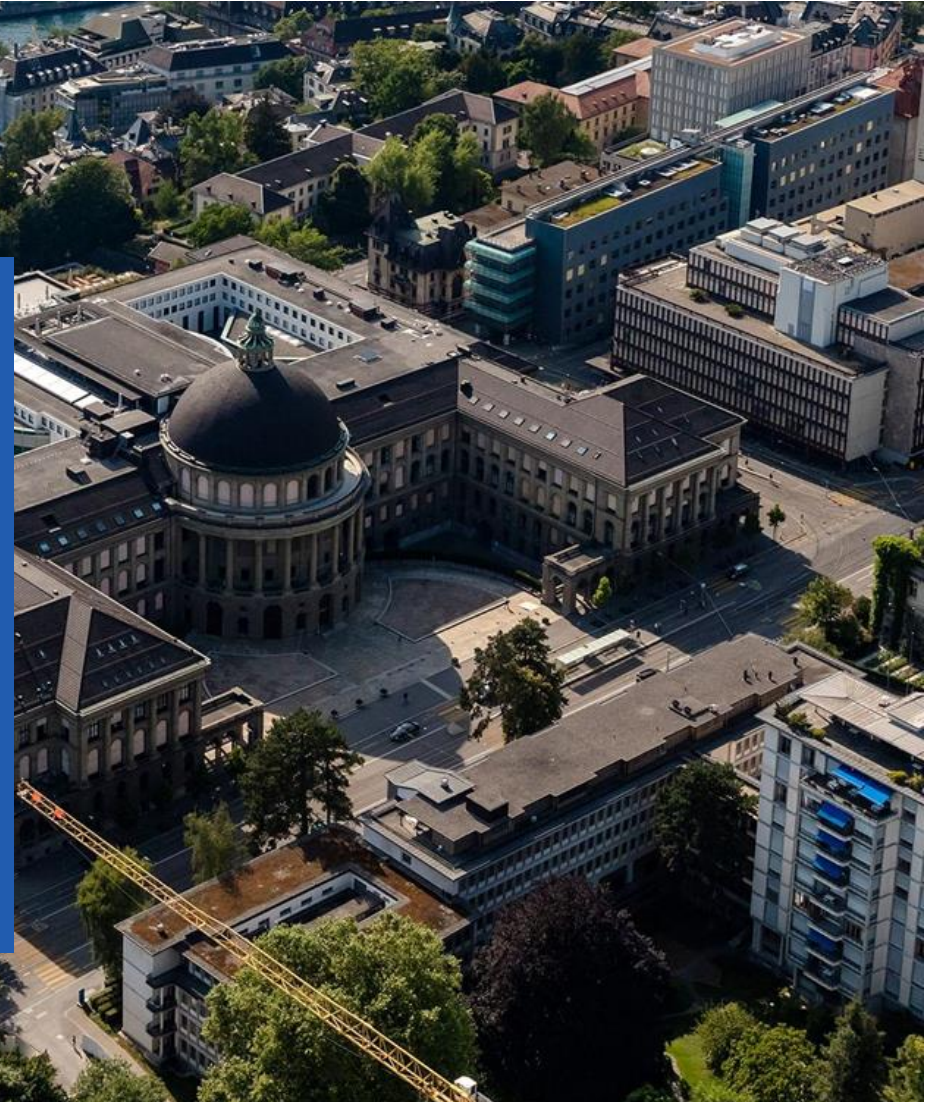


# ICESat-2 spaceborne LiDAR as complementary data source for biomass mapping

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# Introduction

- Carbon uptake by forests has made an important contribution to the global carbon sink over past decades, yet estimates of its magnitude and distribution remain highly uncertain. Reliable and continuous forest monitoring is essential for improving our understanding of the global carbon cycle.
- The PRS group has developed a satellite-based global biomass monitoring system which lacks reference data in the sub-arctic region. The project aims to integrate sub-arctic ICESat-2 data into the biomass mapping system so as to provide reference data in the sub-arctic region.

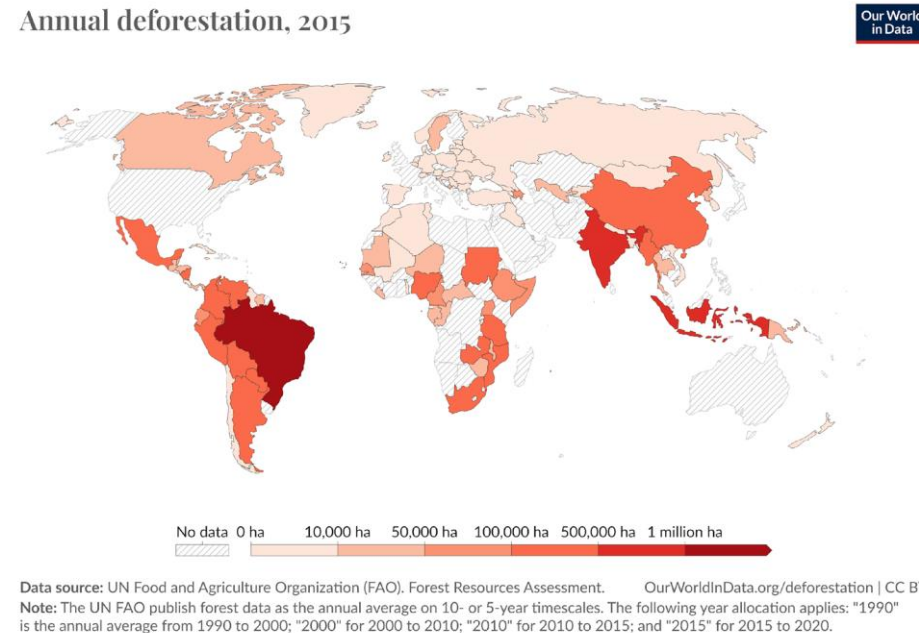
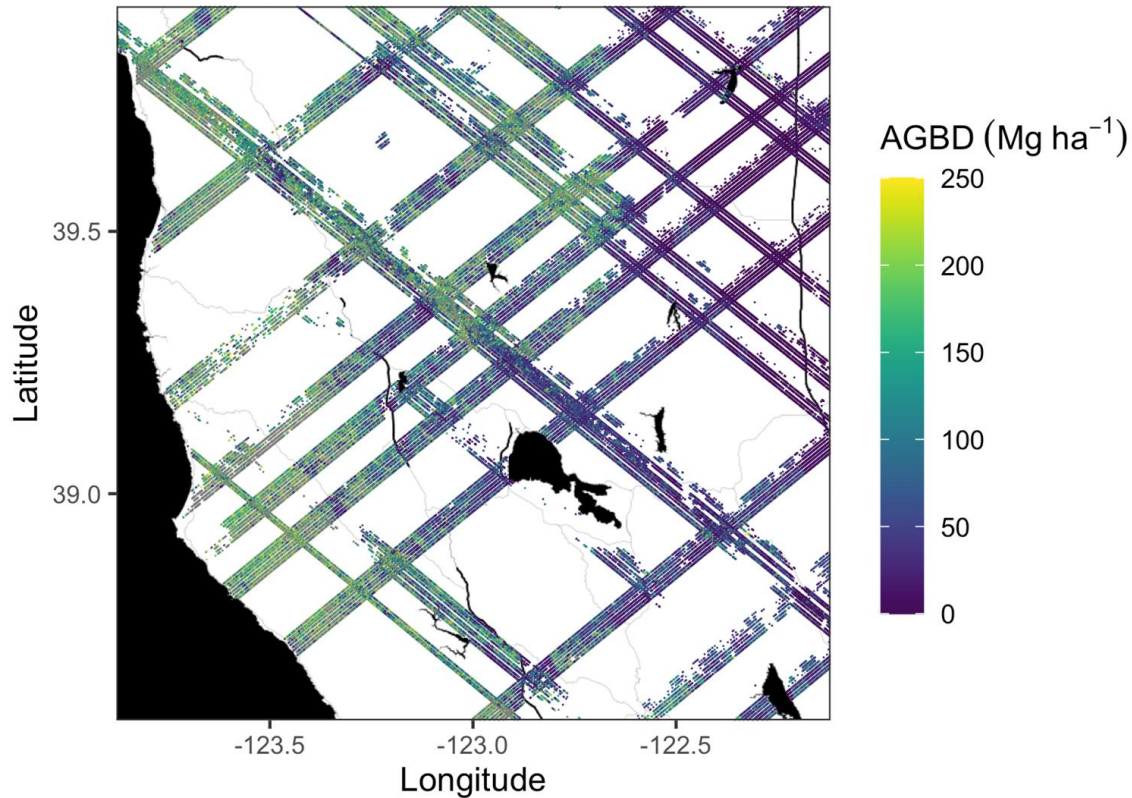


Figure 1: Annual Deforestation, 2015. Our World in Data [1]



# Dataset

## GEDI



Characteristics	
Spatial coverage	Lat: 51.6° N~51.6° S
File format	Point shapefile
Spatial resolution	60 m

Figure 2: Example subset of aboveground biomass density (AGBD;  $\text{Mg ha}^{-1}$ ) predictions from the GEDI Level-4A footprint product

# Dataset ICESat-2

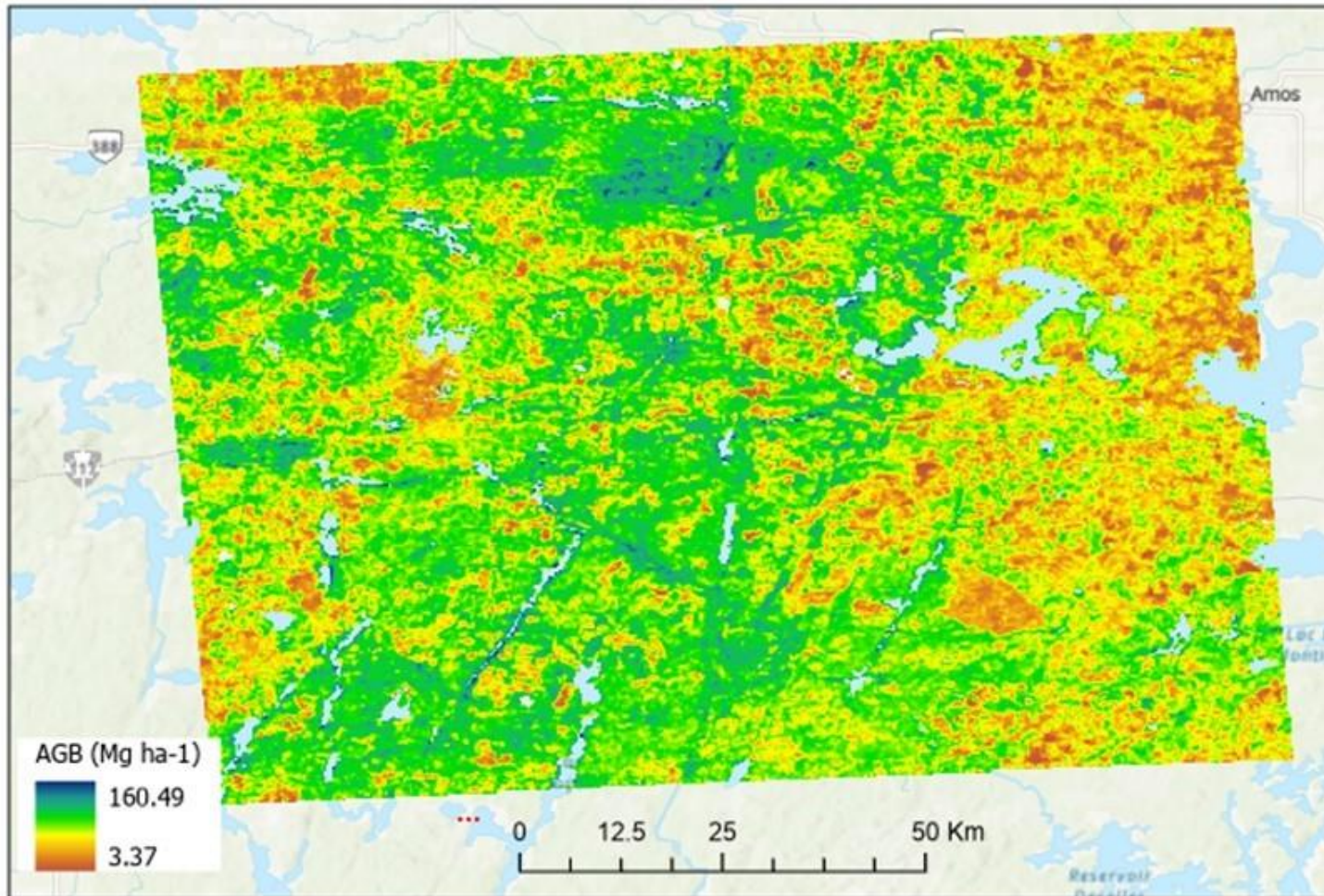


Figure 3: Example of aboveground biomass (Mg ha-1) for boreal forest estimated from ICESat2 imagery

Characteristics	
Spatial coverage	Lon: -179~178 Lat: 43~78
File format	GeoTIFF
Bands	Aboveground biomass density (AGB), standard deviation
Spatial resolution	30-m grid cells
Extent	90 km x 90 km (3000 x 3000 grid cells)



# Dataset

## Sentinel-2 Level-2A

Band	Resolution	Description
B1	60m	Aerosols
B2	10 m	Blue
B3	10 m	Green
B4	10 m	Red
B5	20 m	Red Edge 1
B6	20 m	Red Edge 2
B7	20 m	Red Edge 3
B8	10 m	Near Infrared (NIR)
B8a	20 m	Red Edge 4
B9	60 m	Water vapor
B11	20 m	Short Wave Infrared (SWIR) 1
B12	20 m	SWIR 2

Sentinel-2 Level-2A spectral bands

Characteristics	
Spatial coverage	Global
File format	GeoTIFF
Spatial resolution	10 m, 20 m, and 60 m

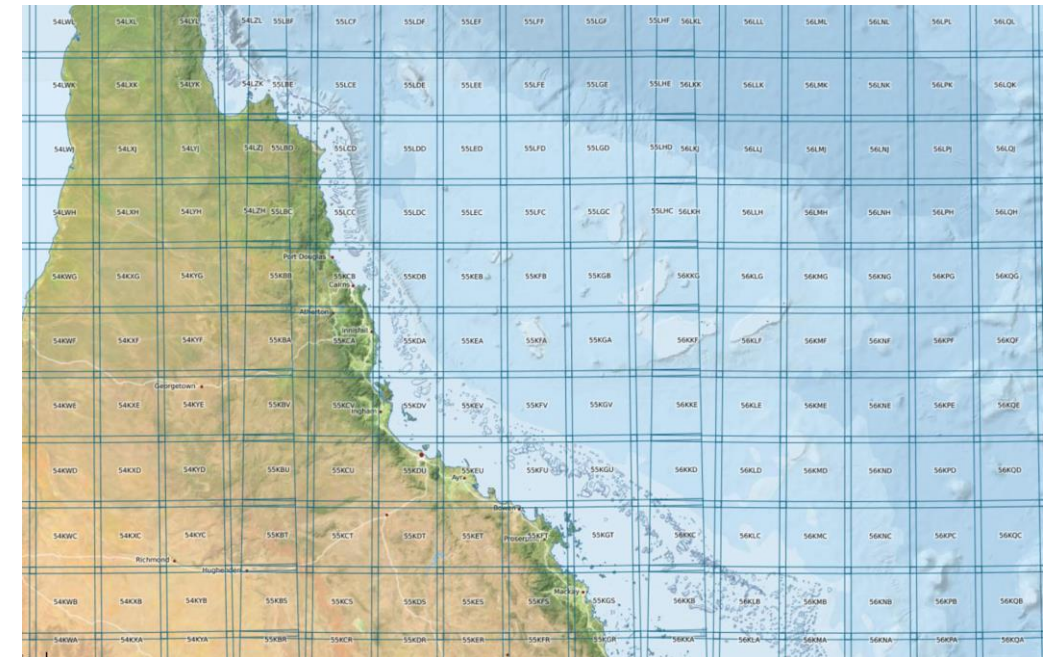


Figure 4: Sample Sentinel-2 UTM  
110x110 km<sup>2</sup> Tiling Grid

# Research area

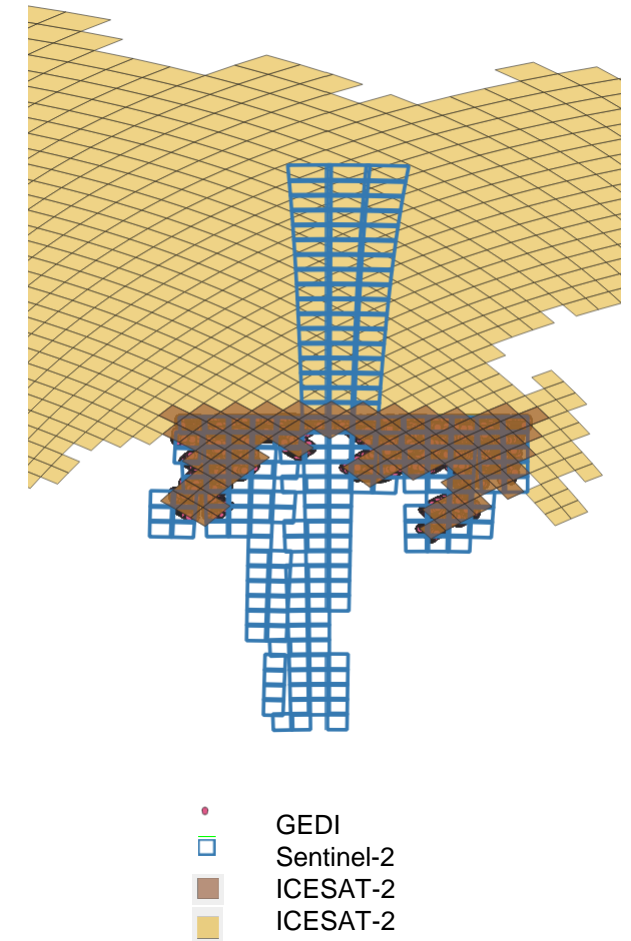
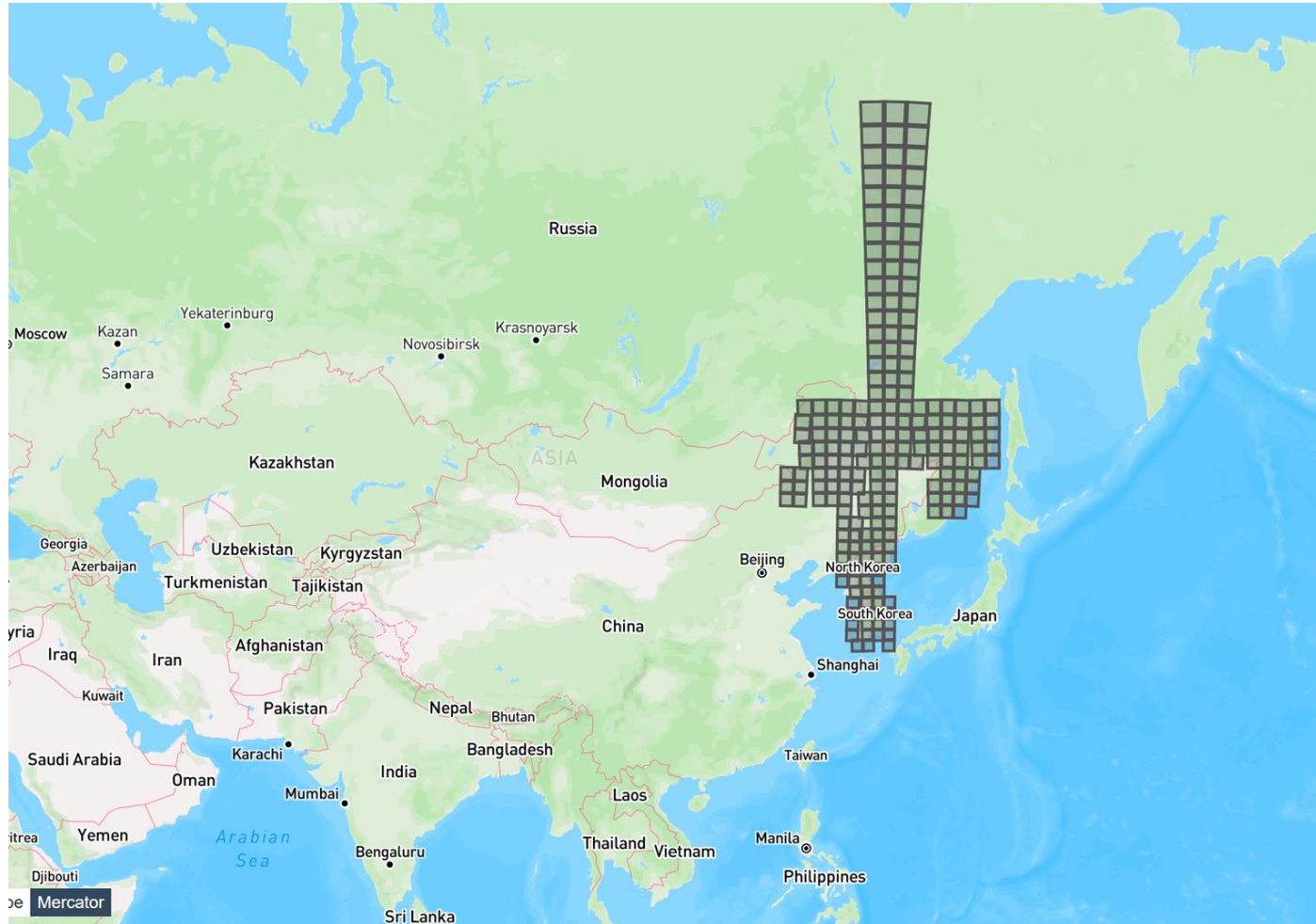
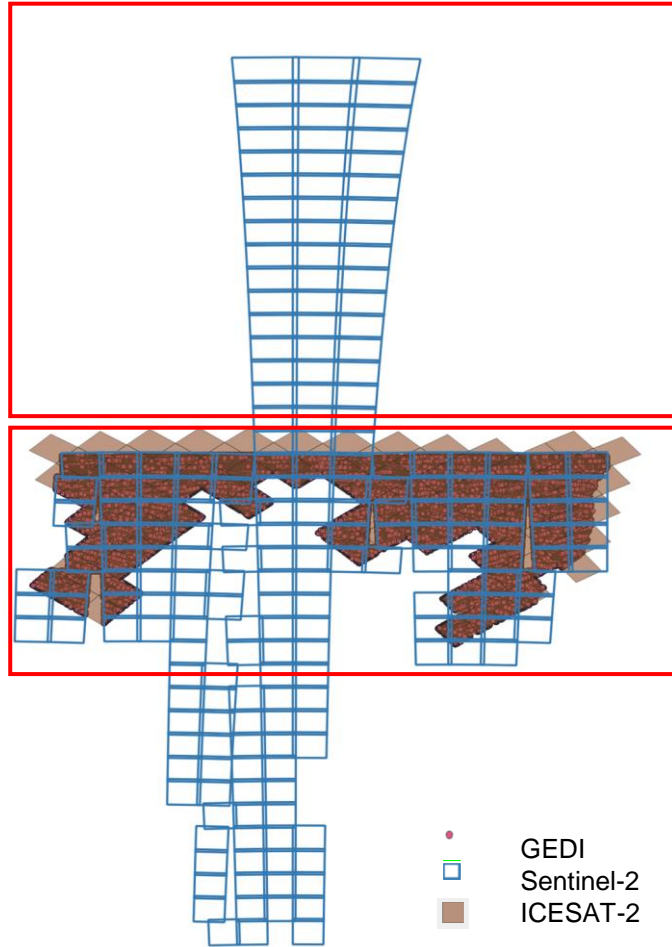


Figure 5: Bounds of Sentinel-2 tiles

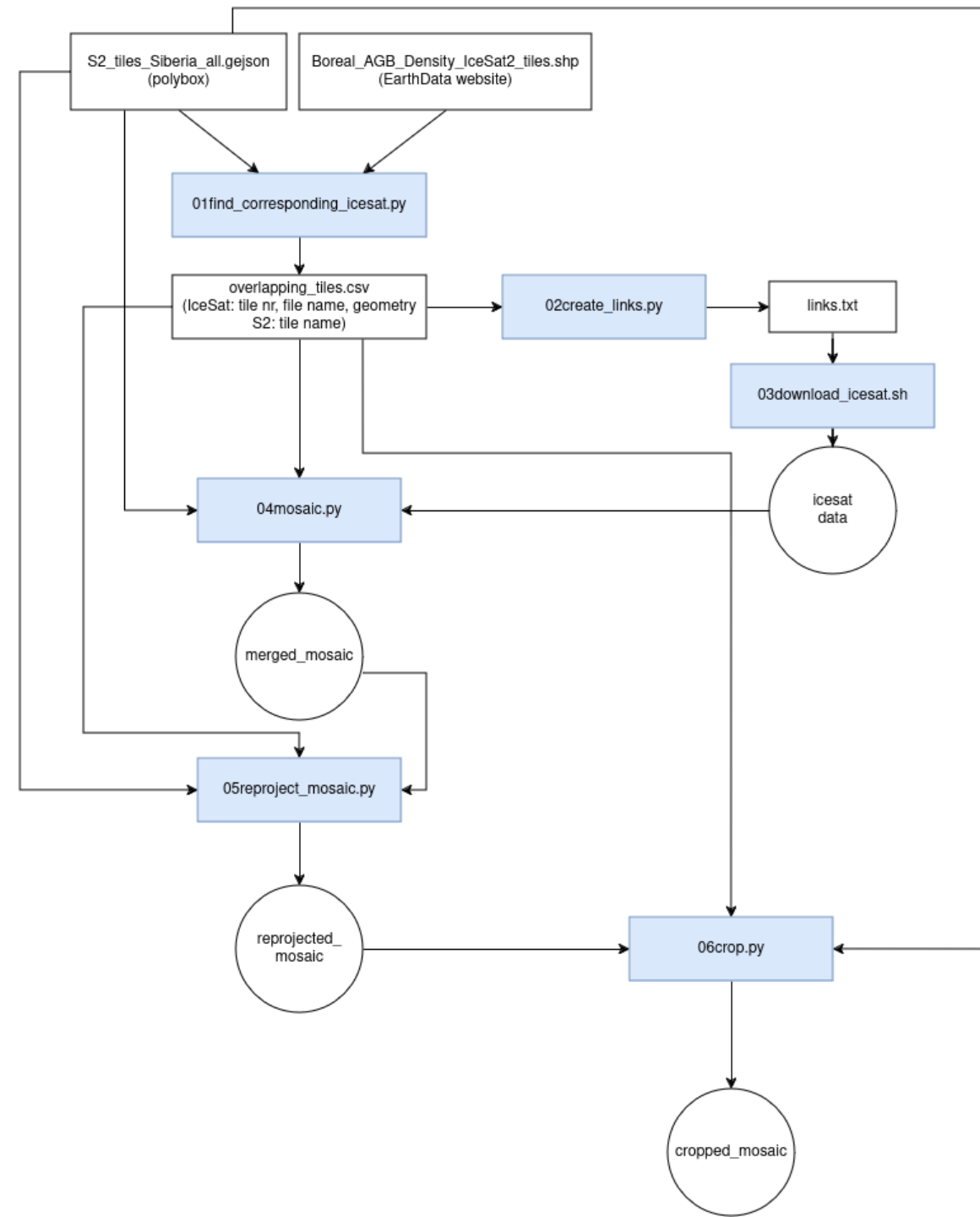
# Procedure

## Data preprocessing



➔ Inference (with Sentinel-2 and ICESat-2 data)

➔ Training (with Sentinel-2, ICESat-2 and GEDI)



# Procedure

## Data analysis

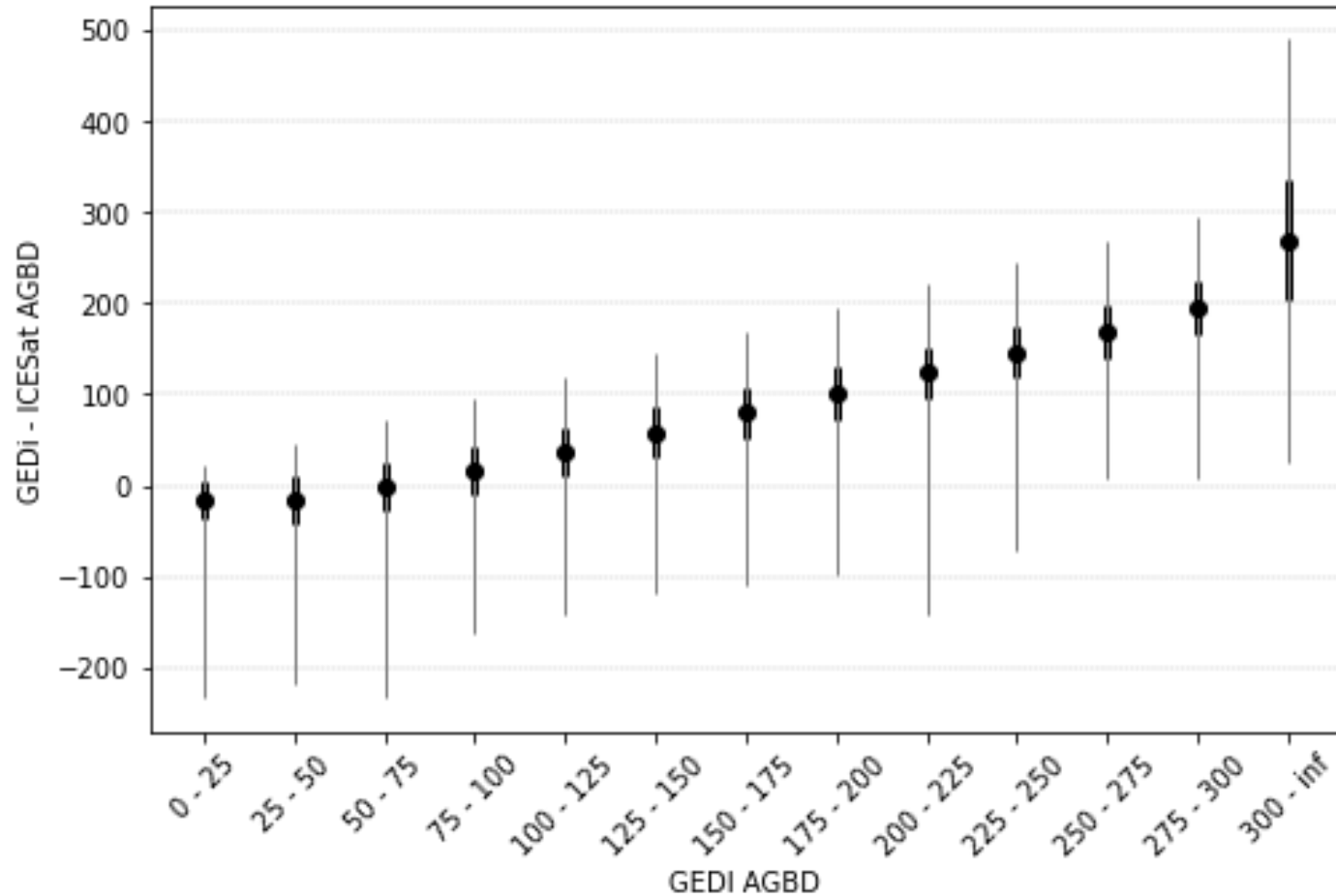


Figure 6: The boxplot of GEDI-ICESat AGBD (on the y axis) for every bin of the GEDI AGBD (x axis).

- ICESat-2 tends to underestimate AGBD for higher GEDI AGBD.

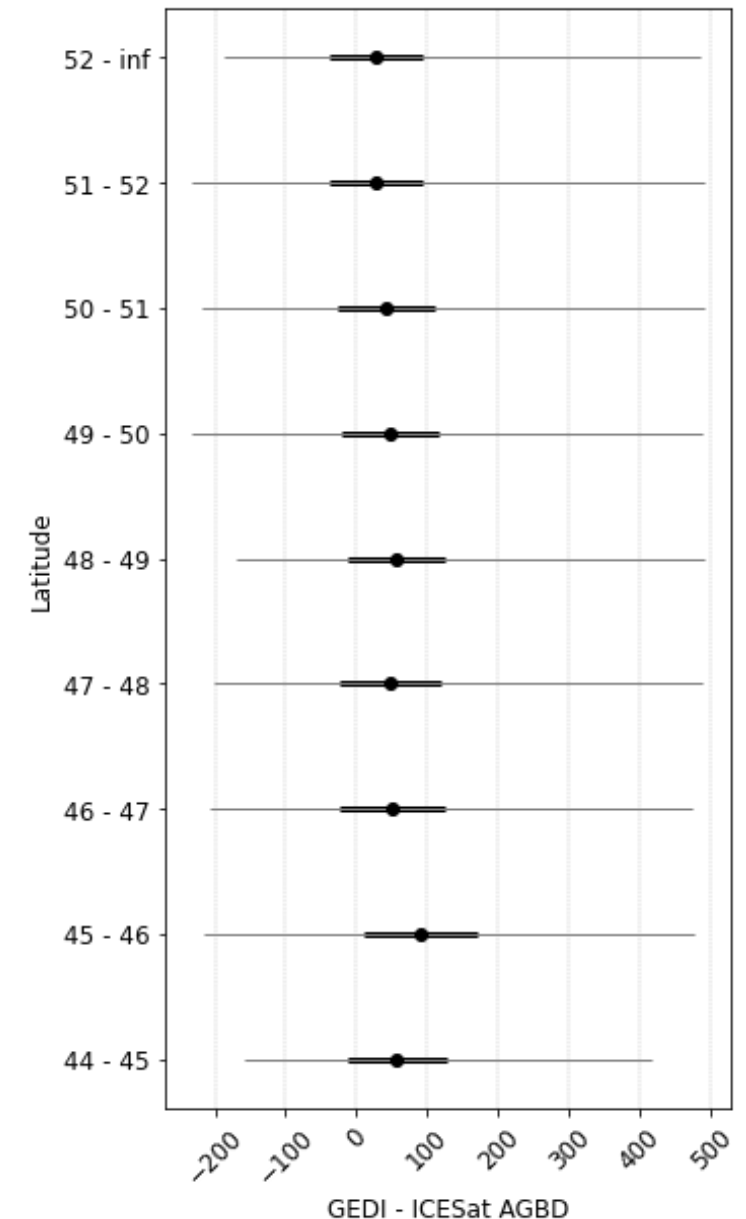


# Procedure

## Data analysis

Figure 7: Box plot of GEDI-ICESat AGBD (on the x axis) for every latitude bin (y axis).

- ICESat-2 tends to underestimate AGBD compared to GEDI AGBD. The difference distribution has little correlation with latitude.



# Procedure

## Data creation

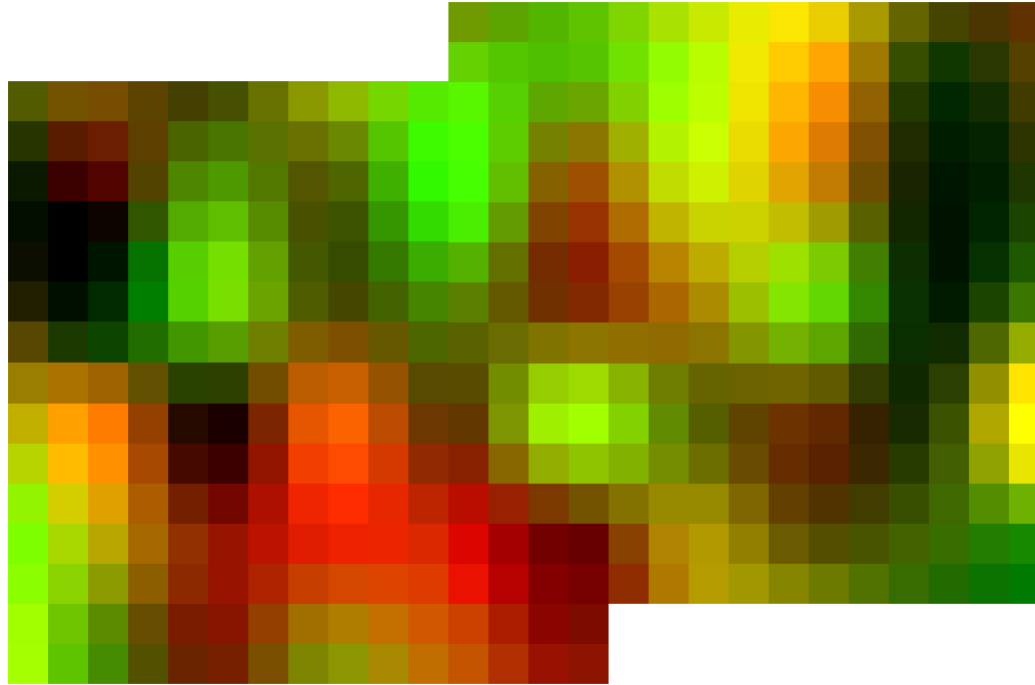
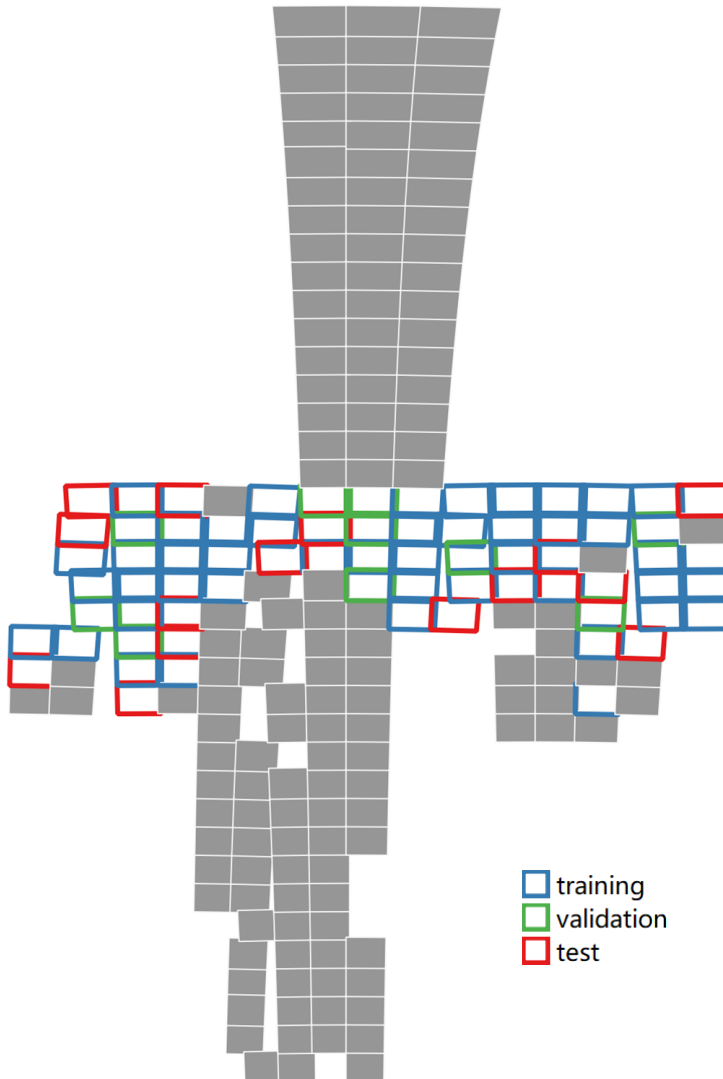


Figure 8: Sample patches for training

- patches of  $15 \times 15$  pixels (corresponding to  $150 \times 150$  m on the ground) both from the Sentinel-2 and the ICESAT-2 mosaic, centered around GEDI footprints.

# Procedure

## Training region



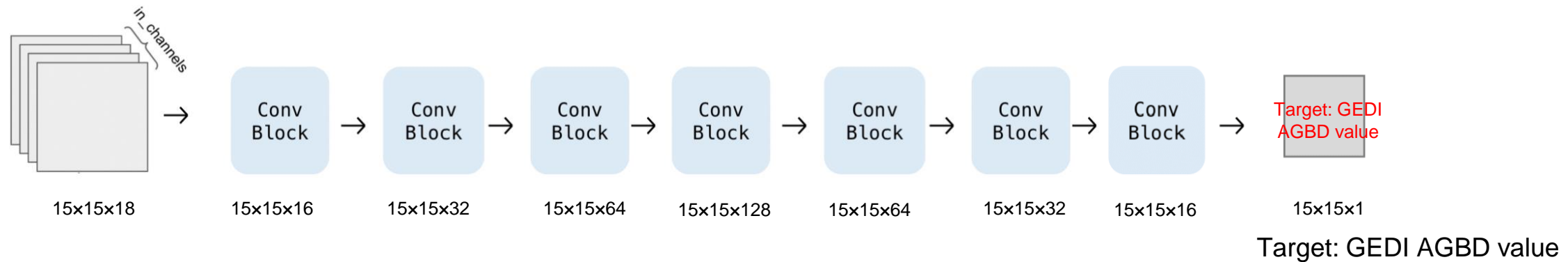
- patches of  $15 \times 15$  pixels (corresponding to  $150 \times 150 \text{ m}^2$  on the ground) both from the Sentinel-2 mosaic and the ICESAT-2, centered around GEDI footprints.

Figure 9: Dataset splitting



# Procedure

## Model architecture (FCN)



Conv Block

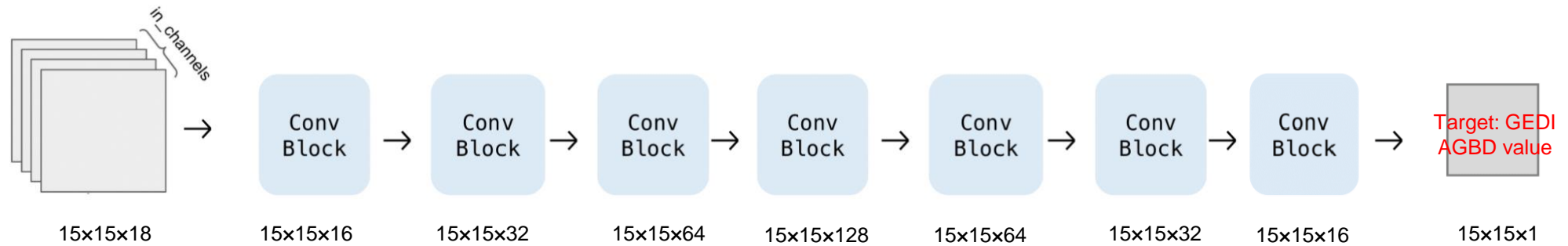


Feature sources	Features
Sentinel-2	12 spectral bands
Position	Cos/sin latitude/longitude
ICESAT-2	AGB, standard deviation

Figure 10: Architecture and features of the Fully Convolutional Neural network (FCN)

- Input: patches of  $15 \times 15$  pixels with 18 features
- Target: GEDI AGBD value of the central pixel of the patches

# Procedure Inference



↓  
×5 with different  
random seed to  
initialize the weights

**Average the prediction**

# Results

## Inference result

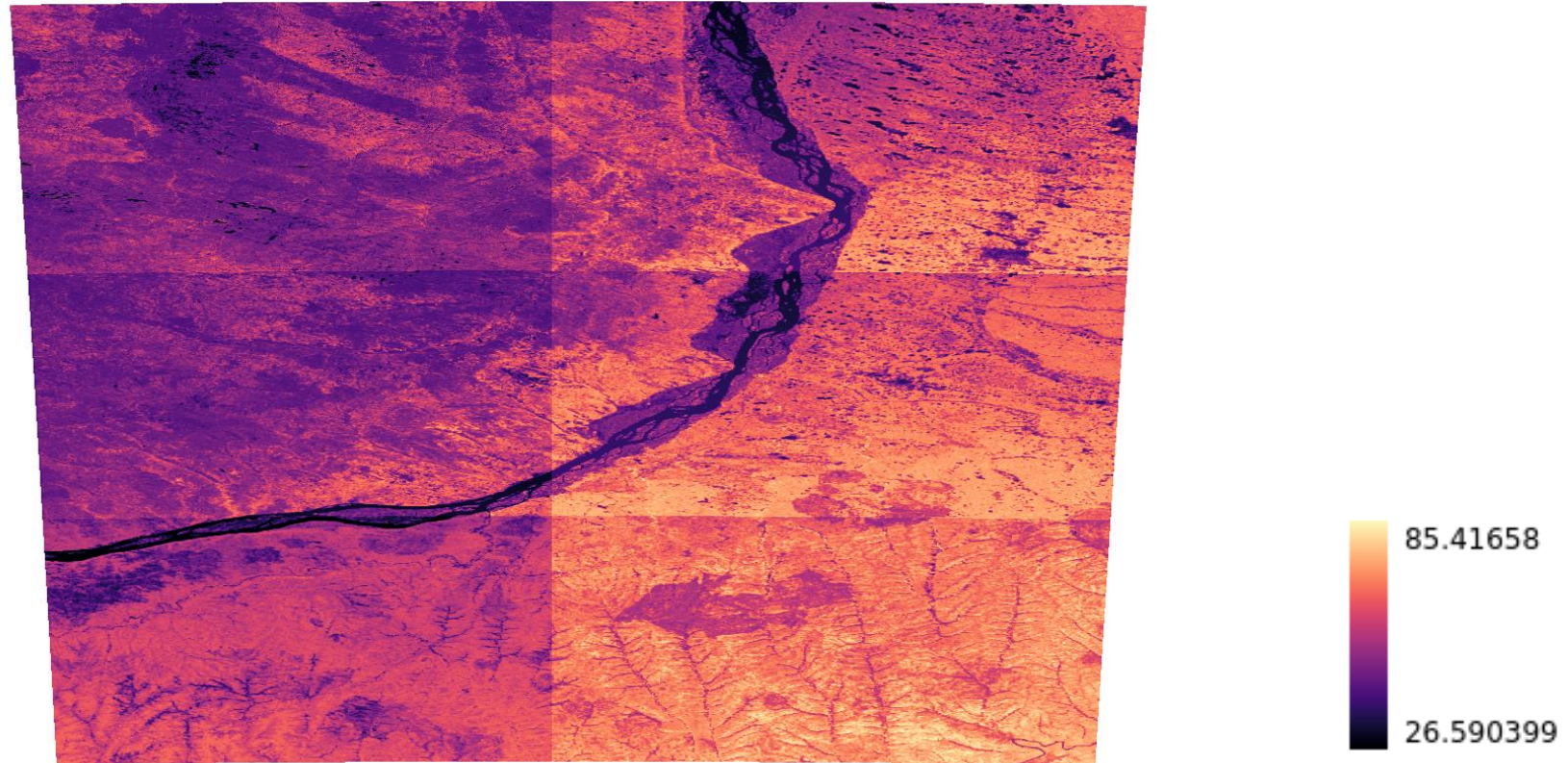


Figure 11: Example biomass inference result in the sub-arctic region



# Conclusion and Outlook

## Conclusion

- The integration of ICESat-2 is a valuable approach for estimating biomass. It can help provide reference AGBD in the sub-arctic region.

## Outlook

- Use more complex models for predictions (ResNeXt, Xception)
- Perform a filtering to exclude potential bad data from the analysis
- All tiles have a certain overlap, so we can apply some methods to create a smooth transition between neighbouring tiles.

# Reference

[1] Ghjulia Sialelli. Global biomass estimation and uncertainty quantification with multi-task bayesian deep ensembles.

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Poster Presentation