

# Sensor-Independent Deep Learning for Cloud Masking

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ESA PhiLab

# ESA $\Phi$ -Lab

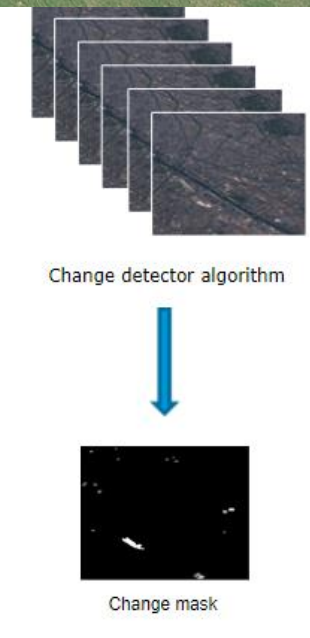
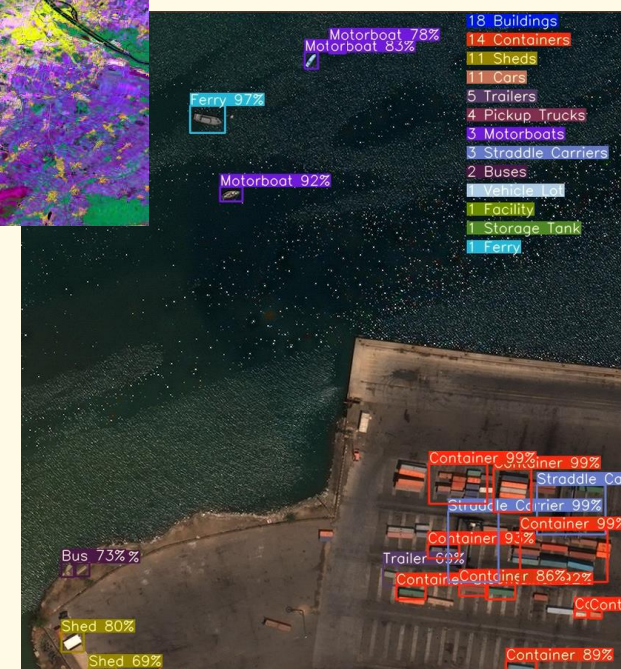
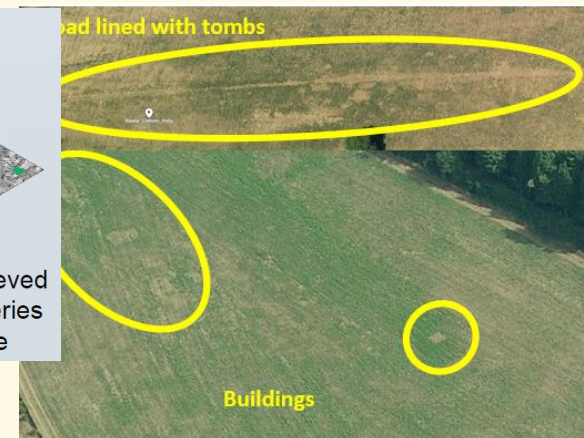
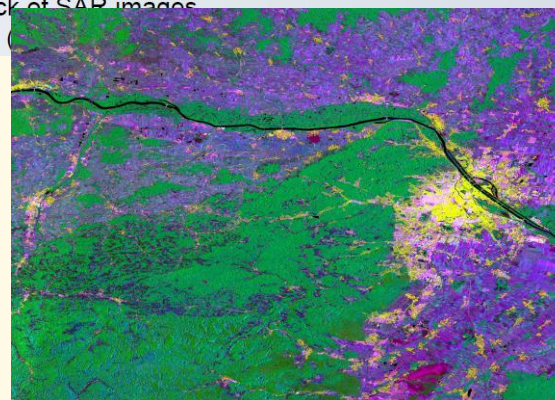
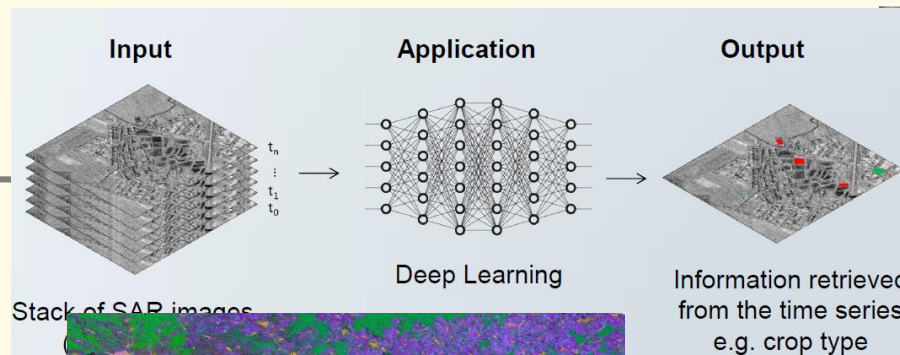


- Researching and investing in ‘disruptive’ technologies in Earth Observation
- In-house focus on Machine Learning and Computer Vision techniques
- Works with other ESA divisions, as well as wider European community



# ESA $\Phi$ -Lab

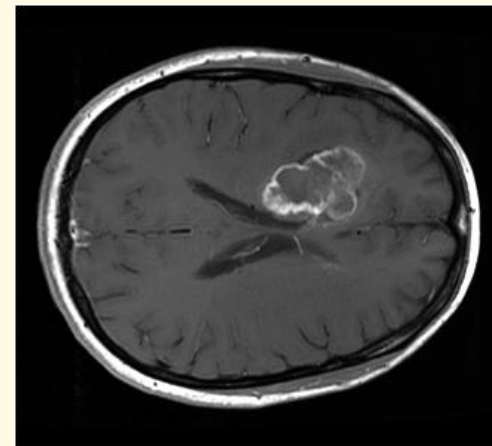
- Projects include:
  - Crop-type classification
  - Archaeological surveying
  - On-board convolutional models
  - Analysis-ready SAR data
  - Many more
- Collaborations like mine are encouraged
- Research Fellowship positions available
- Companies and researchers - get in touch!



# Deep Learning's Promise

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- Deep Learning offers remarkable performance
- Bespoke designs are unnecessary
- Applicable to wide range of problems and domains

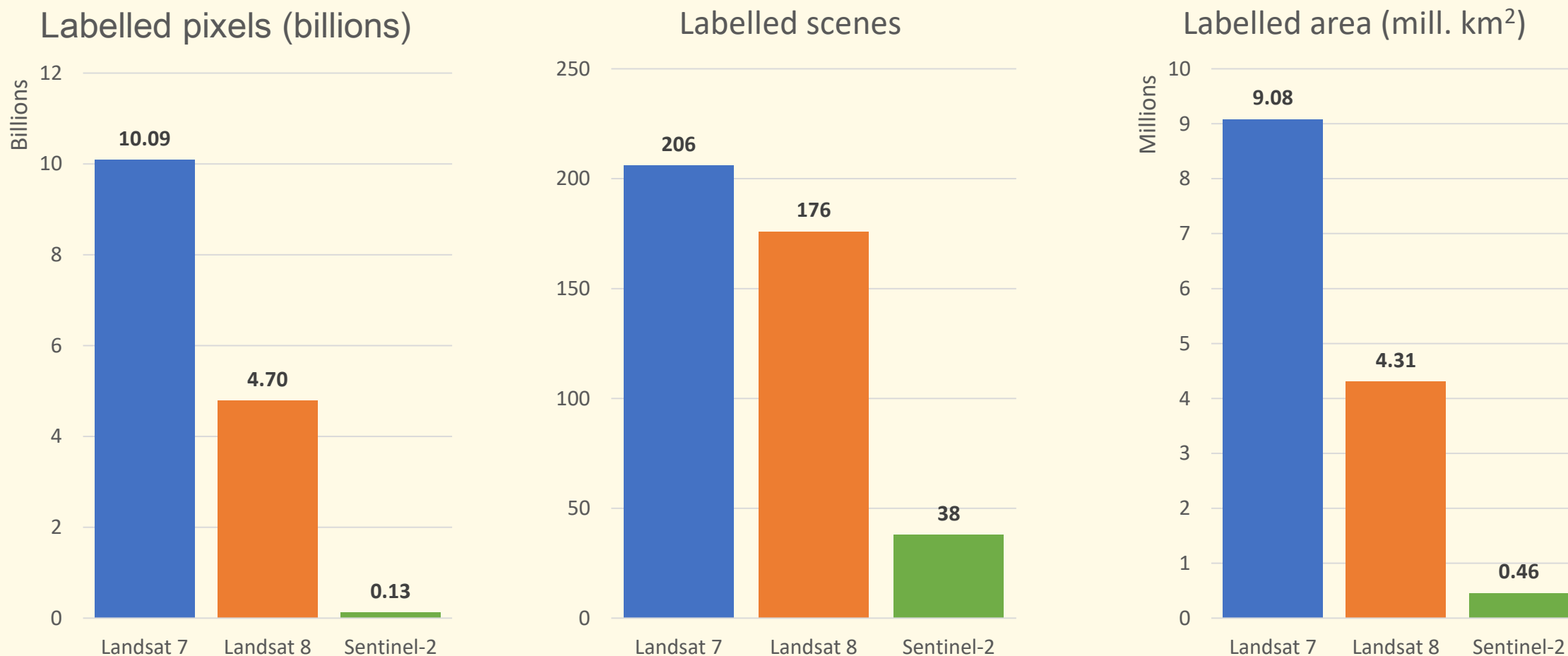


# Remote Sensing vs. other imaging domains

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- Consumer cameras all look similar: datasets are **not** camera-specific
- What's special about multispectral satellites?
  - Different spectral responses
  - Different brightness scales and calibration
  - Different noise characteristics
- New dataset needed for every problem and **for every sensor type.**
- Amount of labelled data multiplied by number of sensors flown!
- Problem is only emphasised as more satellites are launched

# Cloud Masking datasets



\*Aggregated from all publicly available datasets known to authors (not including single-pixel datasets).

How do we get the **most** from the  
labelled data we **already have**?



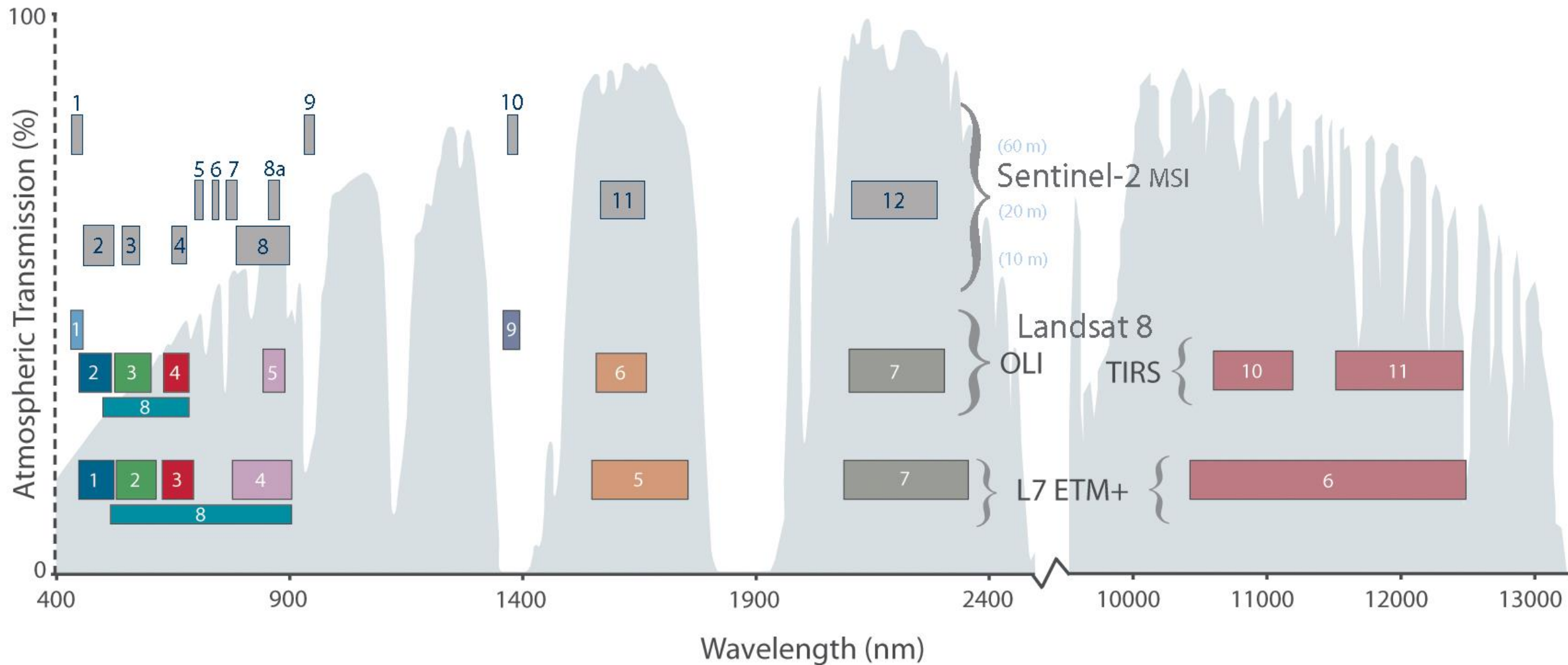


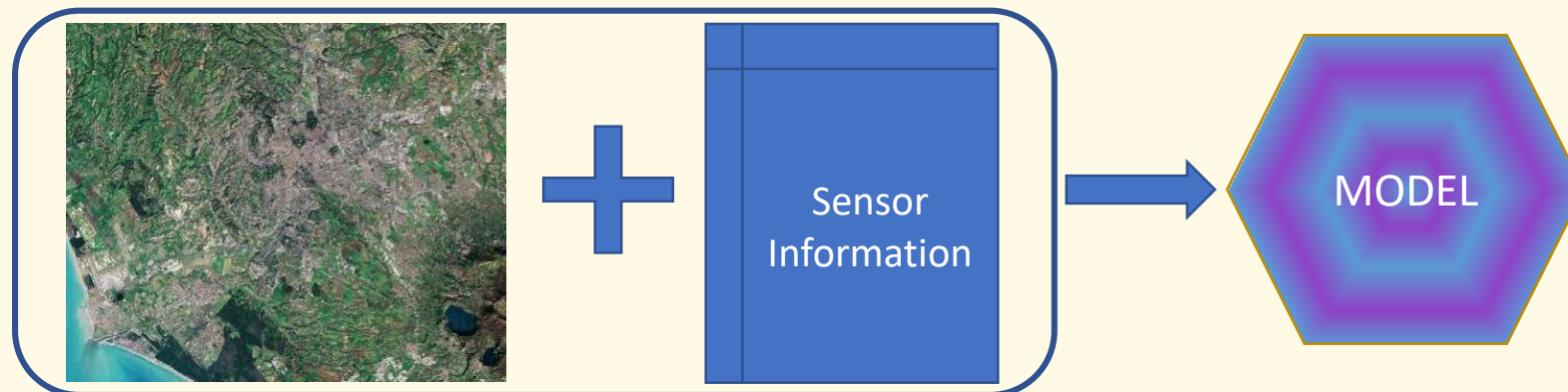
Image courtesy of NASA GSFC



# Sensor-Independent Model

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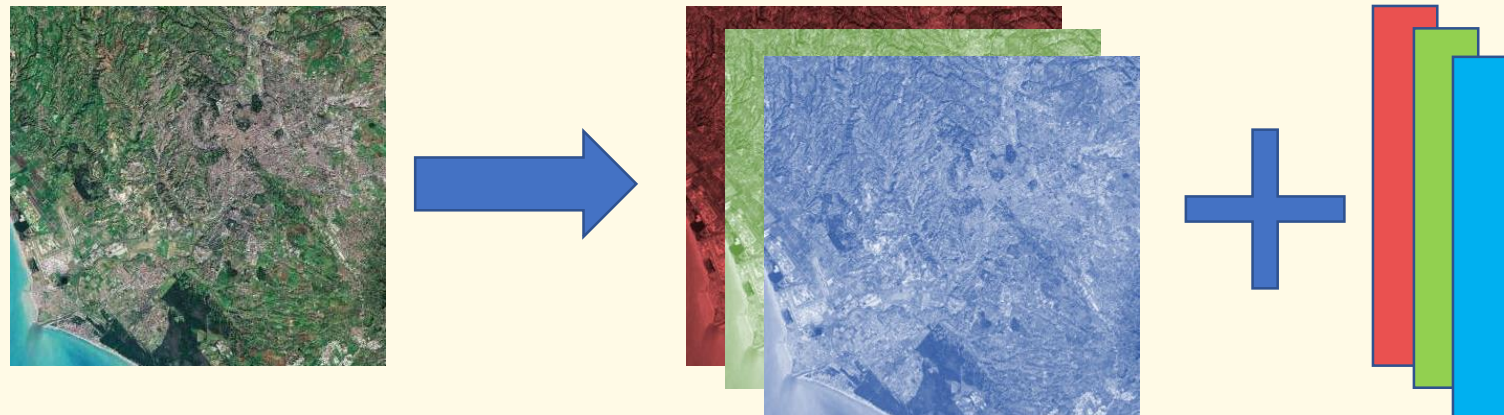
- Train model on all sensors: single unified dataset
- Model recognises and treat sensors in different ways
- Could be used on new satellite without retraining
- New convolutional model design needed



# Sensor-Independent Model

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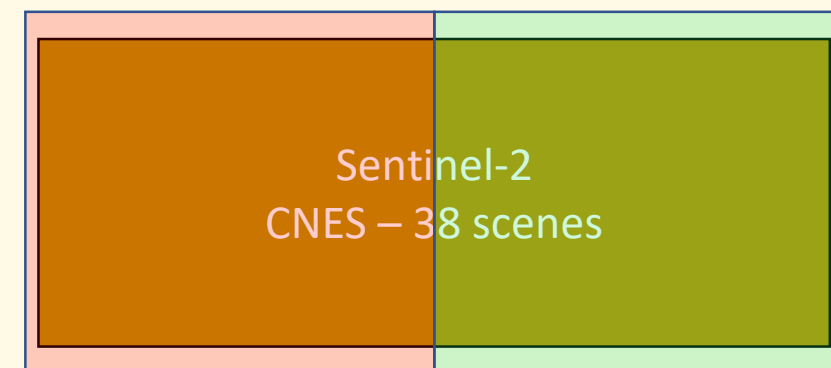
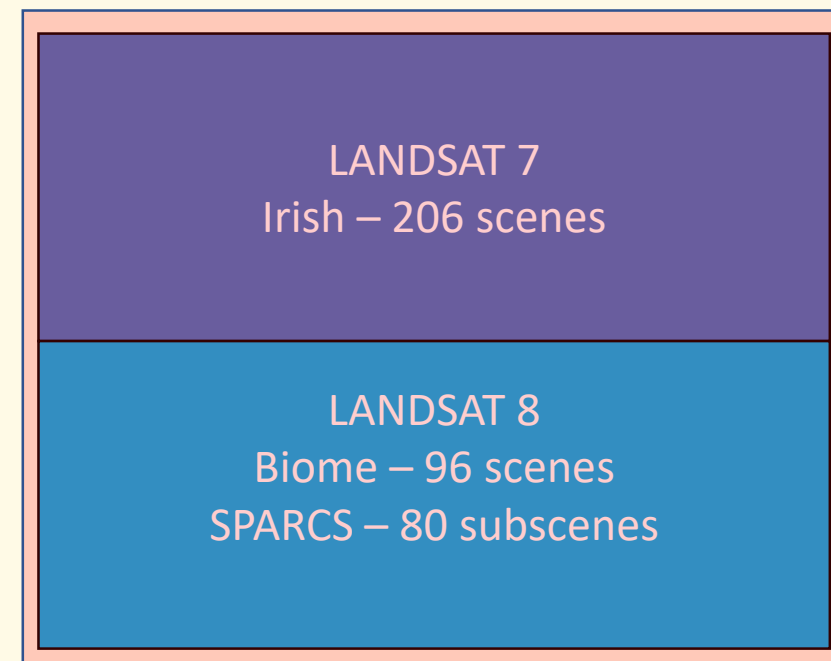
- Each spectral band treated as a member of the set of all possible bands
- Model takes as input **any number of bands** and their **descriptors**
- **Descriptor** is a vector parameterization of band characteristics e.g.:
  - central wavelength and bandwidth



# Experimental Setup

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- Test across Landsat 7/8 and Sentinel-2
- Same model, trained three ways:
  1. Train on Sentinel – Test on Sentinel
  2. Train on Landsat – Test on Sentinel (only shared bands)
  3. Train on Landsat AND Sentinel – Test on Sentinel
- Does data from other satellites help?
- Absolute performance less important than relative performance



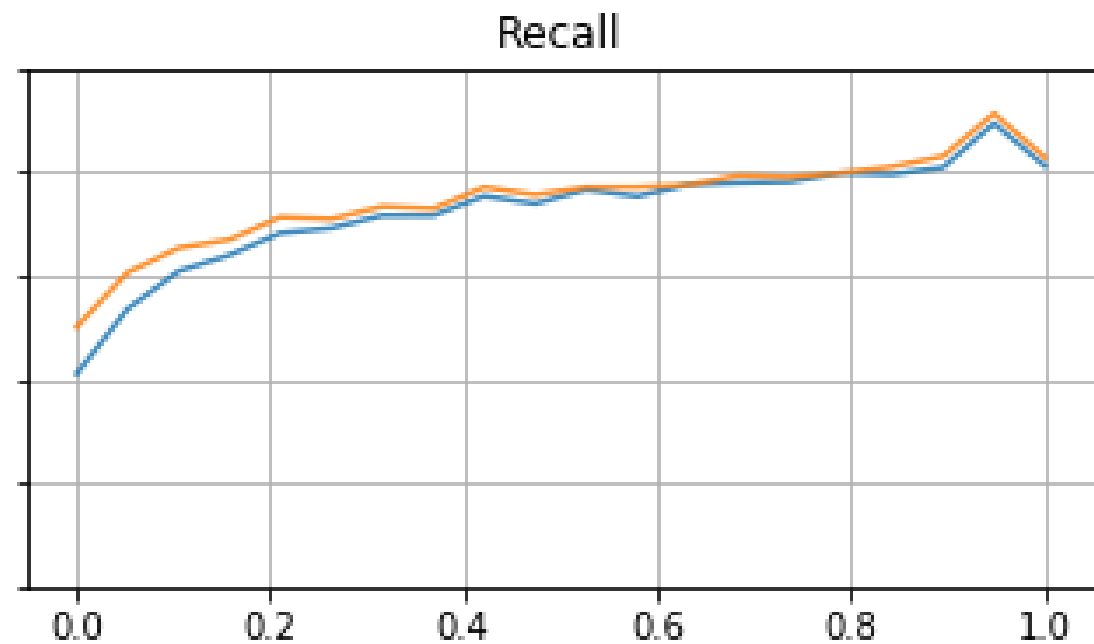
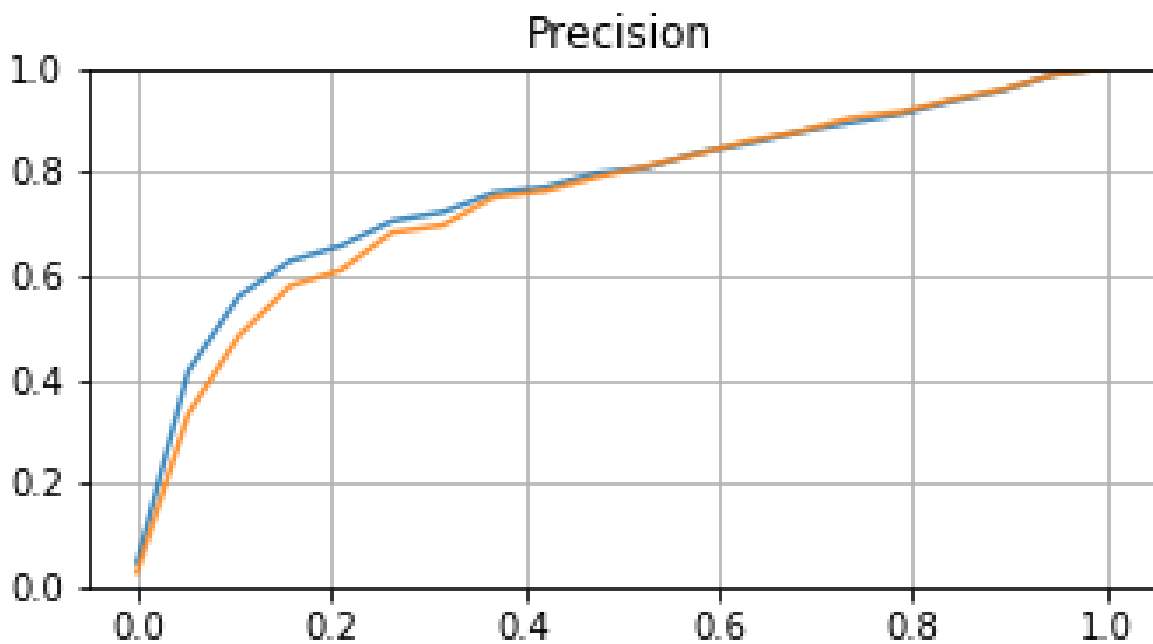
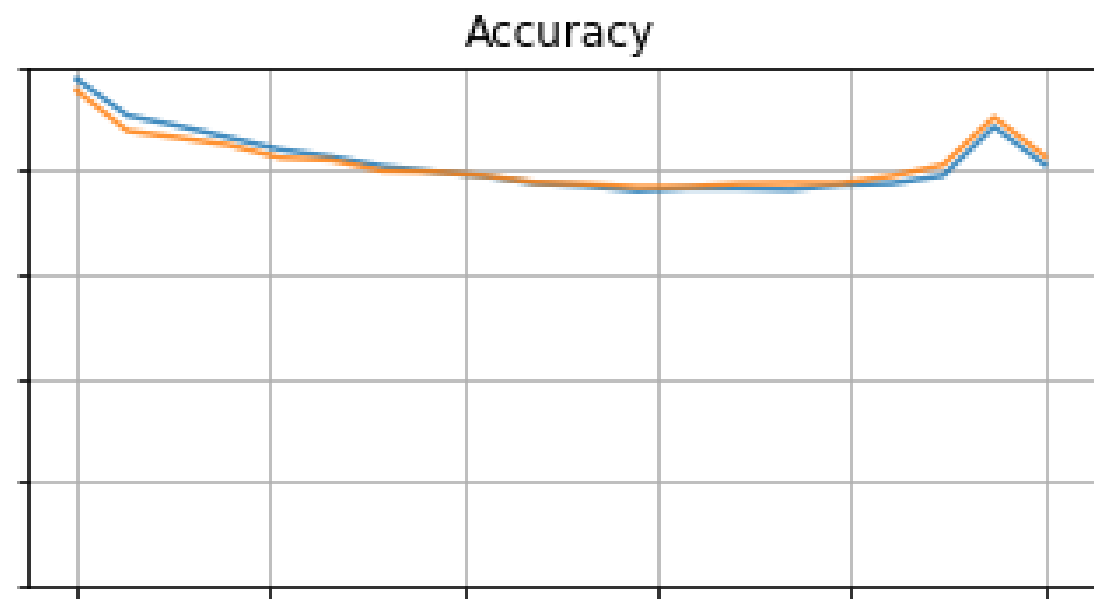
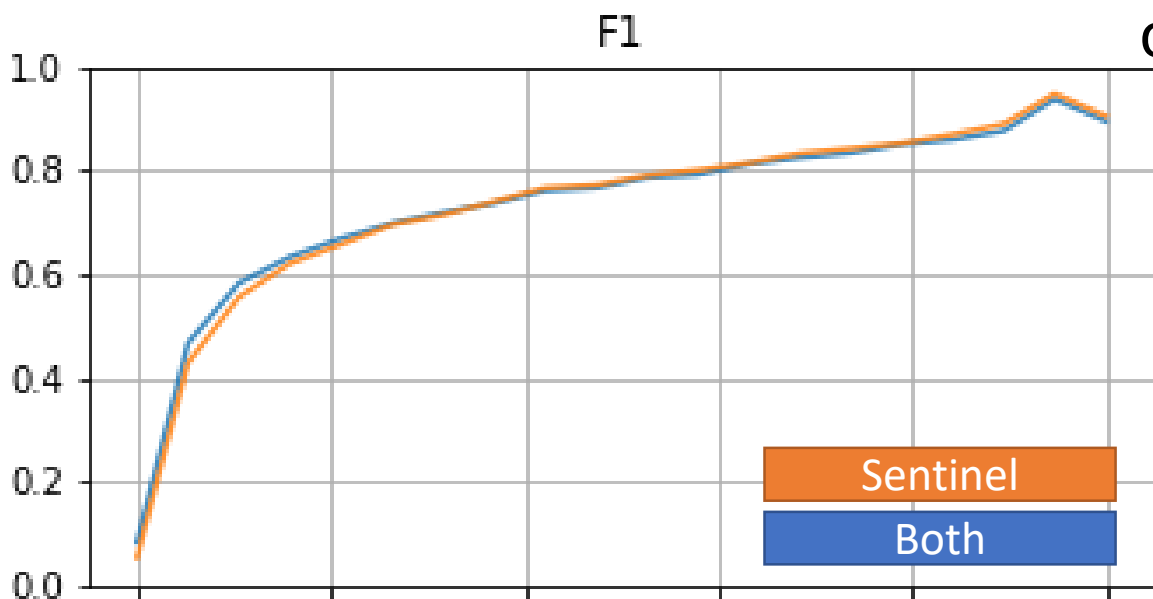
# Results

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MODEL	Accuracy (%)	F1 (%)	Precision (%)	Recall (%)
Landsat	88.6	69.8	<b>86.9</b>	58.4
Sentinel	91.9	80.6	79.1	<b>82.1</b>
Landsat + Sentinel	<b>92.4</b>	<b>82.7</b>	85.1	80.4

- Landsat-only model is not complete failure, but not good.
- Slight improvement in performance when using Landsat and Sentinel

# Metrics per 128x128 window, by cloud



Cloud cover

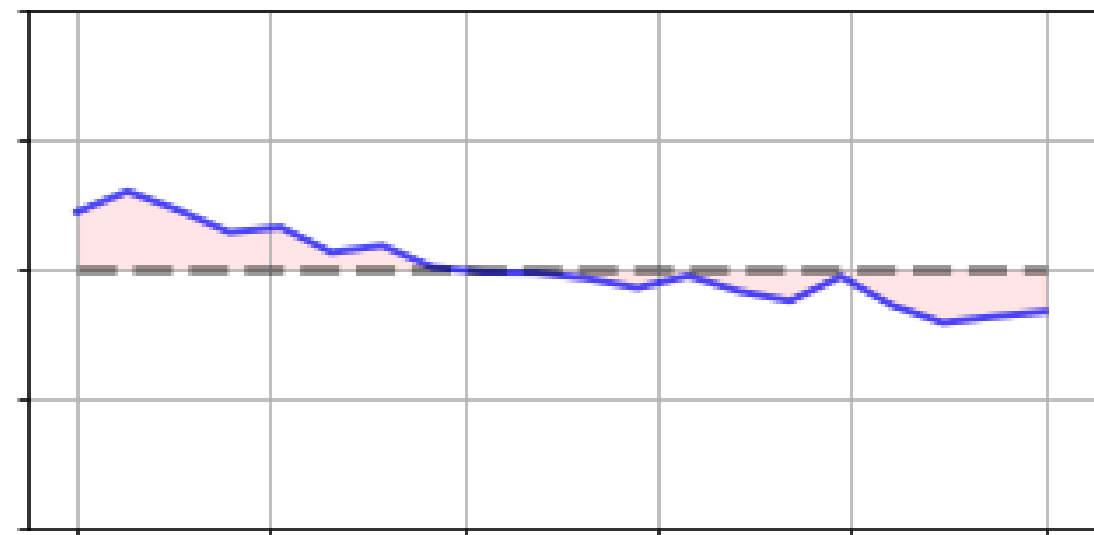
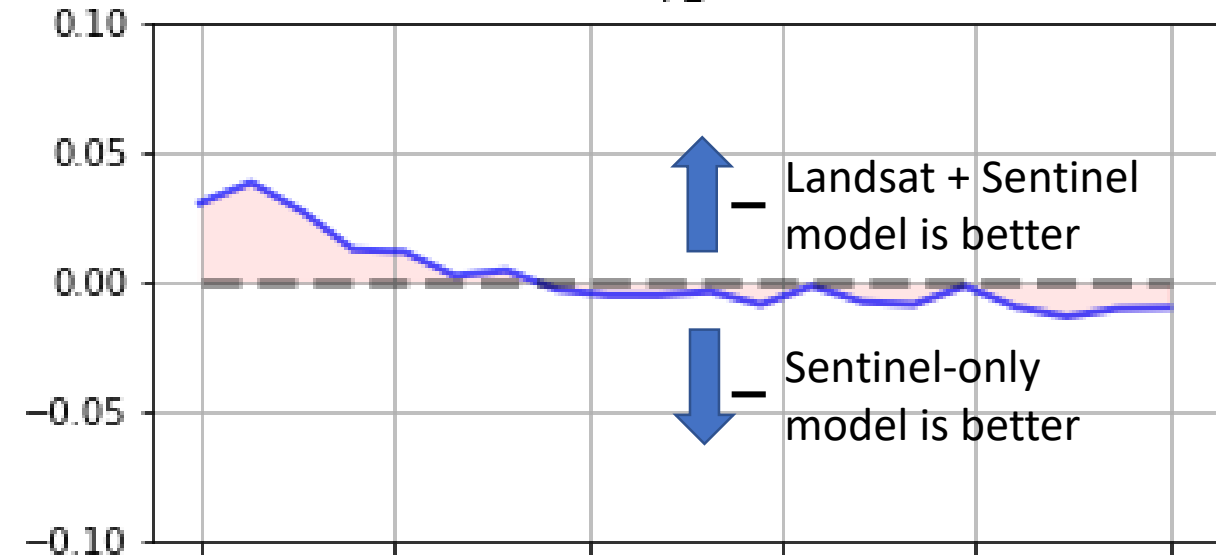
Cloud cover



# Difference between metrics per 128x128 window, by cloud cover

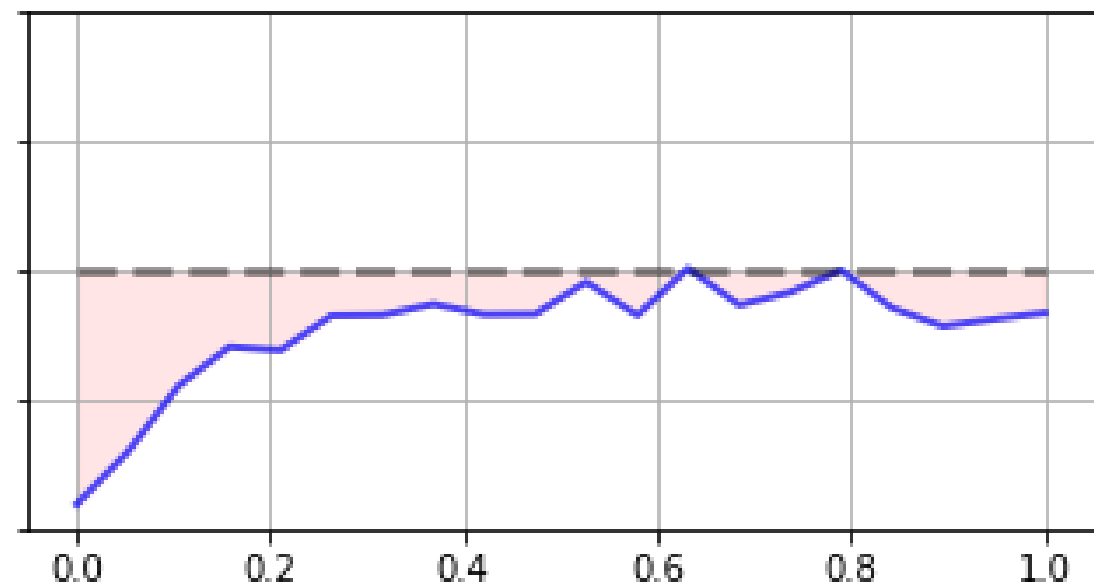
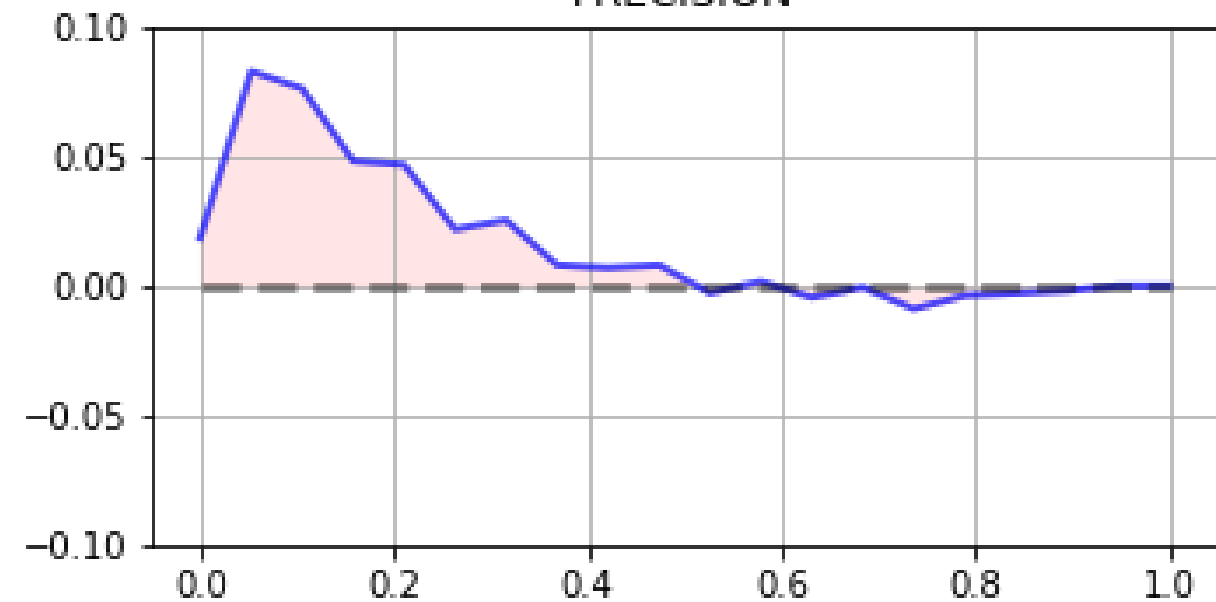
## F1

## ACCURACY



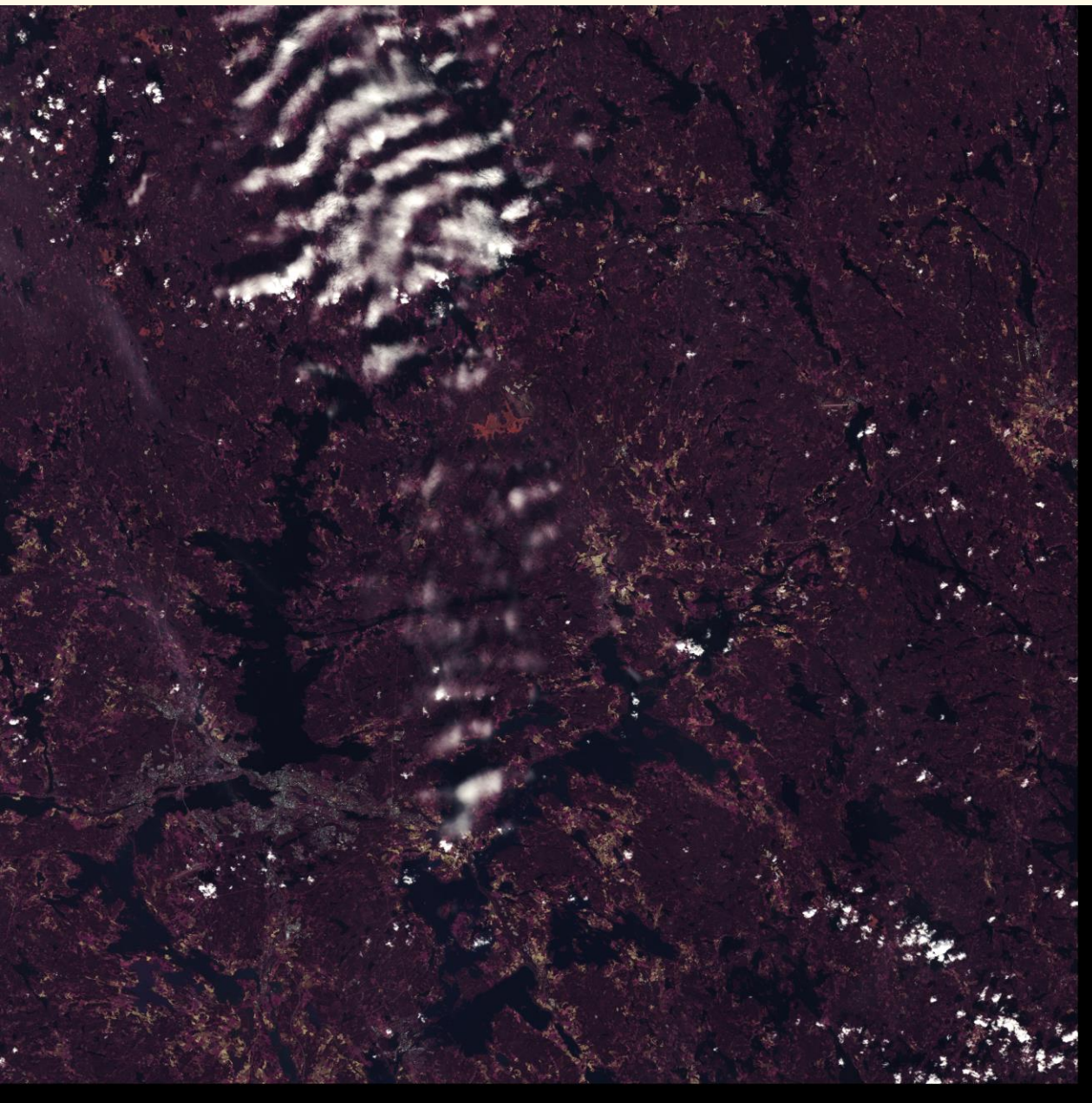
## PRECISION

## RECALL



Cloud cover

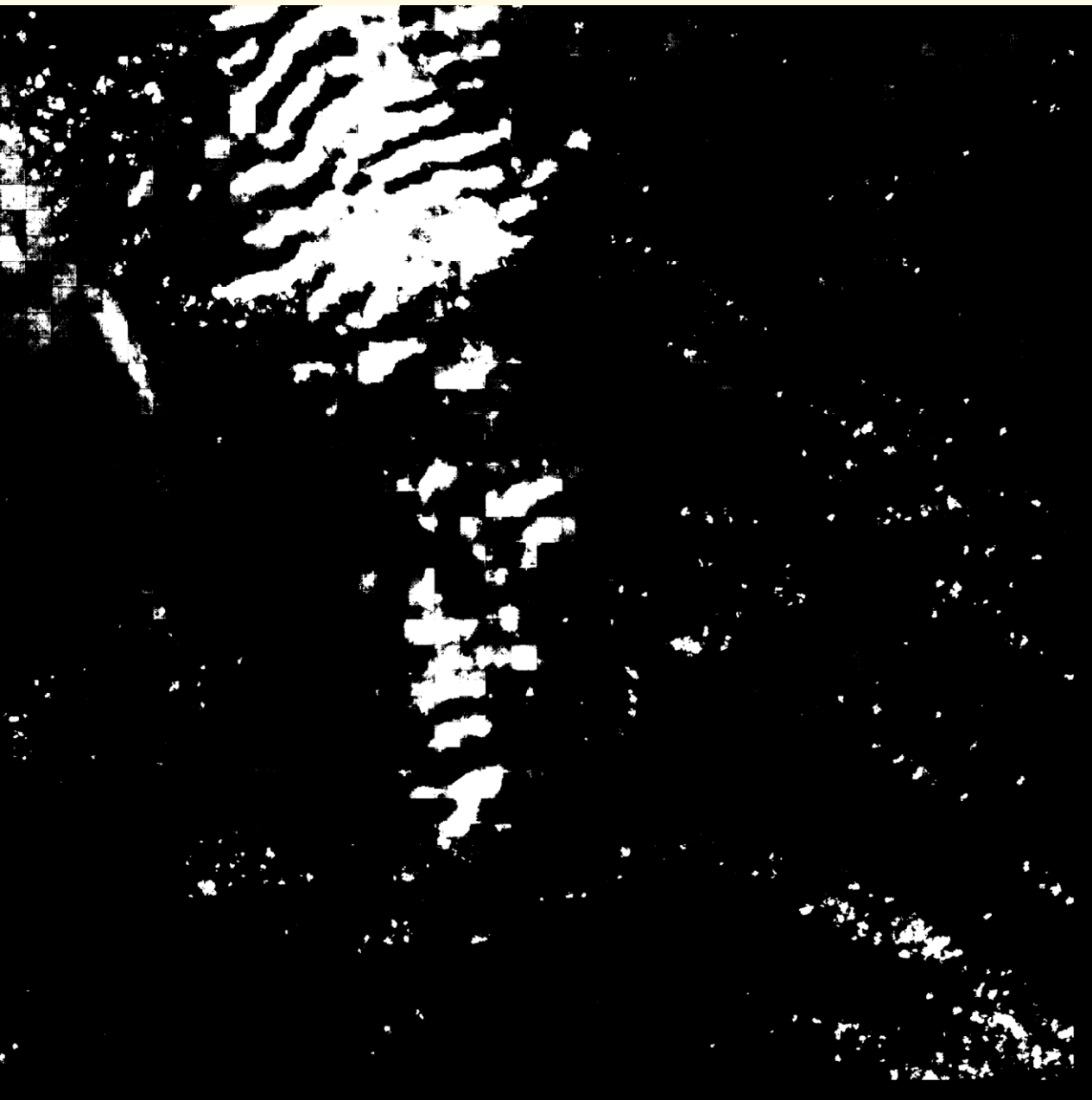
Cloud cover



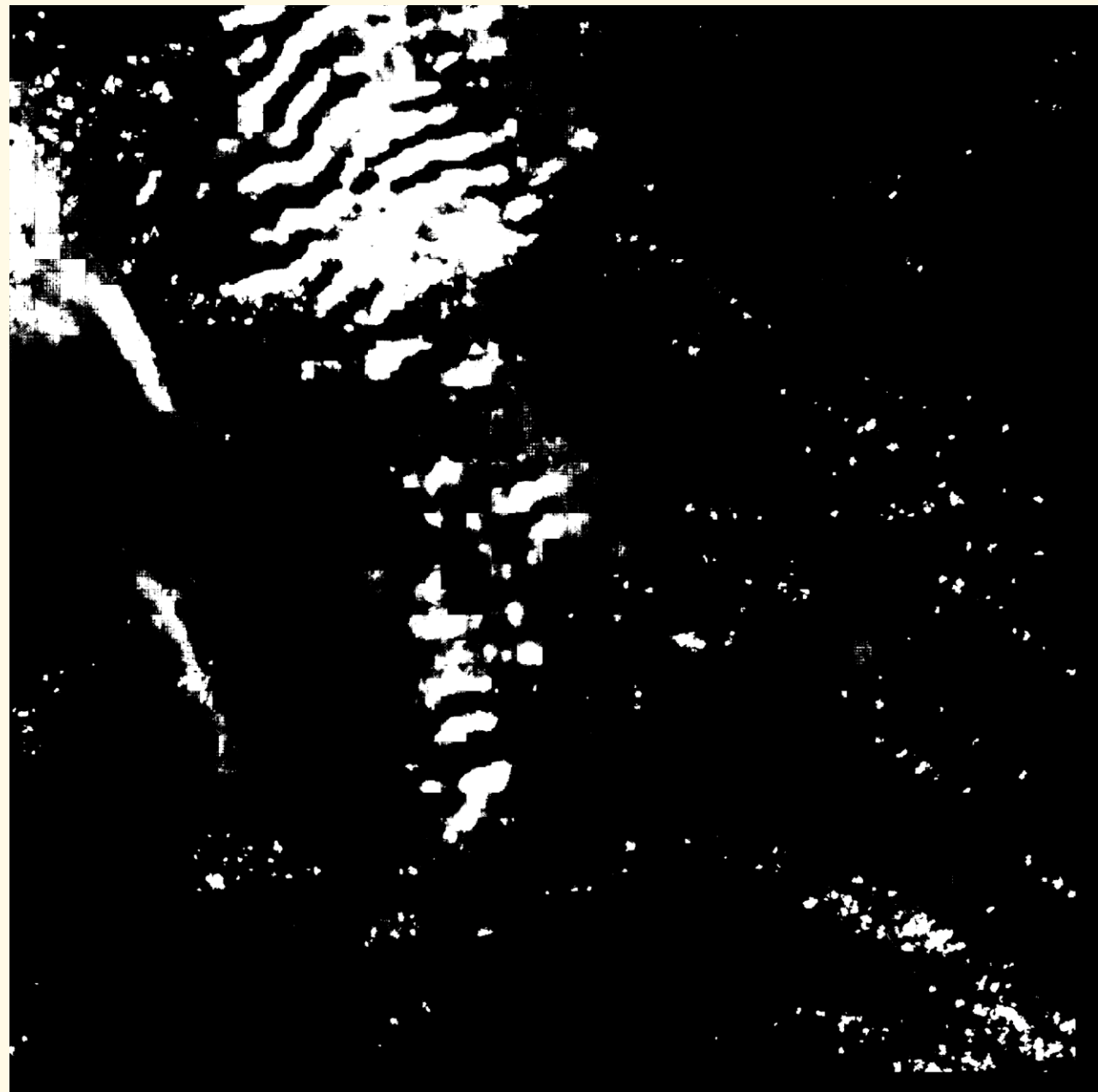
Central Finland



Groundtruth

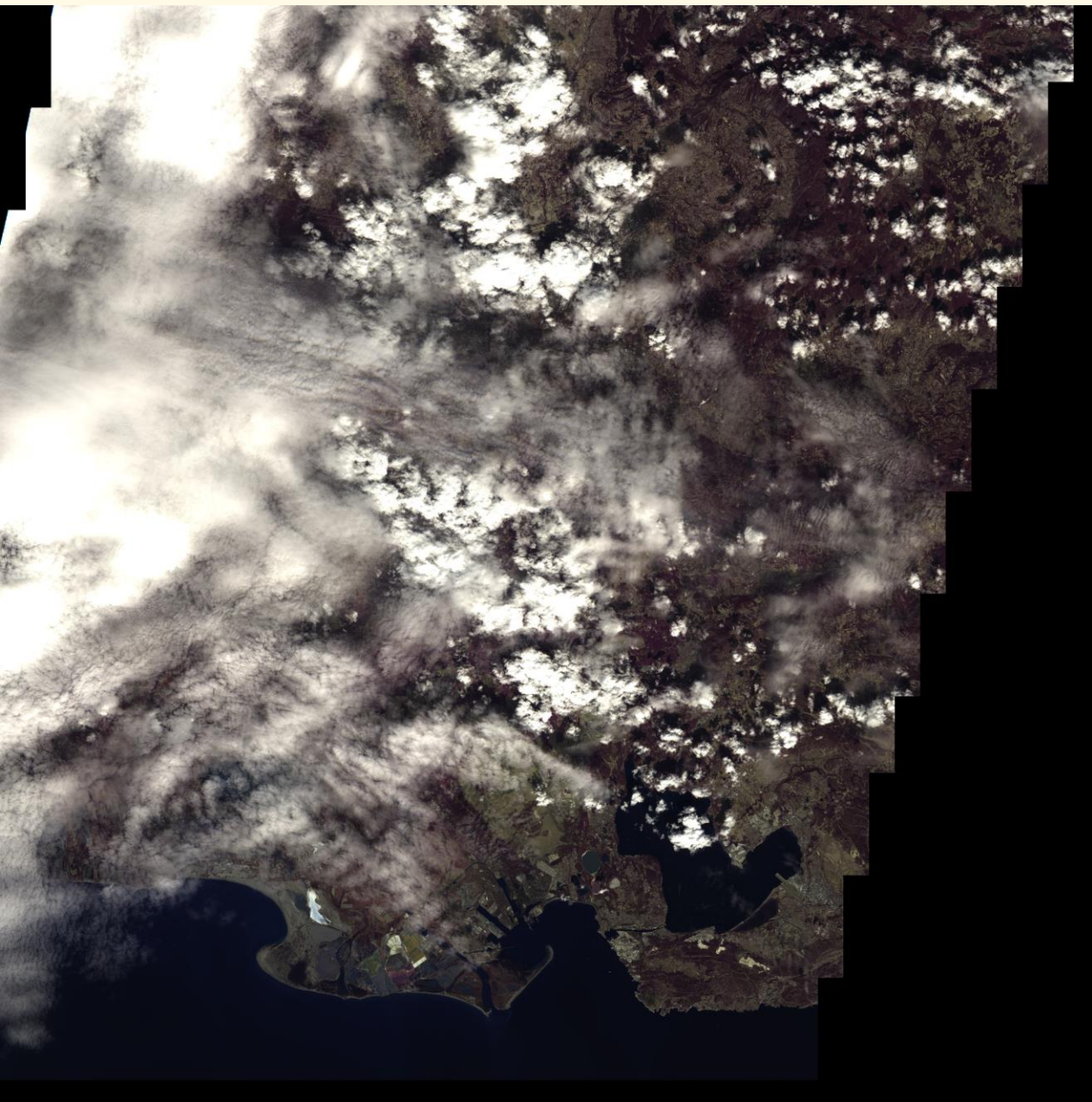


Landsat+Sentinel

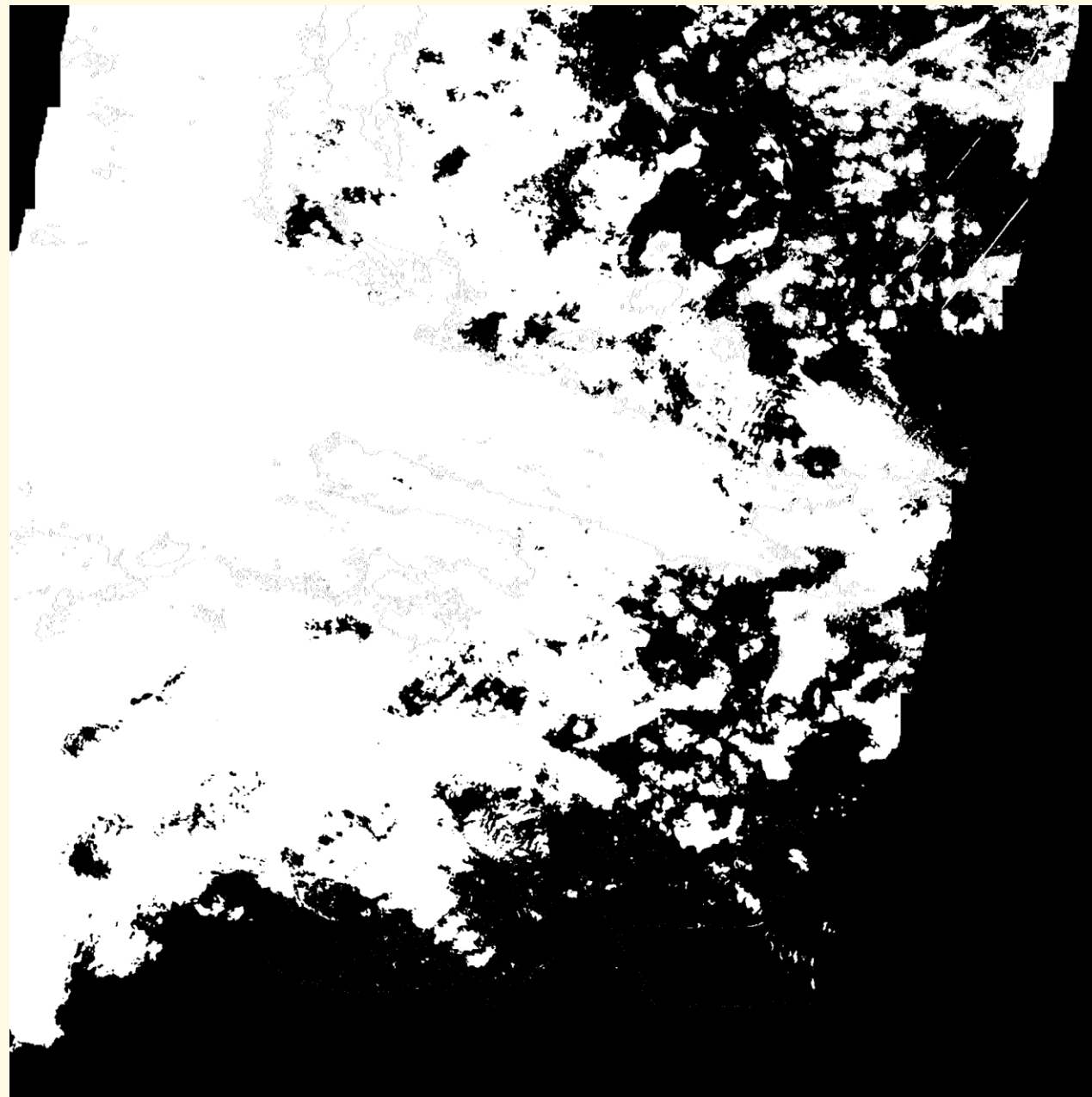


Sentinel





Arles, France



Groundtruth



Landsat+Sentinel



Sentinel



# Takeaways

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- Model is significantly worse if no data used from Sentinel-2.
  - Are there different sampling biases between Landsat and Sentinel datasets?
  - Are the shared bands as visually similar as we posit?
- (Very) tentative evidence that adding data from multiple satellites improves performance
  - Primary indicator of performance is **still** the amount of training data from the target satellite

# Conclusions

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- Novel sensor-independent model has been developed
- Training across multiple sensors results in a somewhat better model
- More labelled data leads to better training **and** better validation
- More work is needed on understanding differences between sensors, and how the model is interpreting these differences

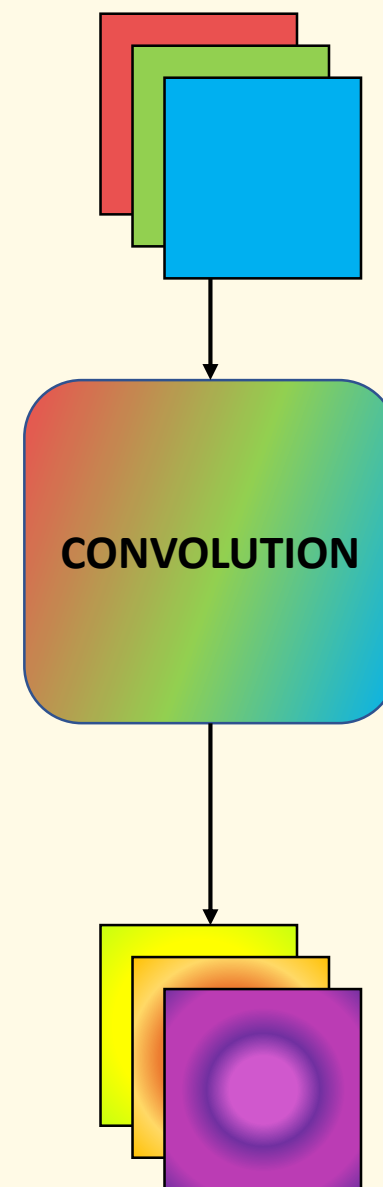
Thanks!

Extra Slides...

# Sensor-Independent Model

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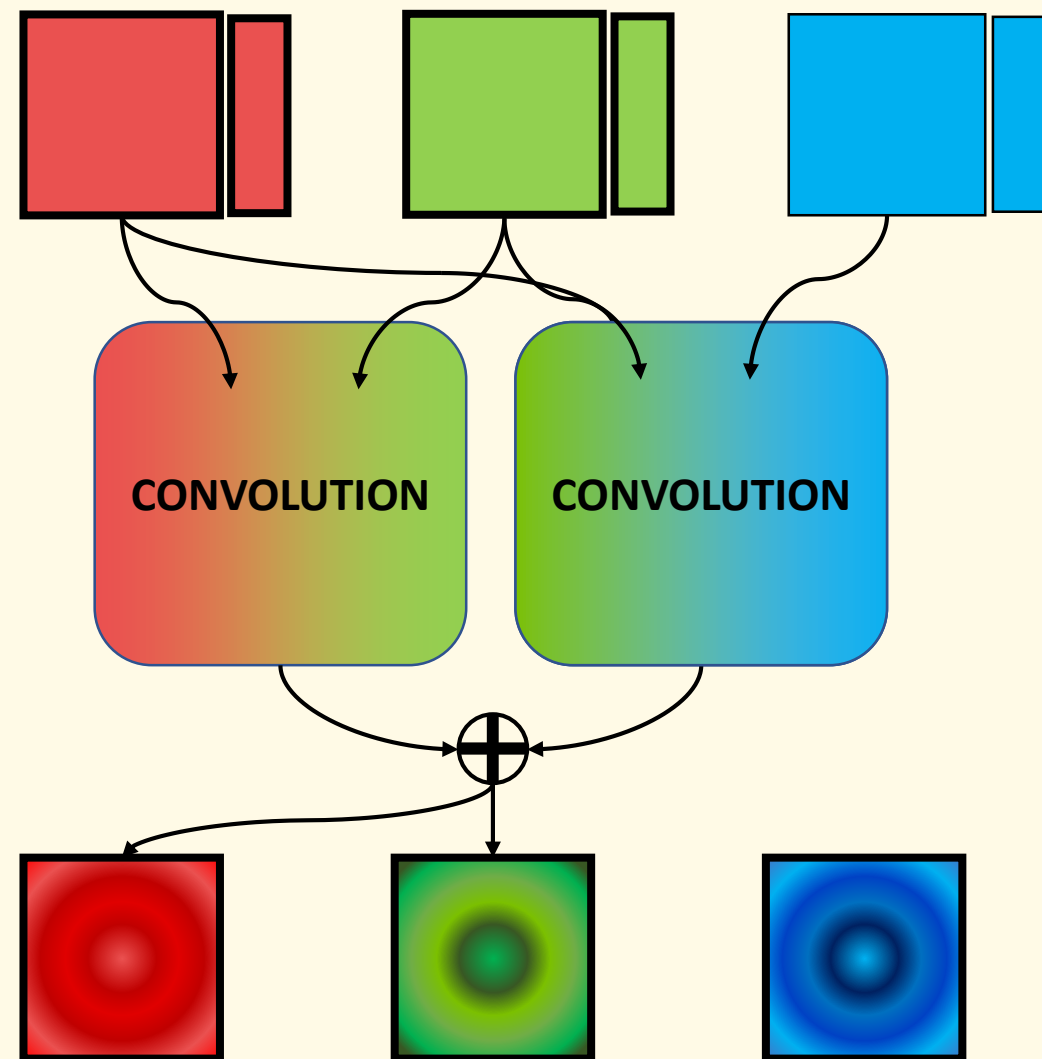
- Convolutional layer replaced by permutational convolutional layer





# Sensor-Independent Model

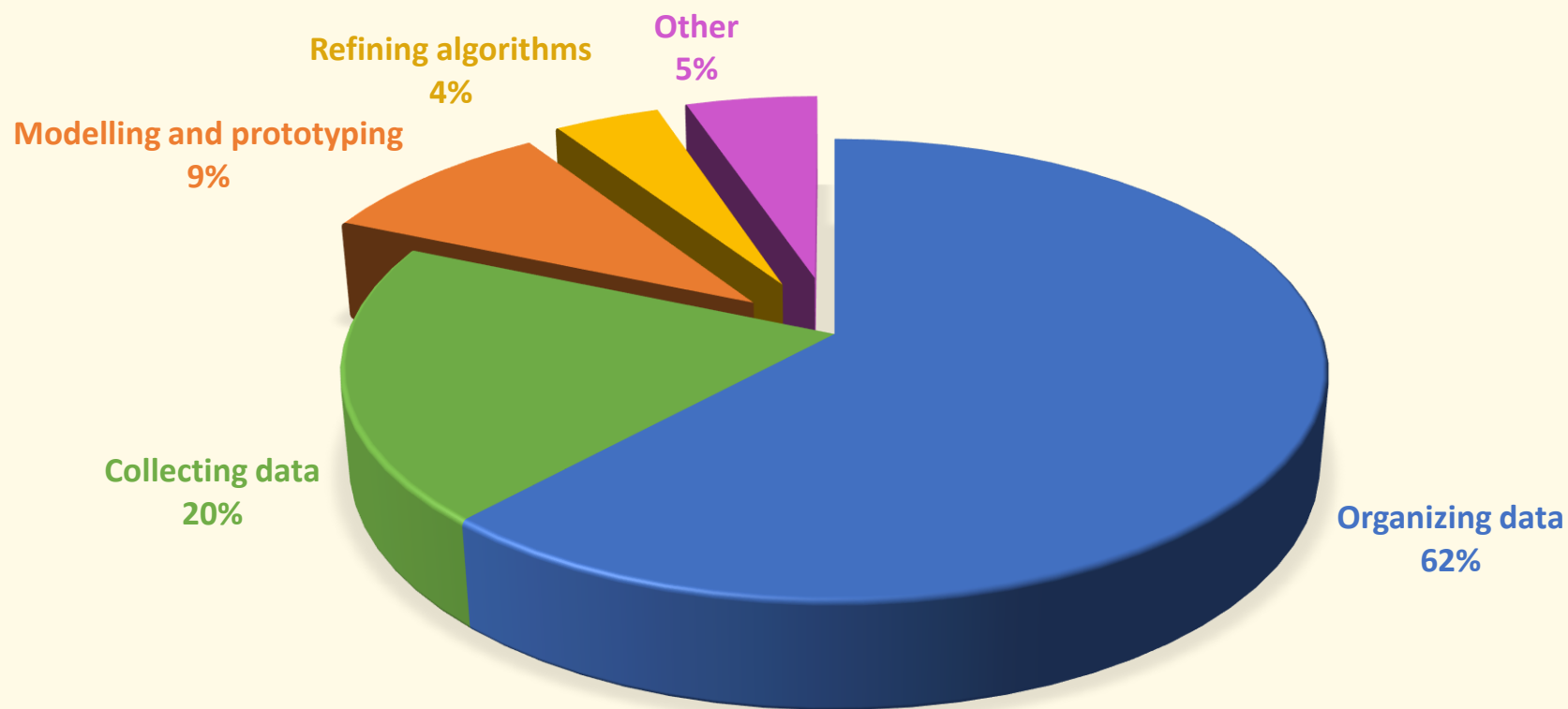
- Convolutional layer replaced by permutational convolutional layer
- Convolve each pair of bands
- Sum pairwise outputs.
- Allows for arbitrary input size, **but**  $O(n^2)$  with number of bands
- Modular, can be substituted in for normal convolutions



# Deep Learning's Problem

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DATA SCIENTISTS' TIME BREAKDOWN



**>80% of time spent on problem-specific tasks**

\*Data taken from CrowdFlower survey