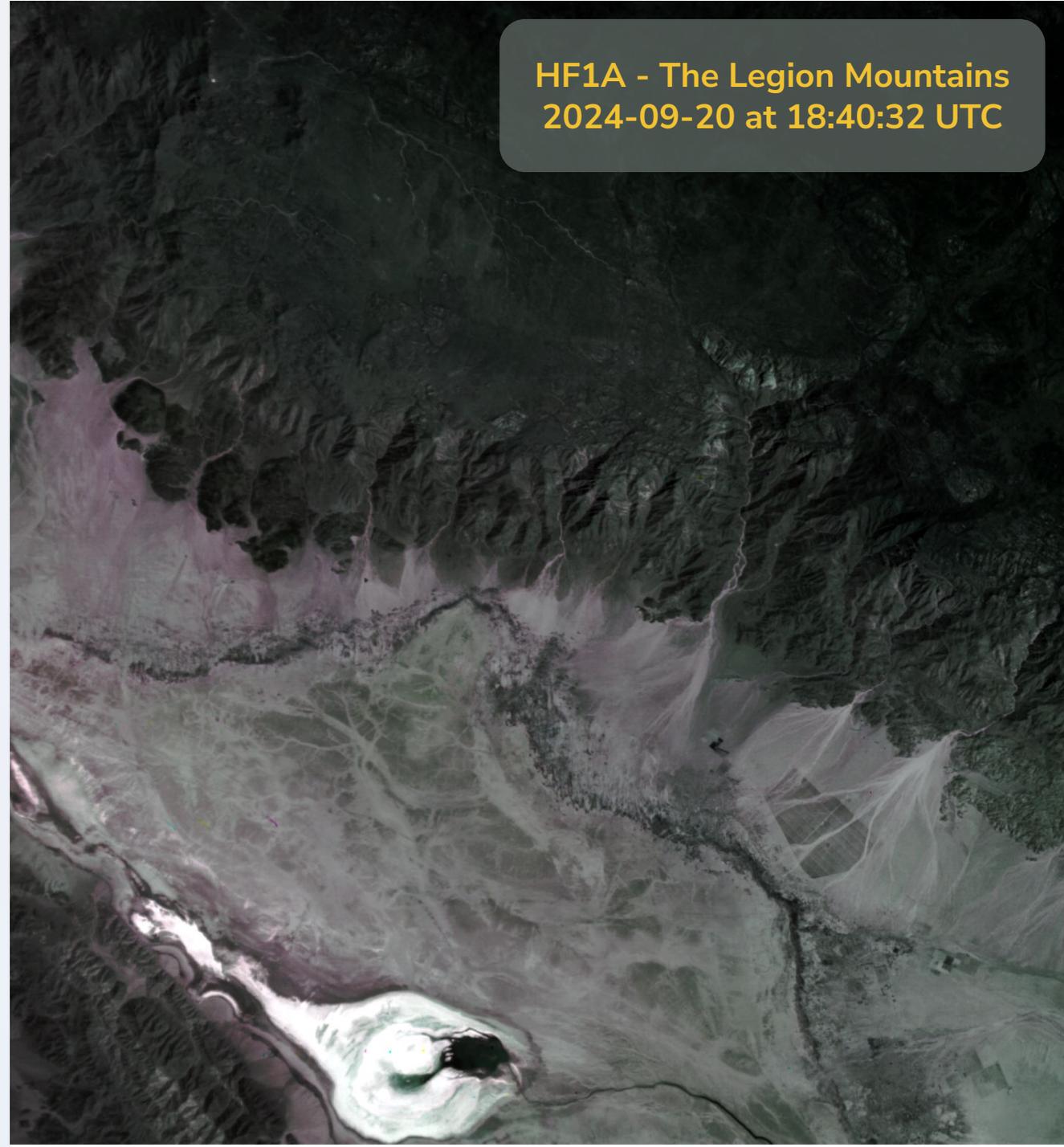


Colfax, USA - 1 November 2024 17:14:53 UTC

Conclusion

- How much “instrument agnostic” are the current state of the art algorithms?
 - Tailored for specific EO missions
 - Fmask → Landsat + Sentinel
 - Handcrafted thresholds and band ratios
 - Requires mission-specific inputs
 - S2cloudless requires 10 S2 bands
 - CloudSEN12 adds S1 (SAR), DEM, surface water occurrence and land cover masks
- Can the AI based approaches really become instrument agnostic?
 - Yes, but data and algorithms go hand in hand
 - Key =
 - Common & minimalistic data set, with a ...
 - sufficiently complex model architecture that ...
 - lead to rich image representations (training)
 - “An uncalibrated cloud remains a cloud”
 - SSL offer promising avenues for better generalization

HF1A - The Legion Mountains
2024-09-20 at 18:40:32 UTC





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**TOGETHER TOWARDS A
SUSTAINABLE PLANET AND
PROSPEROUS HUMANKIND**



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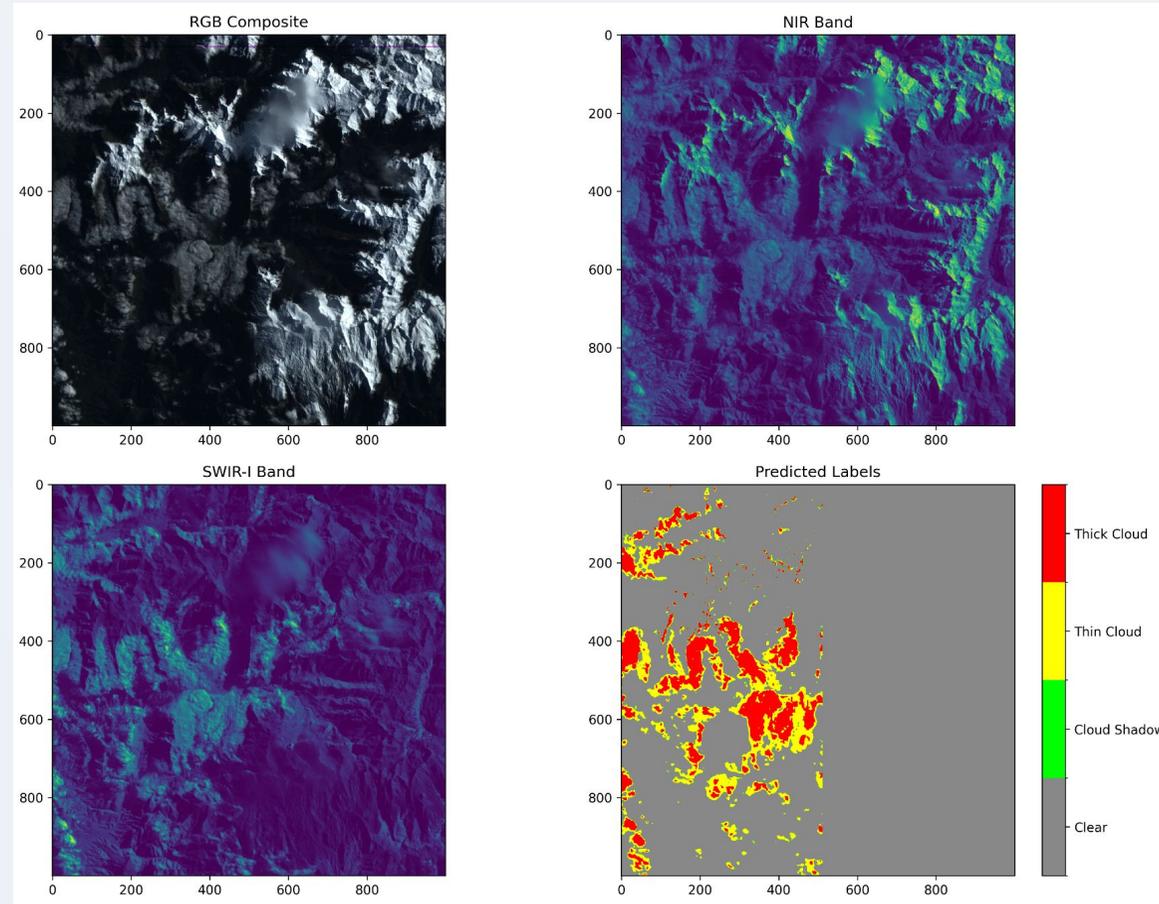


kuvaspace.com

On-ground Cloud Detection

Known Limitations

- Missing Cirrus Band @1.37 μ m
 - Bad distinction between ice / snow / high altitude clouds.
 - HF-2 will integrate SWIR-I
- Spectral Sensitivity Analysis
 - What if we add more bands?
 - Explainable AI to help identify the importance spectral channels
- Tradeoff size vs. Performance [WIP]
 - How does ViT/S-4 perform?
 - How about ViT/S-6?

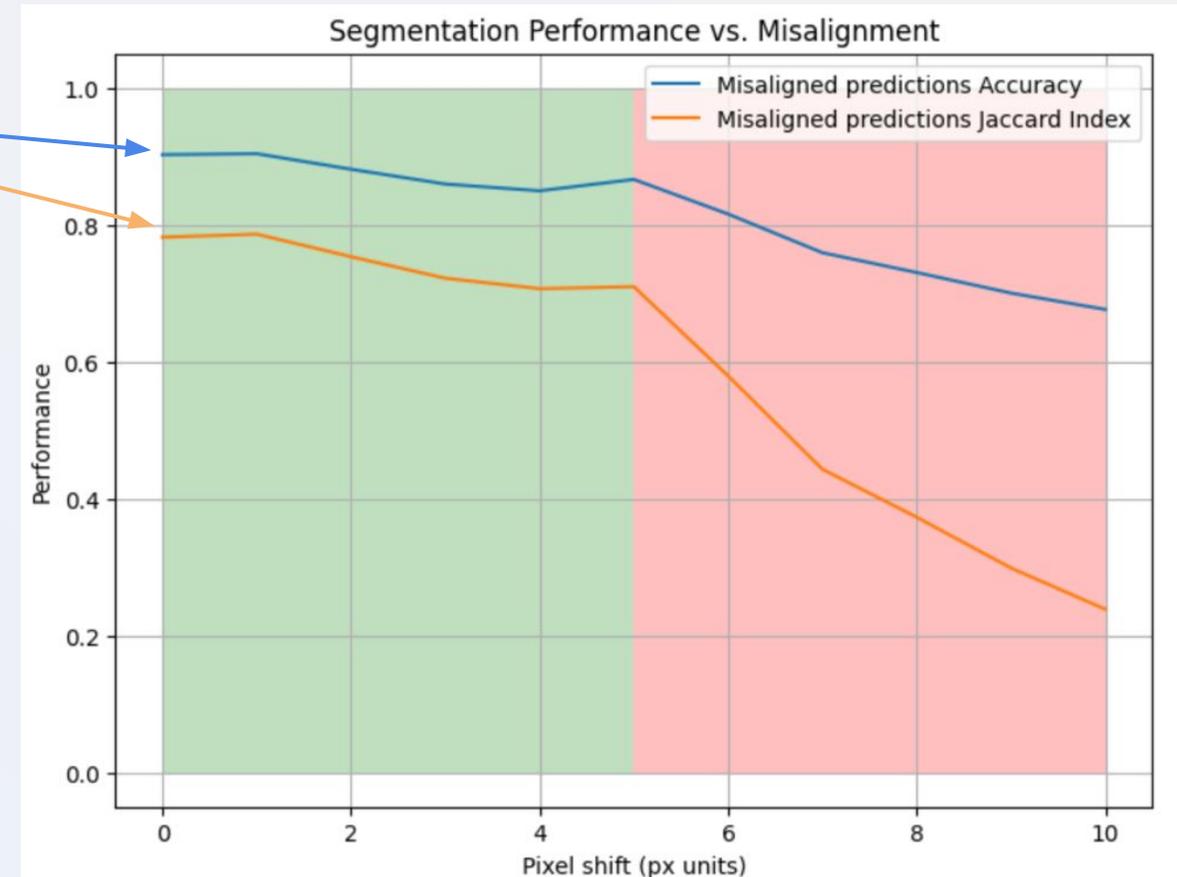
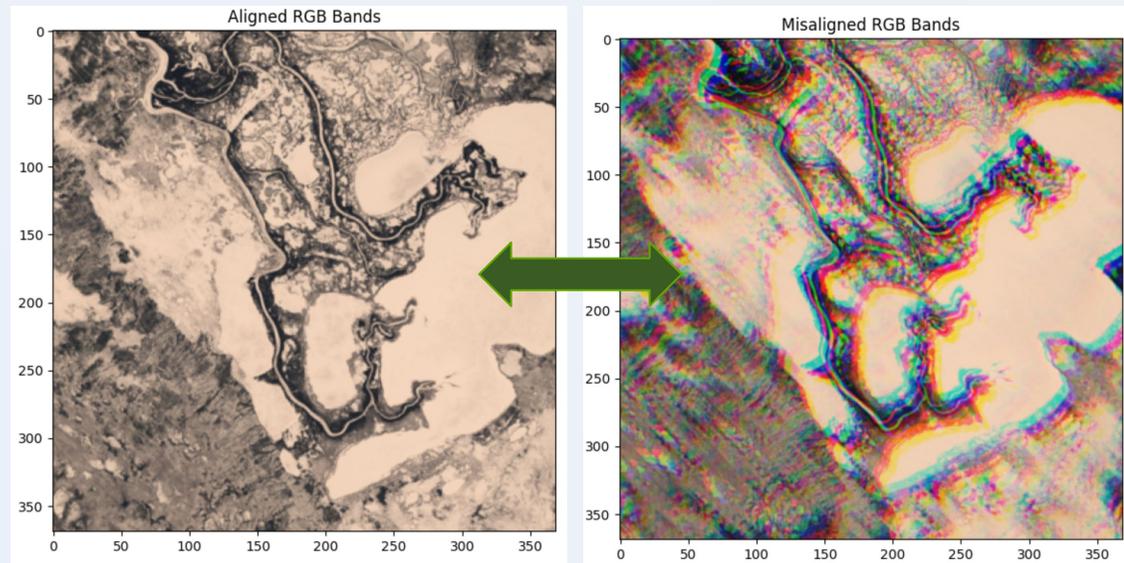


On orbit EO pipeline

Cloud Detection

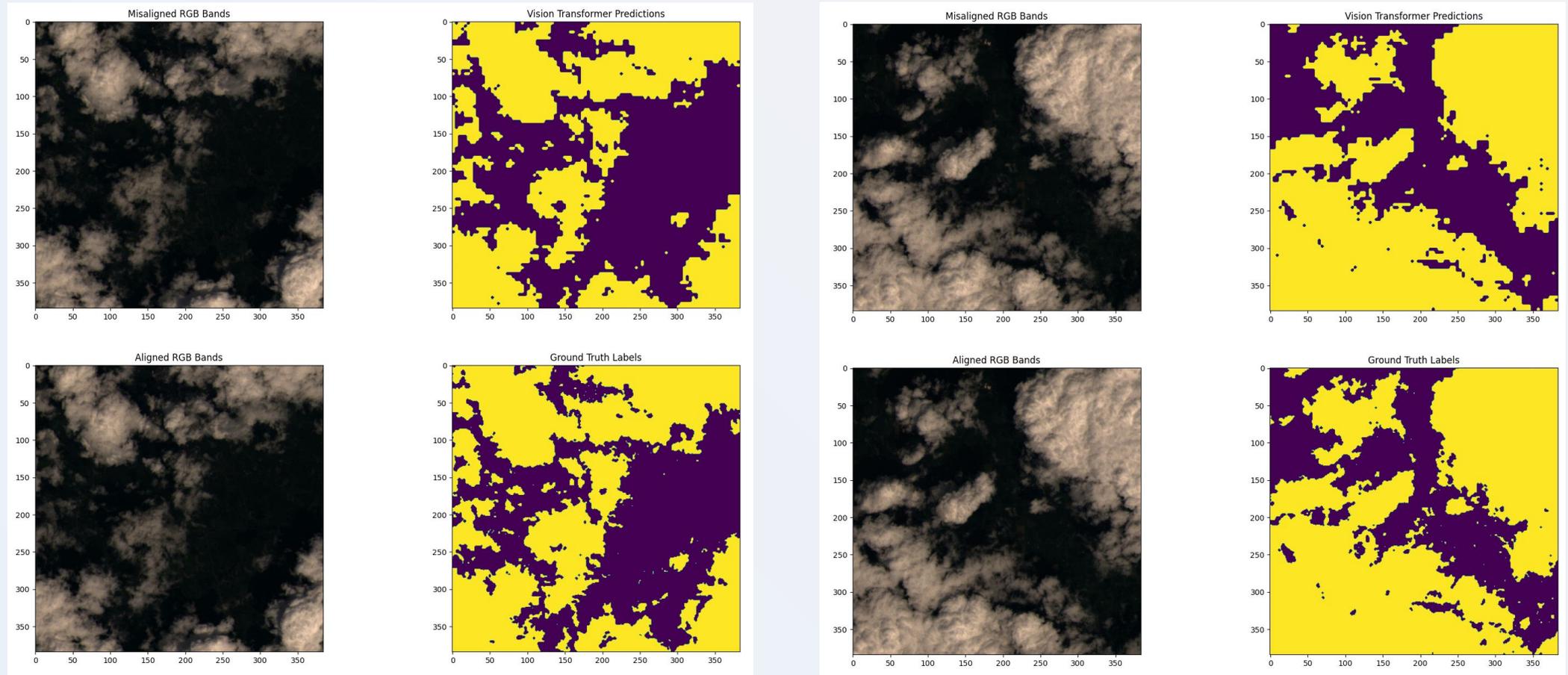
Robustness against misalignment

- Accuracy / JI as function of channel misalignment
- Acceptable performance up to **5 pixels shift (~125m)**
- With constant $v = 7.68 \text{ m/ms}$ \rightarrow 16.28 ms timestamp error



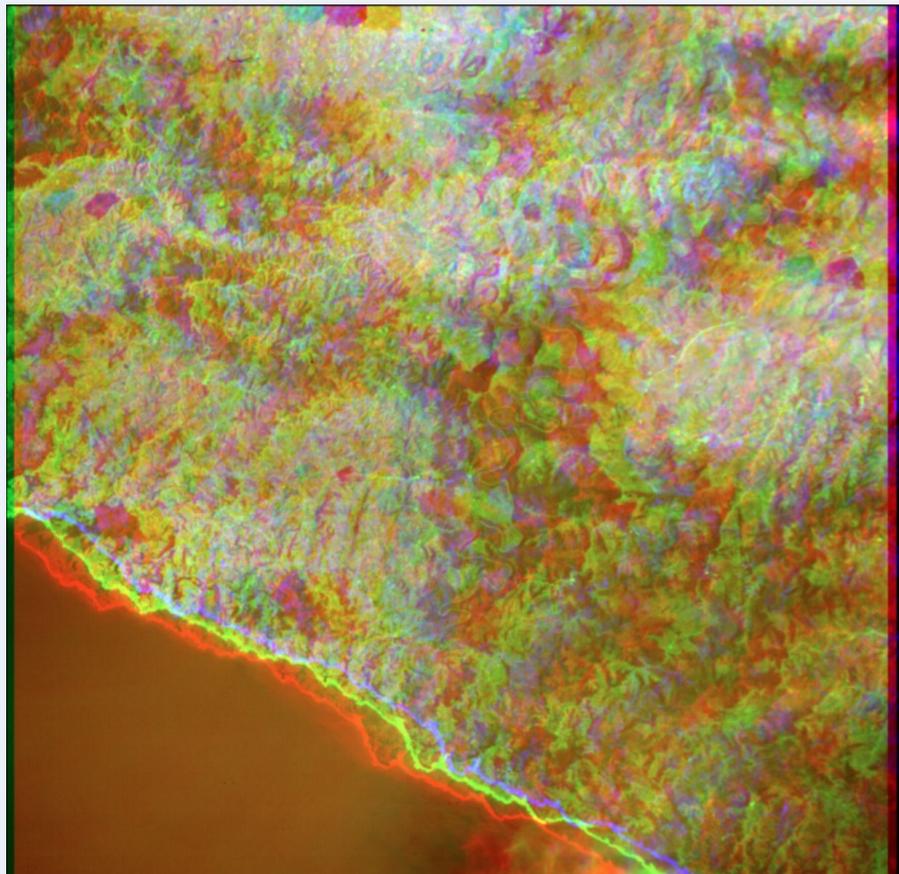
On orbit EO Pipeline

Cloud Detection under channel misregistration (10 pixels)

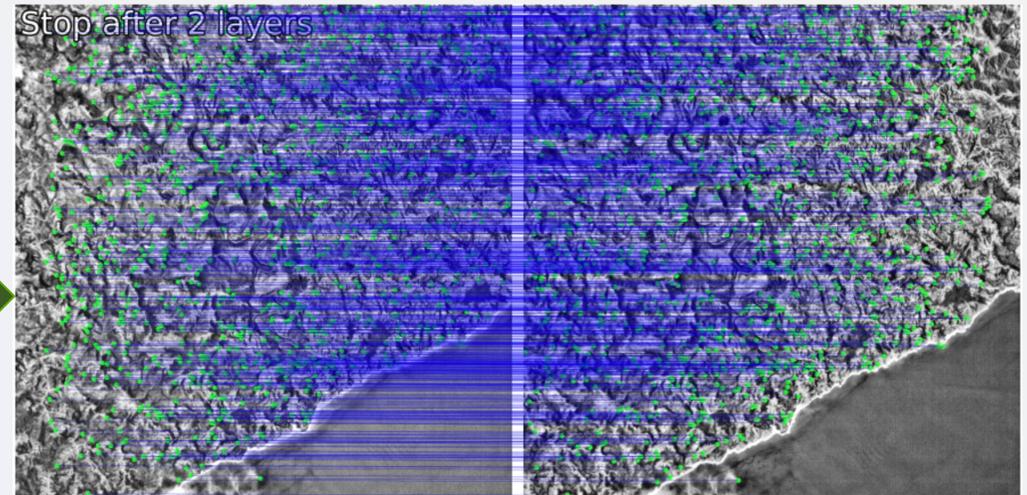


On-orbit Cloud Detection

Performing Band Alignment



ALIKED +
LightGlue



~150x faster!

TLE Aligner

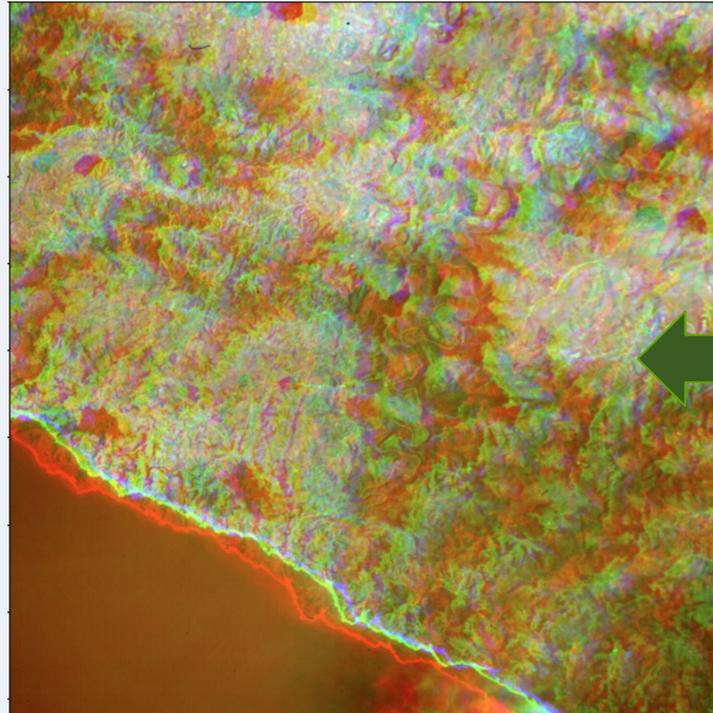


On orbit EO pipeline

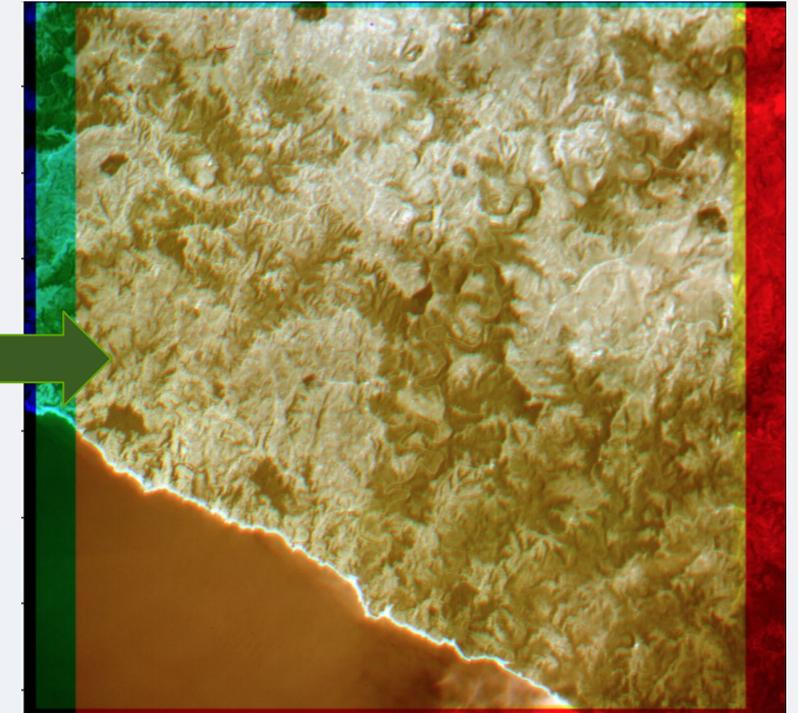
Two-line Element Aligner

- Underlying assumptions
 - Satellite trajectory is smooth
 - Telemetry is stable
- Velocity-based alignment
 - Δt between acquisitions
 - Shift bands by integer #pixels
- Sources of uncertainties
 - Acquisition time stamps
 - Velocity of satellite

Raw unaligned image



TLE-aligned image



HF1A - Drakensberg Mountains (South Africa) - 10 October 2024 08:23:09 UTC

Q: What is the effect on downstream cloud detection?

On-orbit EO pipeline

Copernicus Security Services

Hyperfield for rapid response

- On-orbit processing of HF data
- On-orbit detection and monitoring
- Leverage sat-to-sat and sat-to-IOT

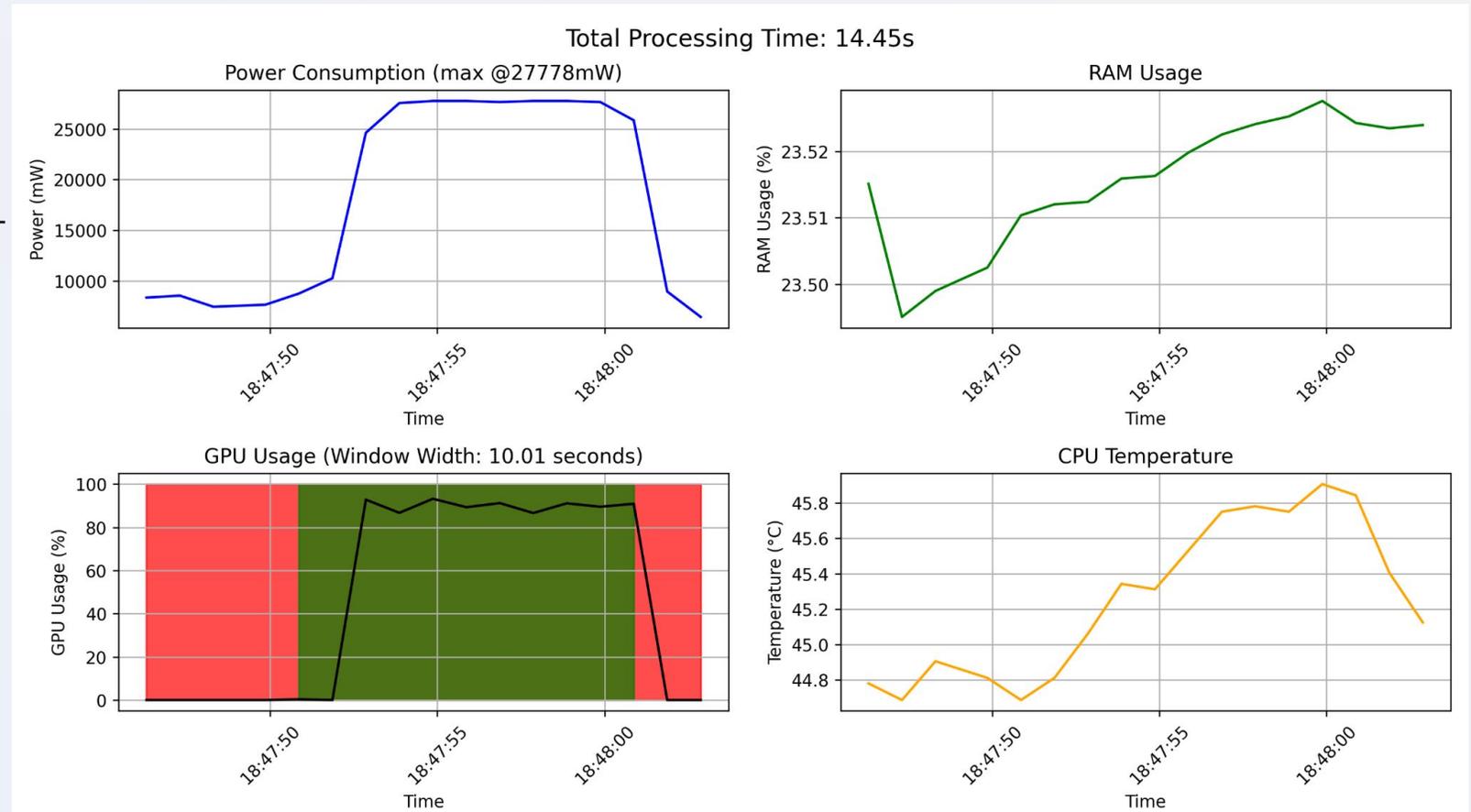
Benchmarking on-orbit GPUs

- NVIDIA AGX Orin 64GB
- NVIDIA Orin NX 16GB
- NVIDIA Jetson Nano 8GB

Various on-orbit processing scenarios

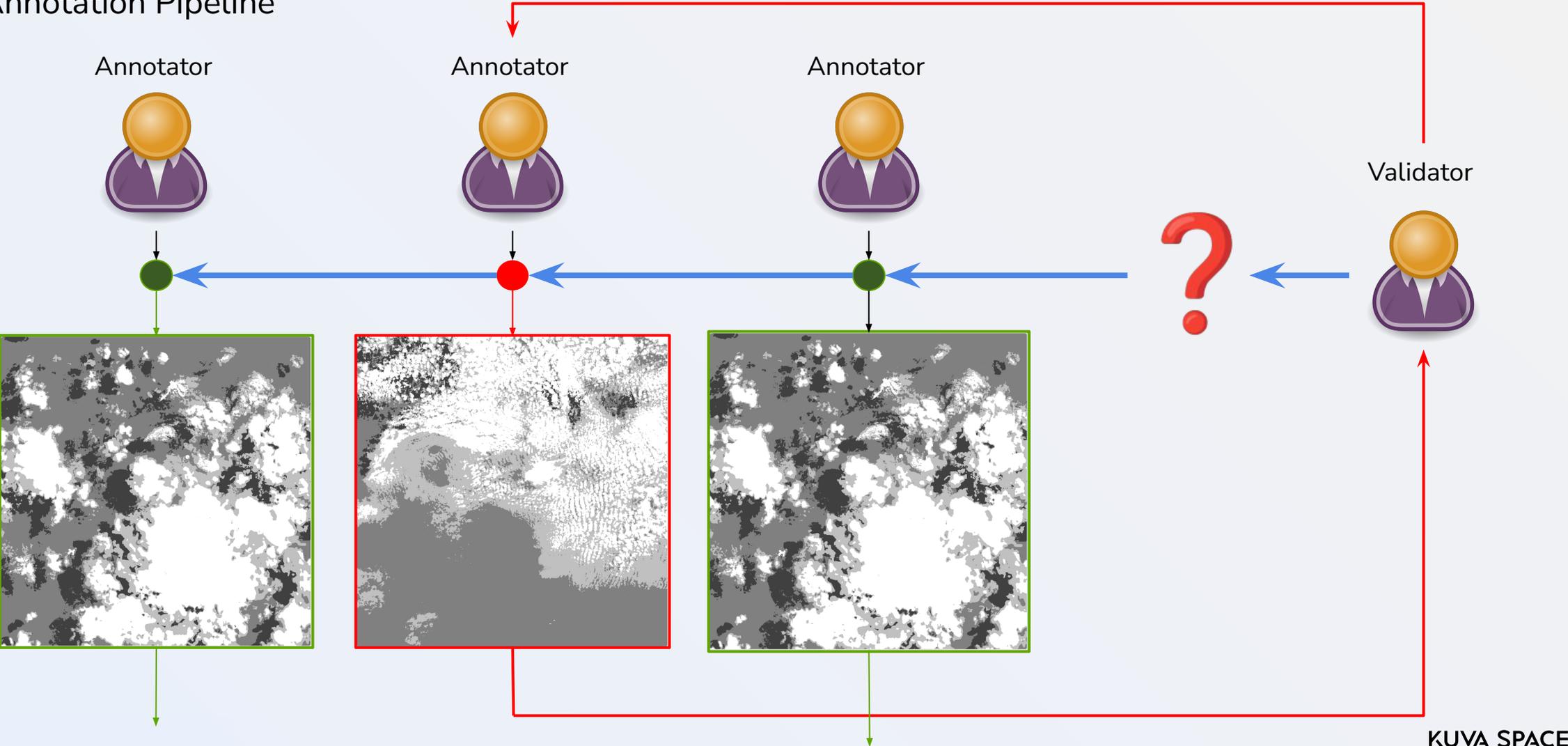
- Band alignment
- Cloud detection
- Georeferencing

Example of tiny ViT running onboard an NVIDIA AGX Orin @50W power mode



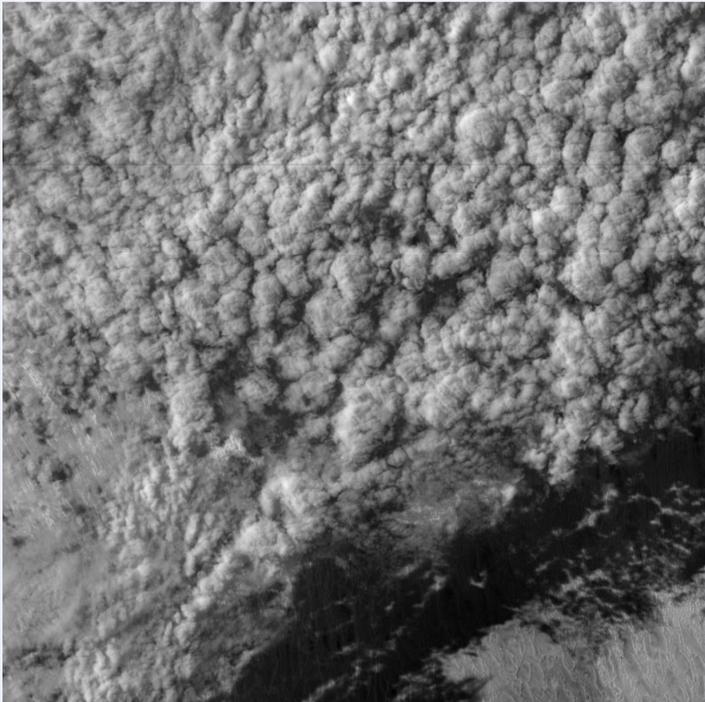
Encord Annotations

Annotation Pipeline

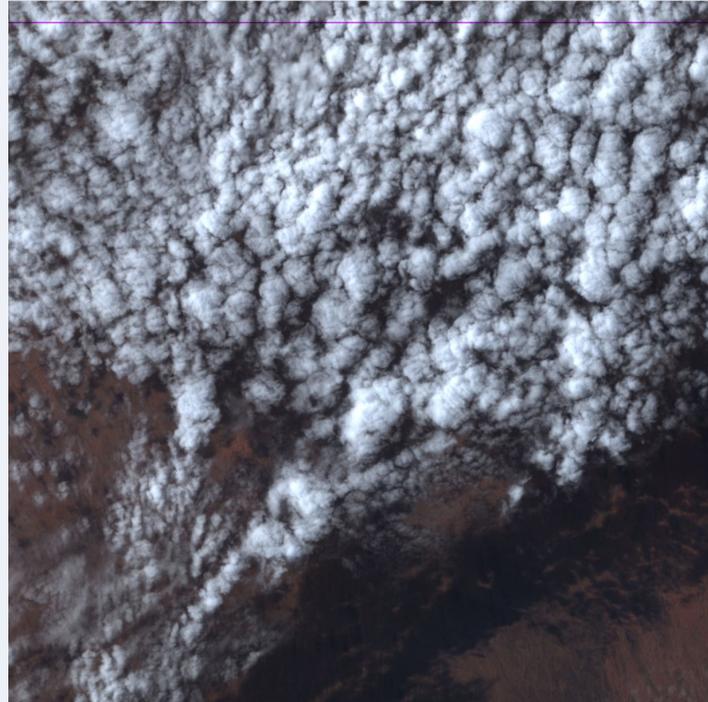


On-ground Cloud Detection

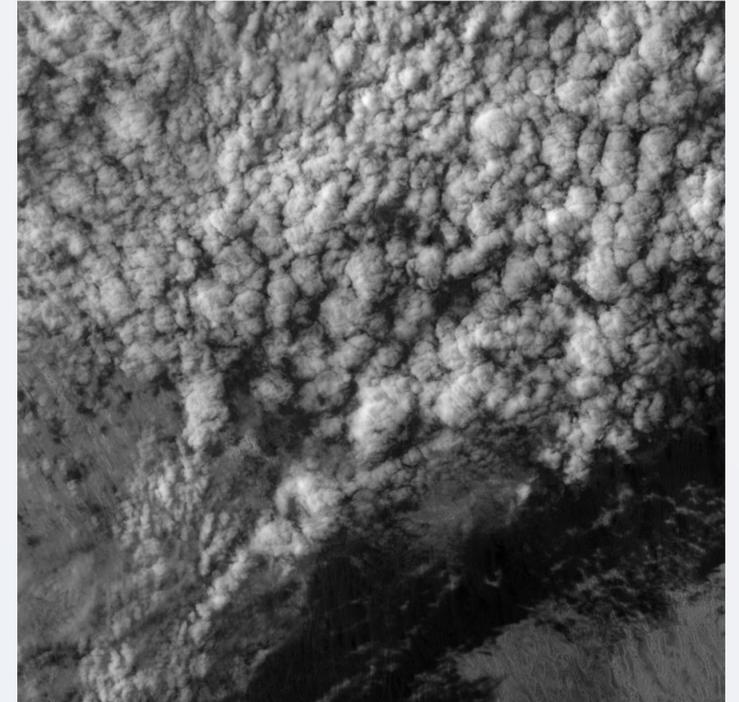
Encord Input Images



NIR



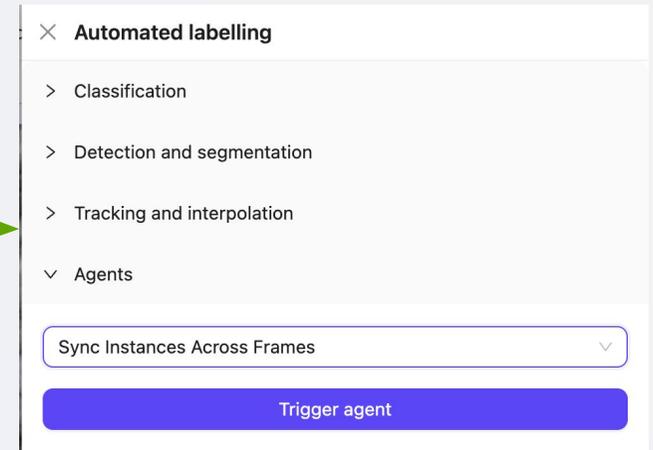
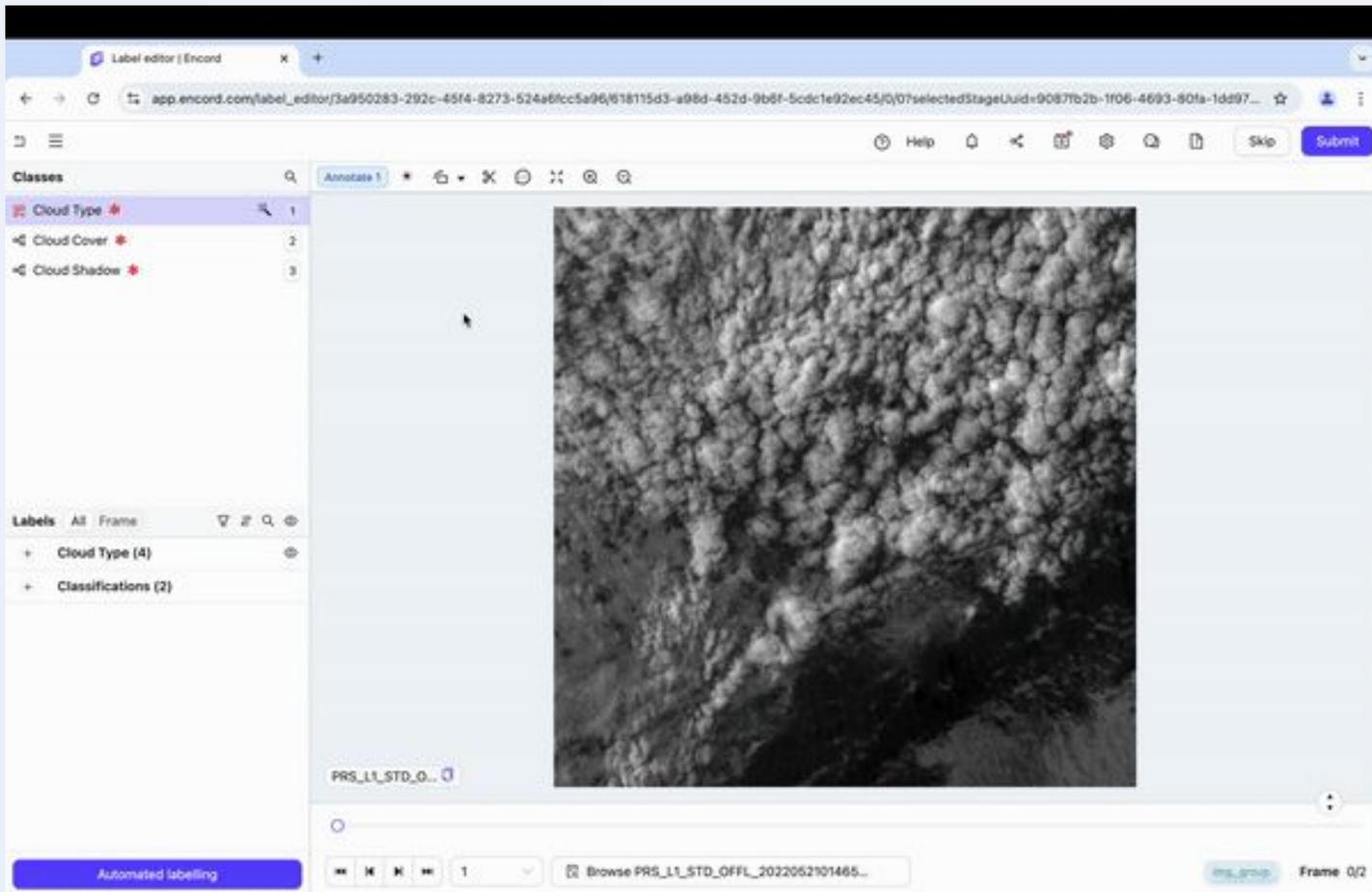
VIS (RGB)



SWIR

Encord Annotations

Thresholding the NIR bands leads to accurate cloud shadow masks



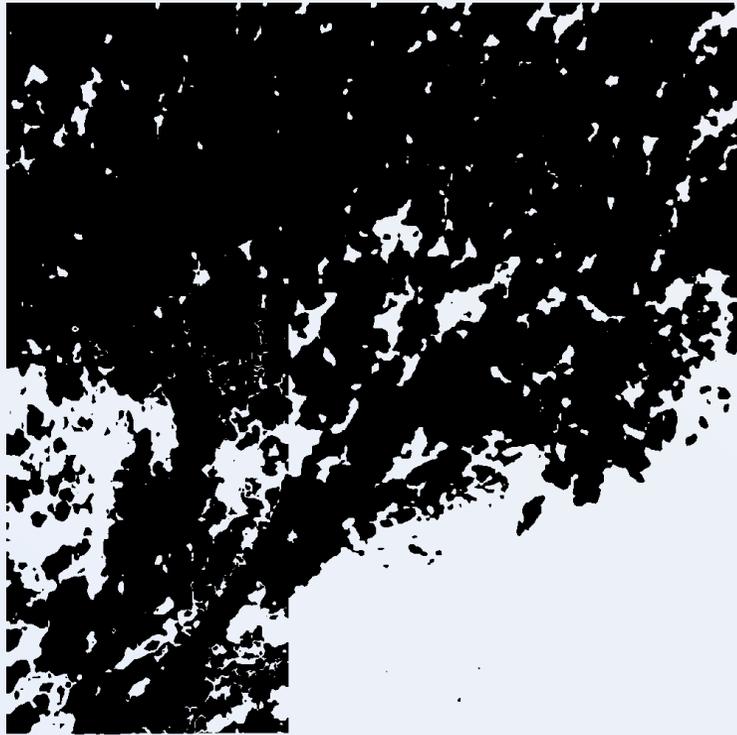
Agent tool allows to copy annotations across frames

Encord Annotations

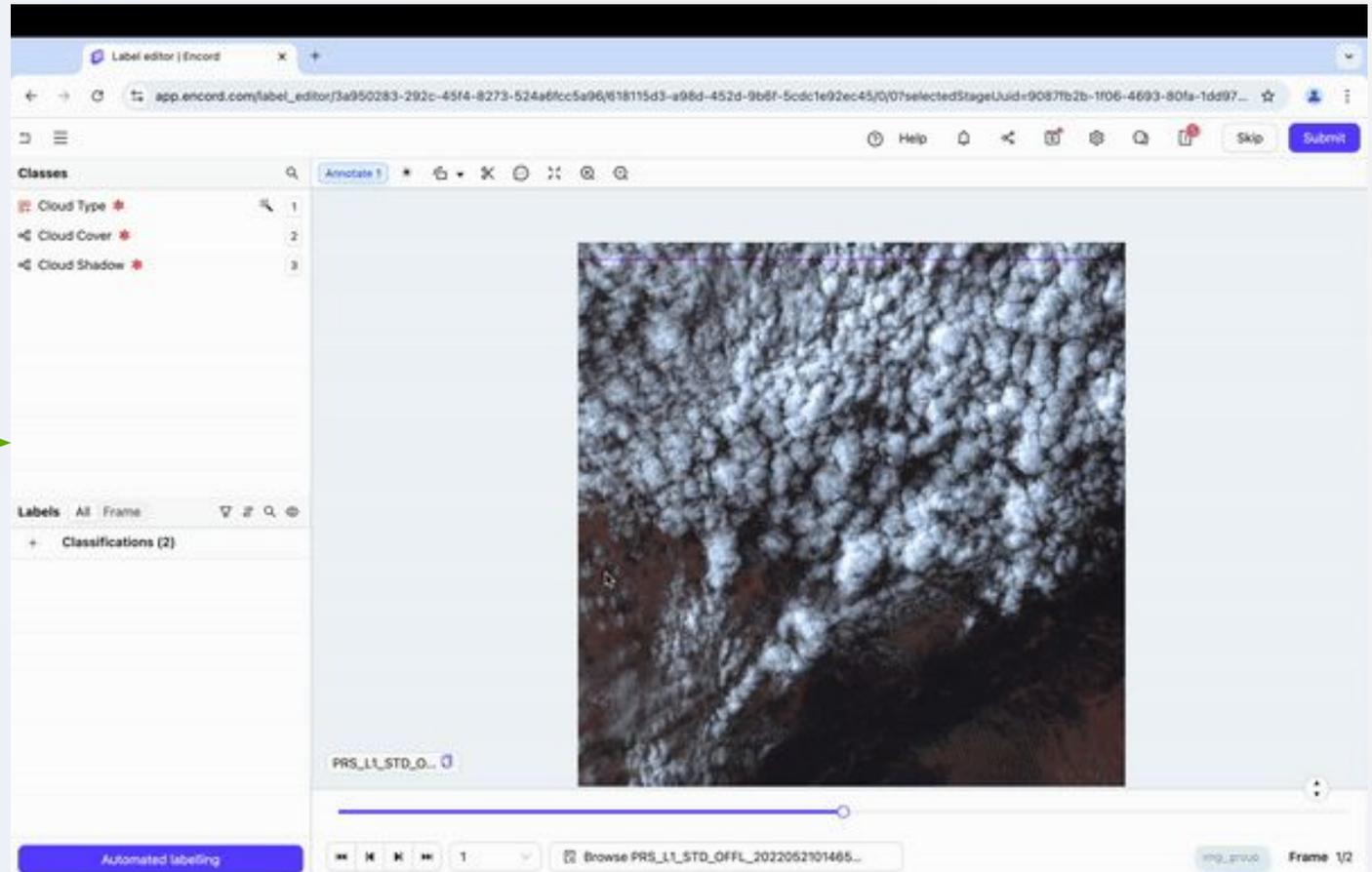
Python API for convenient pre-annotations

Annotations are orders of magnitude **faster** and increasingly **easier**

Inference using ViT on 256 x 256 patches



pre-annotated .tif



Icons

