



# Swin Transformers and U-Net for remote sensing based surface water monitoring

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# remote sensing based surface water monitoring

- Water monitoring from space
  - U-Net
  - Sentinel-2 and Sentinel-1 as inputs
  - Focus on temporal dimension
- Water monitoring airborne
  - Swin-Transformer + UPerNET
  - RGB+NIR orthophoto (@25cm) as inputs
  - Focus in spatial dimension



SEE  
THE  
BIGGER  
PICTURE

# Water monitoring from space



# Water monitoring from space

## Sentinel-2

- + clear water pattern
- + high resolution
- moderate revisit time
- unreliable observation frequency

## Sentinel-1

- many confusing factors
- moderate resolution
- + high revisit time
- + cloud independent

→ combine complementary strengths

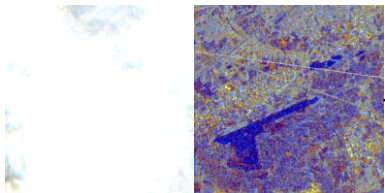


# Setup

Sentinel-2  
+  
closest Sentinel-1



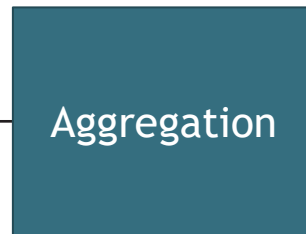
⋮



Single scene  
water prediction probabilities



⋮



Monthly  
water frequencies



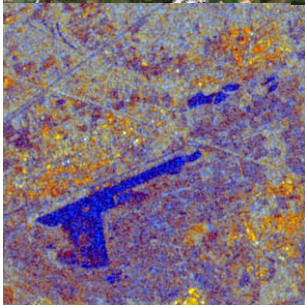


# Setup

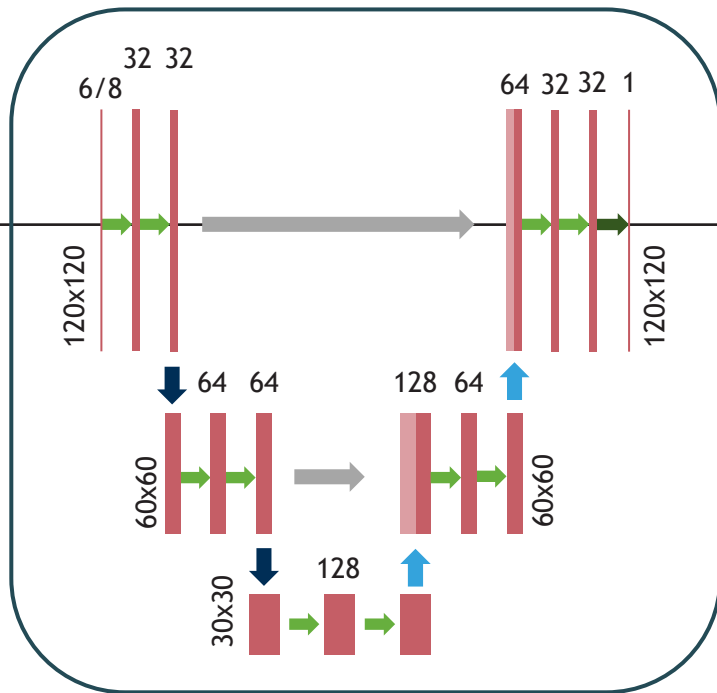
Sentinel-2



closest  
Sentinel-1



## U-Net



Single scene  
water probabilities



→ conv 3x3, ReLU

→ skip connection

↓ max pool 2x2

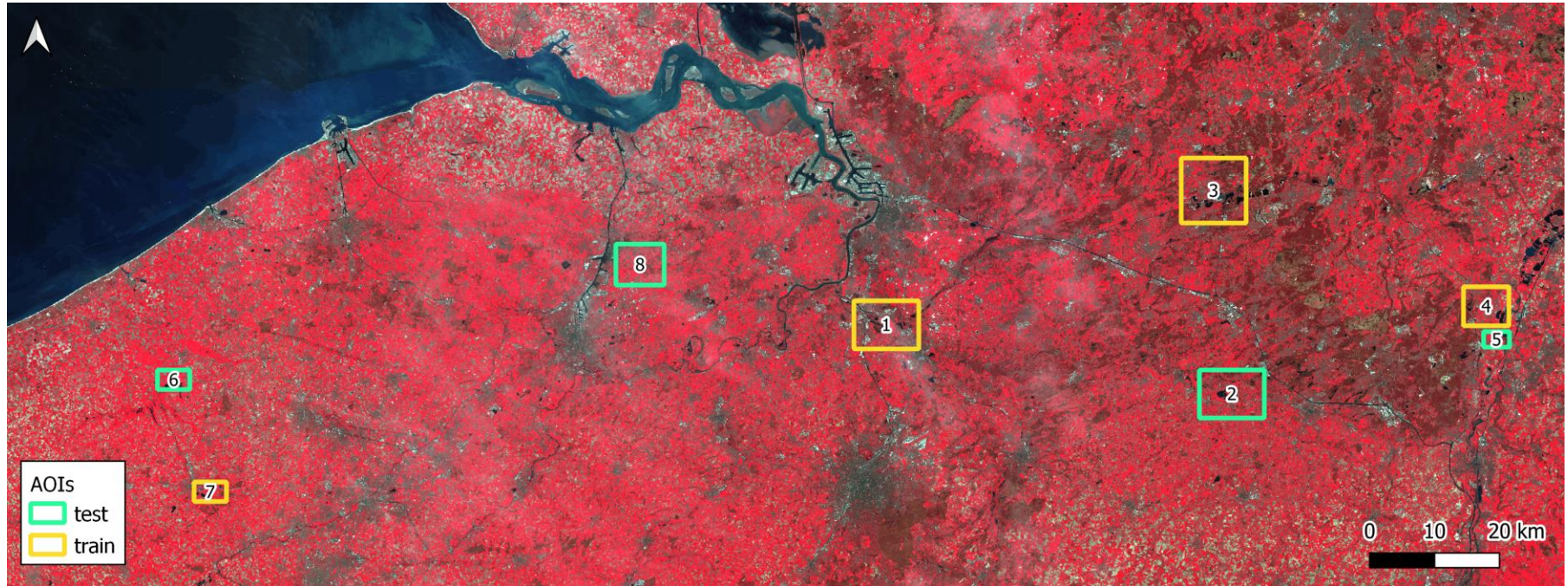
↑ up-conv 2x2

→ conv 1x1 [remotesensing.vito.be](http://remotesensing.vito.be)





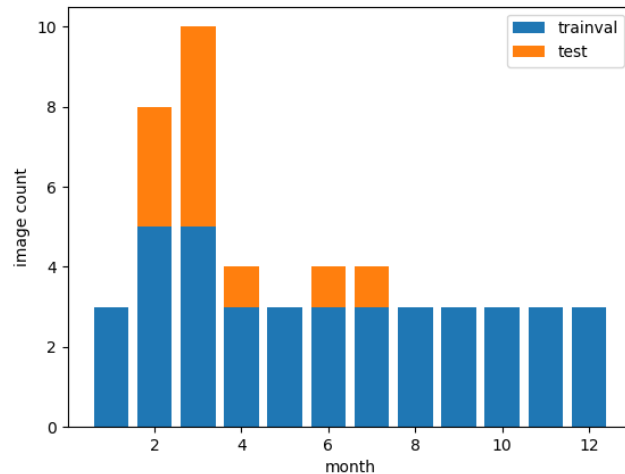
# Training setup: AOIs





## Training setup: inputs

- Sentinel-2 / Sentinel-1 pairs with  $\Delta t < 24h$   
2018 - 2021
- Training: uniform spread across year
- Testing: matchup with yearly orthophotos
- Cloud-free + cloudy dataset







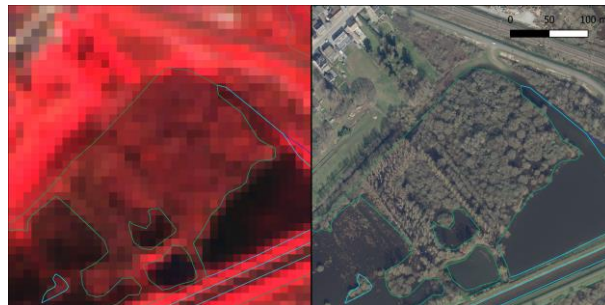
# Training setup: labels

- Manual annotations starting from static INBO dataset
- Reference: 25cm yearly orthophotos + Sentinel-2
- Subclass labels  
shallow, saturation, vegetation, trees, invisible

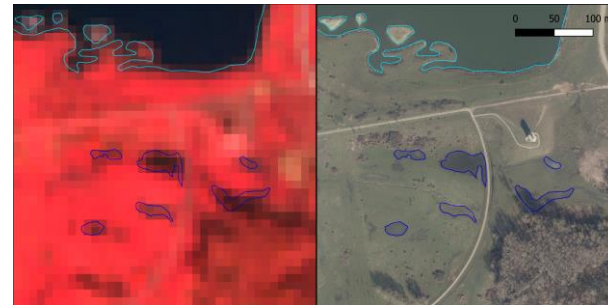
Vegetation



Trees

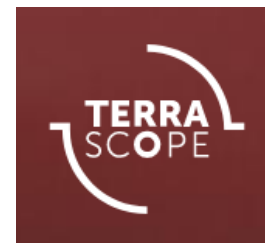


Shallow water

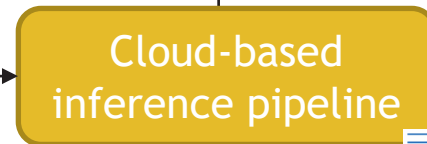
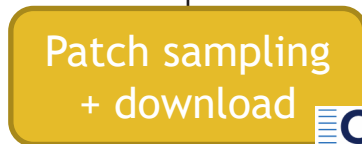




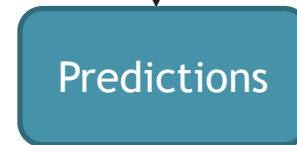
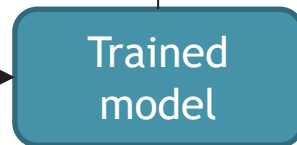
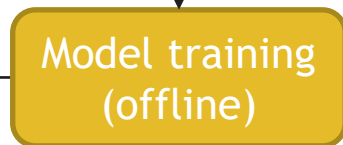
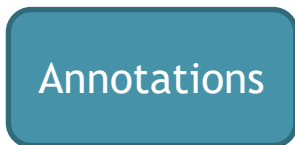
# Workflow



[viewer.terrascope.be](http://viewer.terrascope.be)



[openeo.cloud](http://openeo.cloud)



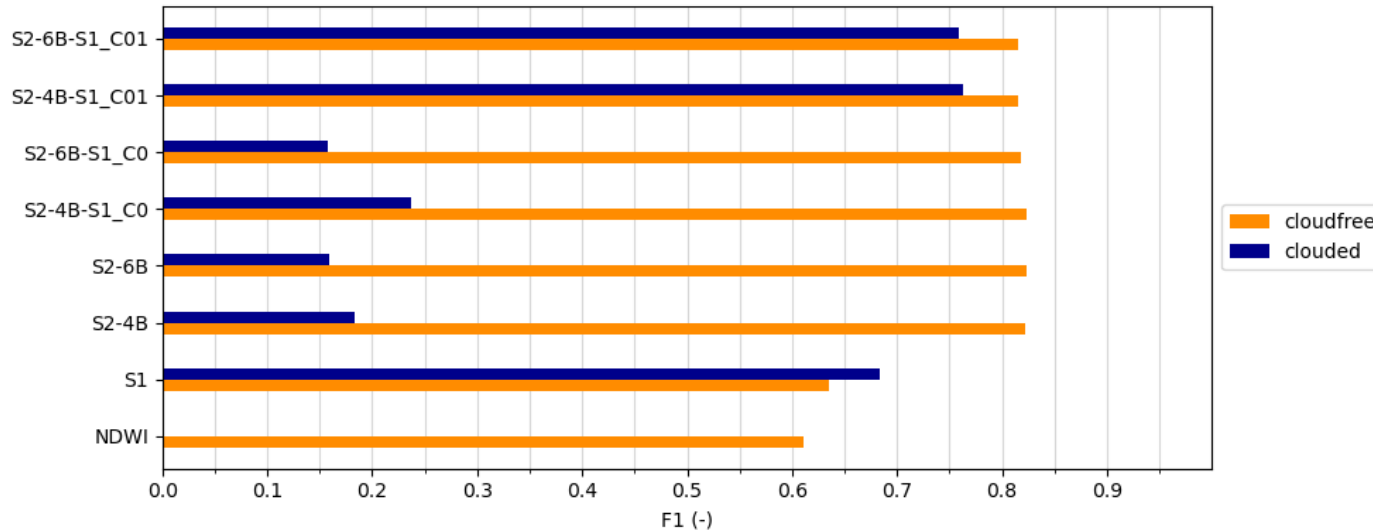
TensorFlow  
 Adam optimizer, binary cross entropy  
 50 epochs + early stopping  
 Variable learning rate starting at 0.001



[remotesensing.vito.be](http://remotesensing.vito.be)



# Results: single scenes



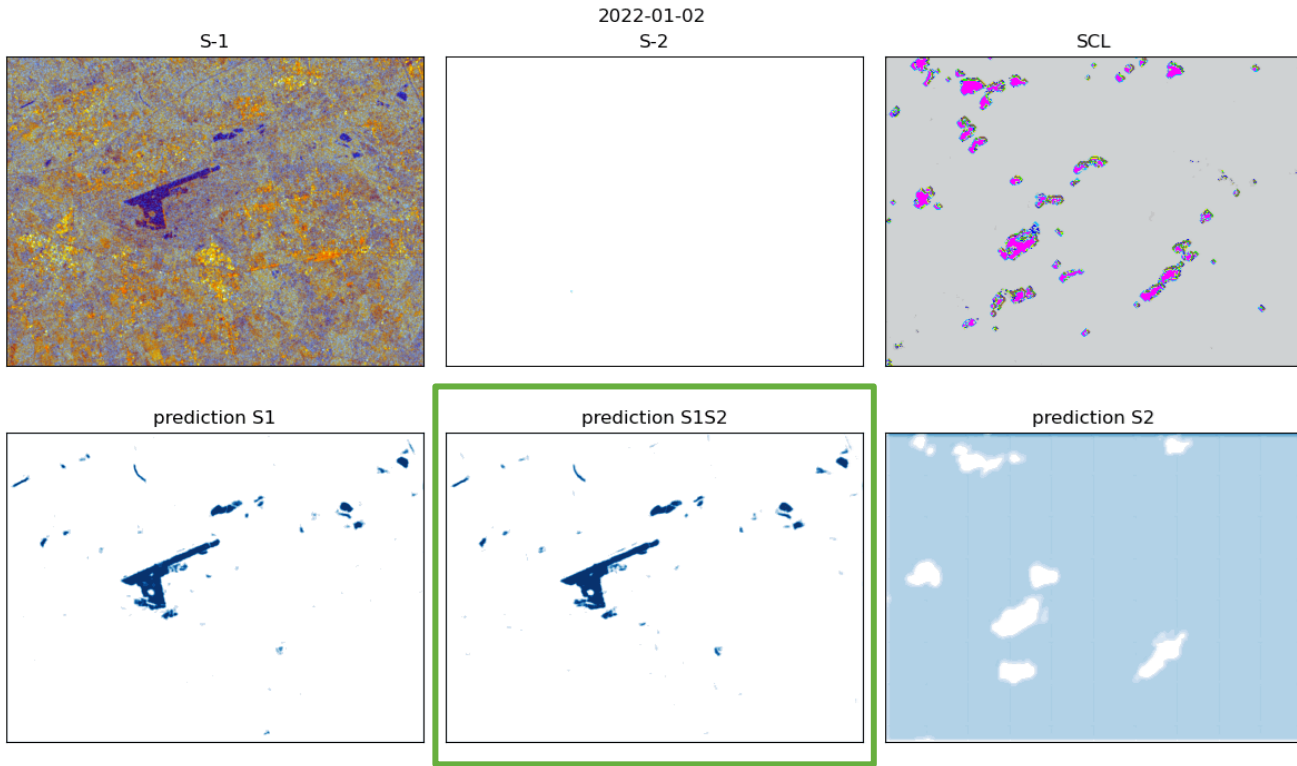
S1: VV, VH

S2-4B: B2, B3, B4, B8

S2-6B: B2; B3, B4, B8, B11, B12

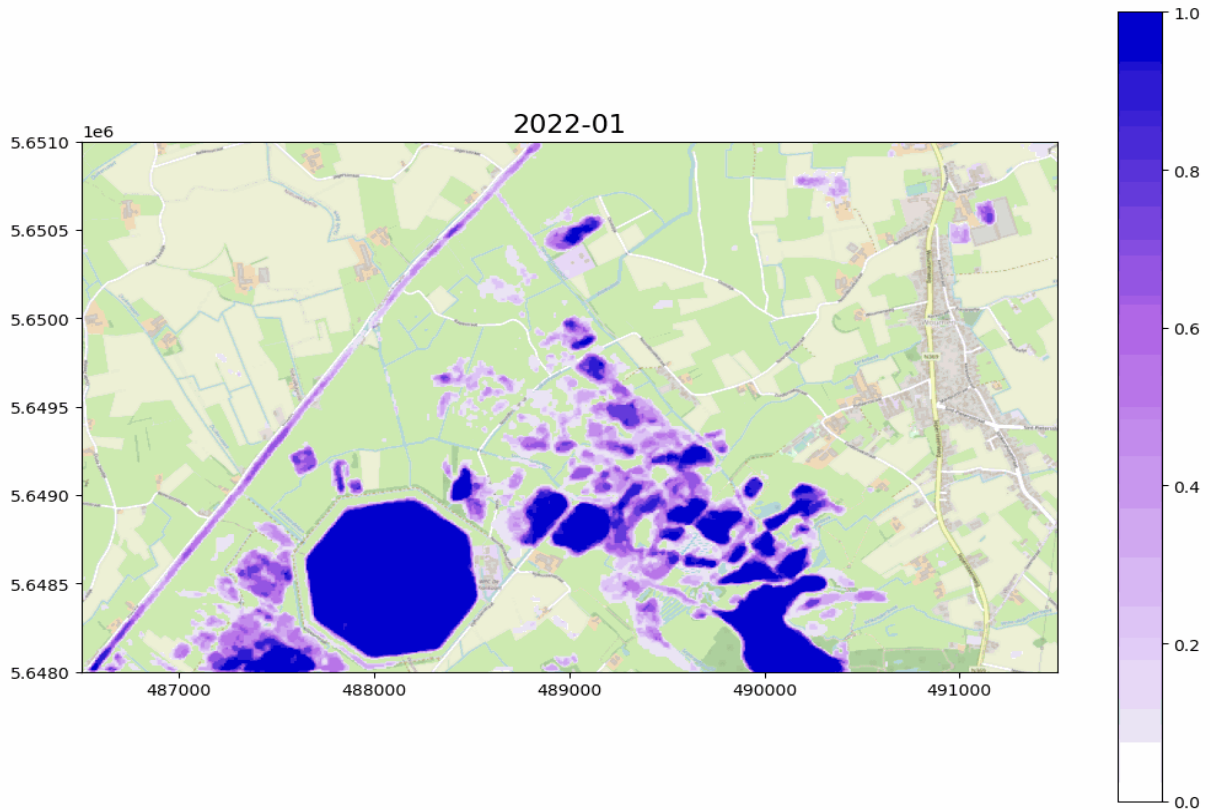


# Results: single scenes





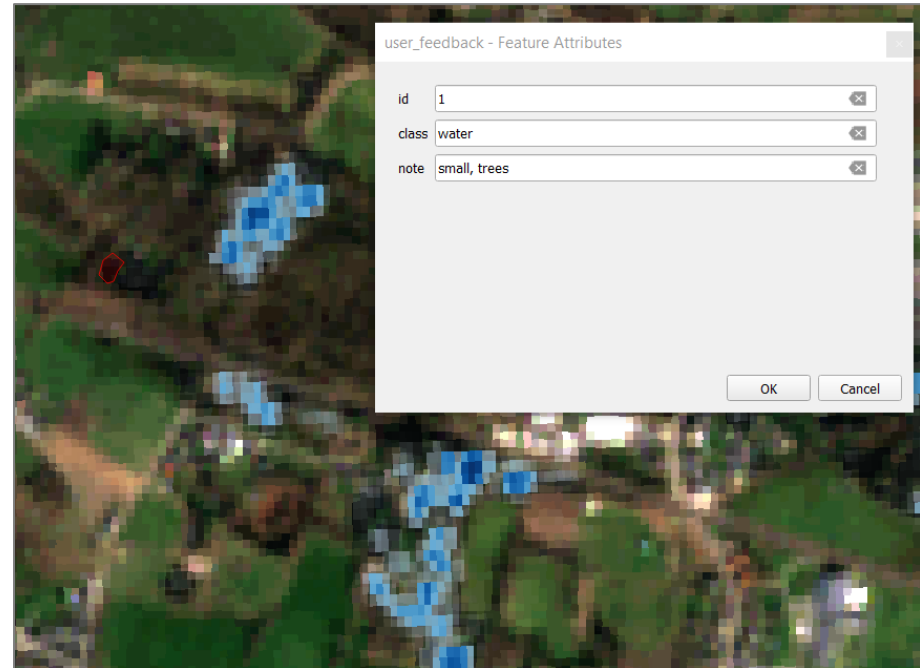
# Results: time series





# User interaction

- Visualization
- Feedback for active learning





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THE  
BIGGER  
PICTURE

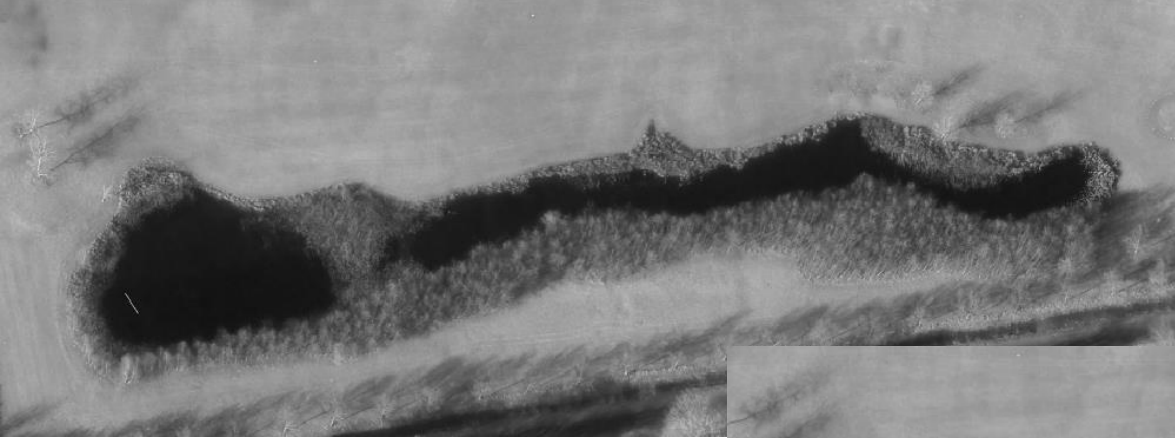
# Water monitoring from the air



# Water monitoring airborne

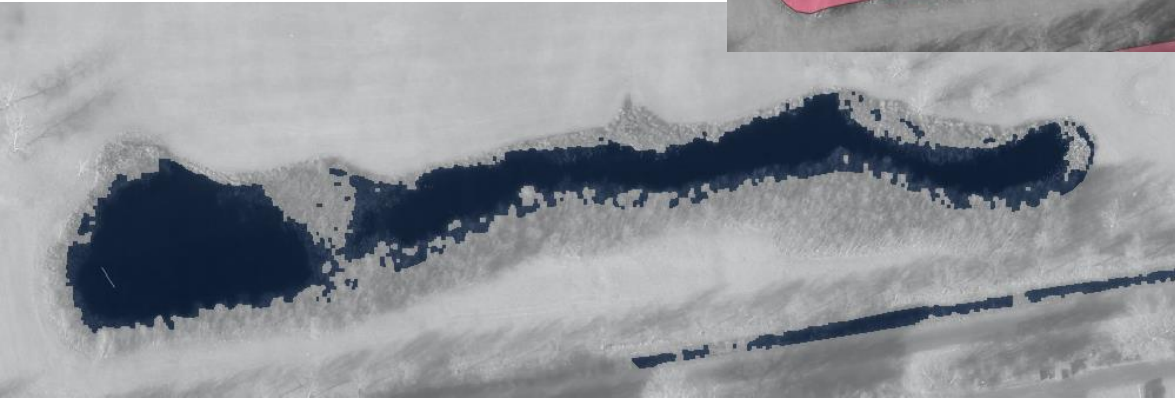
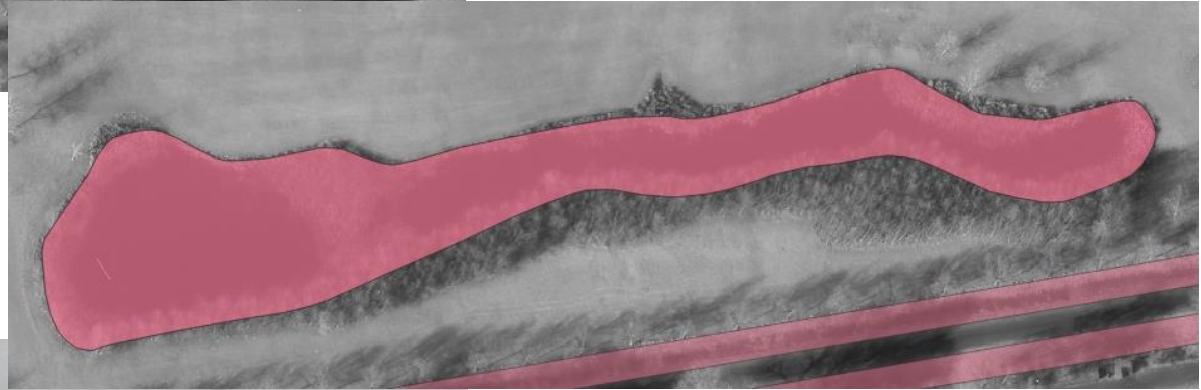
- RGB-NIR
- 25cm GSD
- AOI 1, 2 and extra AOI8





NIR image

Manual annotation

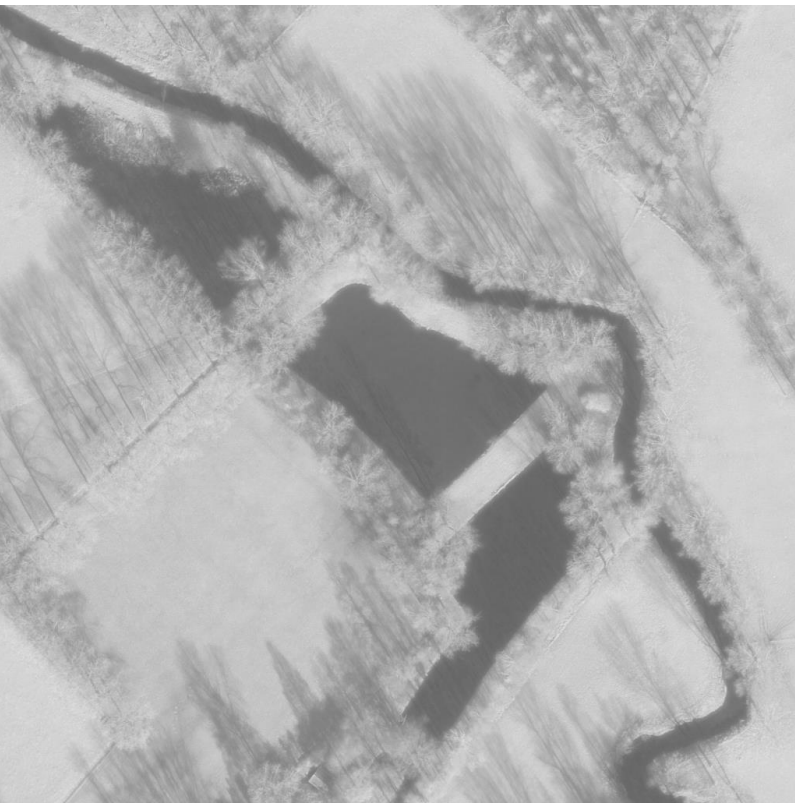


Thresholded annotation





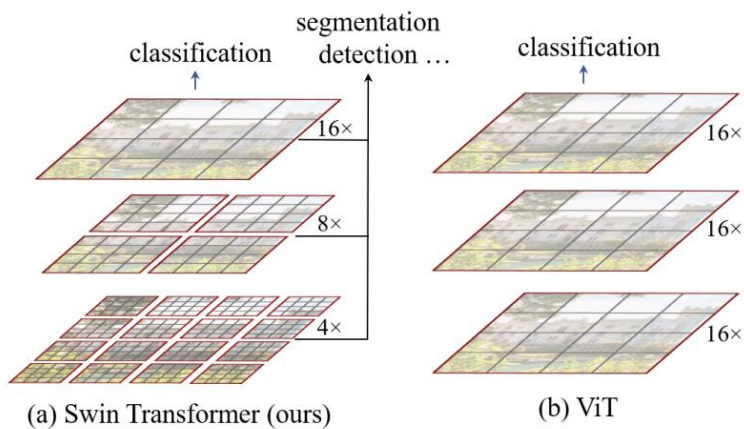
# NIR preprocessing: CLAHE



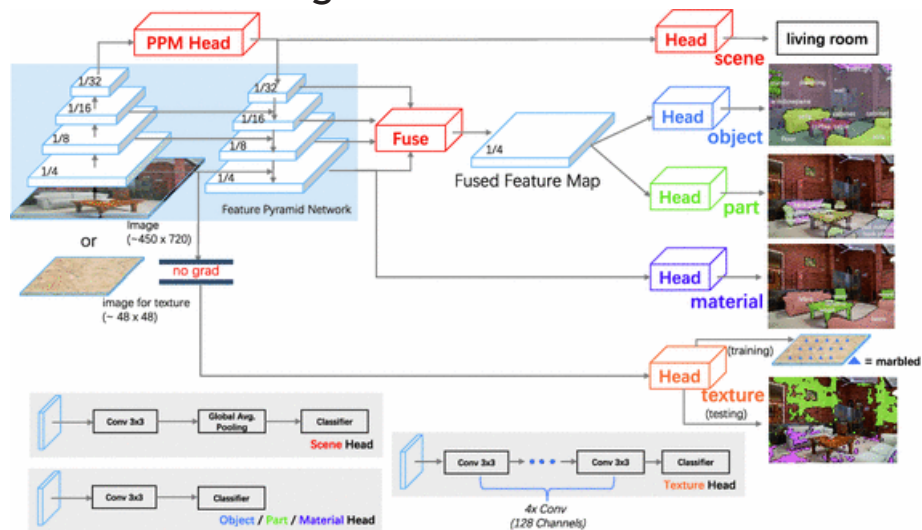


# AI detection model: SWIN backbone + UPerNet

## Swin Transformer backbone



## Unified Perceptual Parsing for Scene Understanding

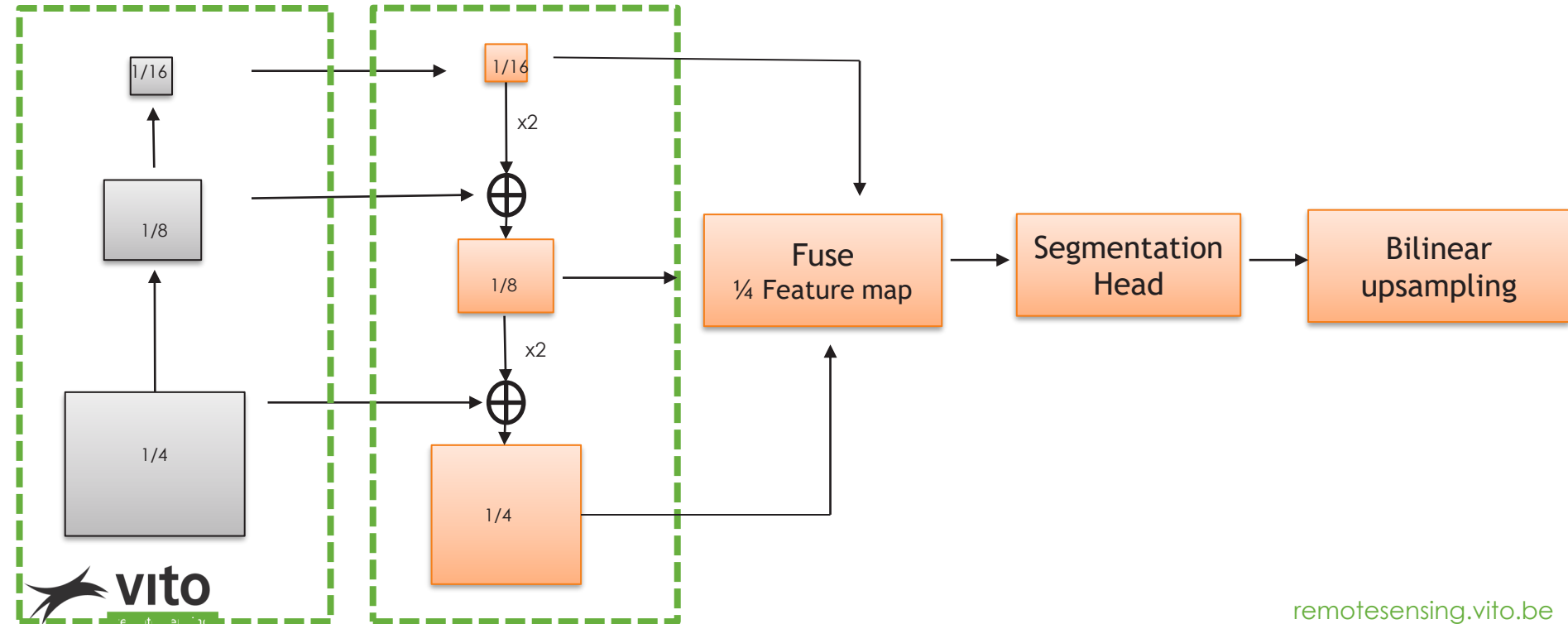




# AI detection model: SWIN backbone + UPerNet

Swin backbone

Feature Pyramid Network

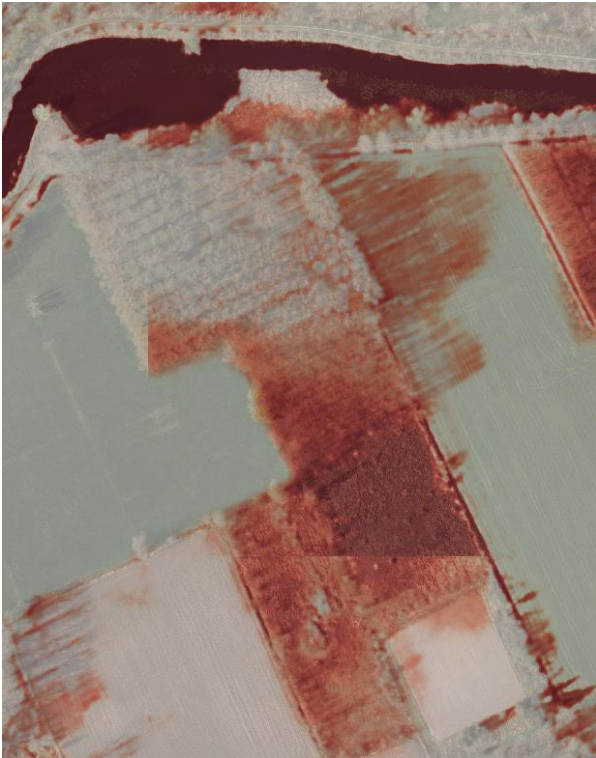






# Water monitoring airborne: results

No CLAHE, training set v1



CLAHE, training set including shaded areas



# Water monitoring airborne: results





# Conclusion & future perspectives

- Spaceborne:
  - S-1 & S-2 successfully combined
  - Good results for open water, narrow & shallow water more challenging
  - Main remaining error: S-1 “water-a-likes”
- Airborne:
  - Good results for different NIR quality inputs
- Iterative training:
  - improve cloudy predictions for spaceborne
  - Update training dataset for airborne with client feedback



INSTITUUT  
NATUUR- EN  
BOSONDERZOEK



Remote sensing and deep learning for  
environmental policy support



THANK YOU

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