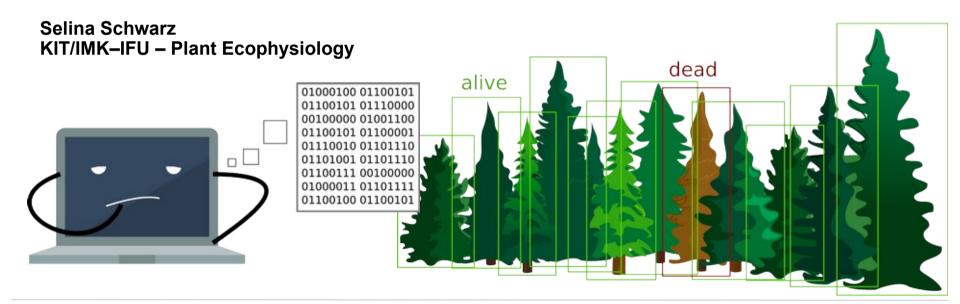






Deep Learning Hackathon 2023

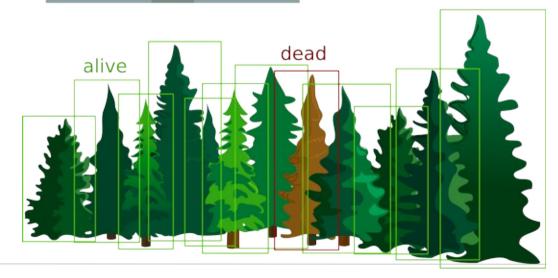


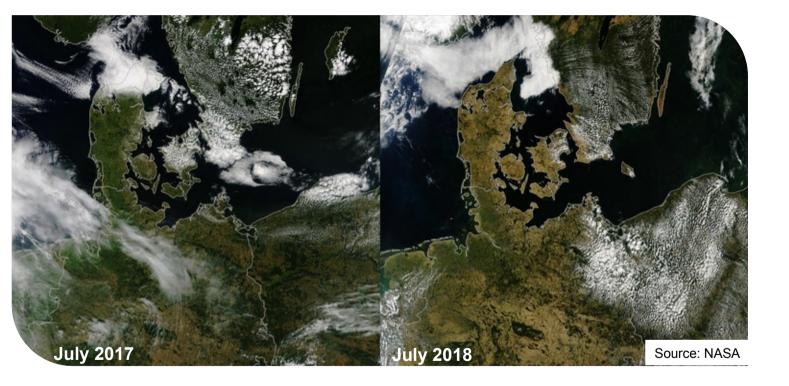
Presentation structure

- 1) Background
 - Drought in Europe
 - Luxembourg
- 2) Data
 - Study site
 - Reference Data
 - Garbage in Garbage out?
- 3) Model
 - Structure
 - U-net
 - ResNet34
 - Loss functions



01000100 01100101 01100101 01110000 00100000 01001100 01100101 01100001 01110010 01101110 01101001 01101110 01100111 00100000 01000011 01101111 01100100 01100101





Drought damages in Upper Franconia, Germany (Jörg Ermert, FVO) $\,$



Drought damages in Upper Franconia, Germany (Jörg Ermert, FVO) $\,$





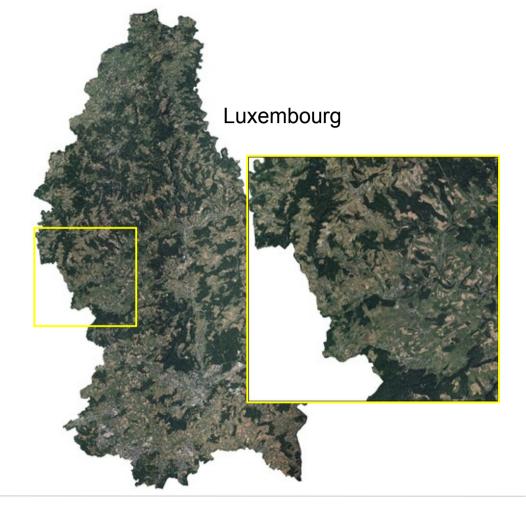
Drought damages in Upper Franconia, Germany (Jörg Ermert, FVO)

Introduction | Luxembourg

- + No pay wall
- + Annual data
- + High resolution (20 cm)

~320 km²

2017 + 2019



Data

Aerial images (Orthophotos) 2017 + 2019

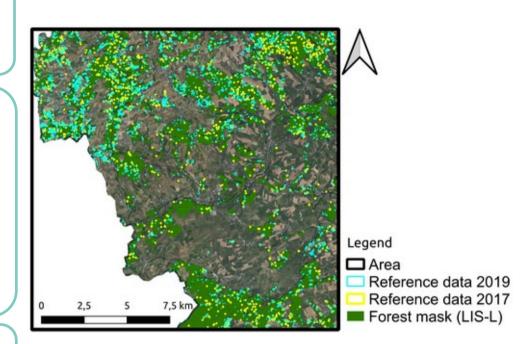
- raster data
- resolution: 20 cm

Reference data 2017 + 2019

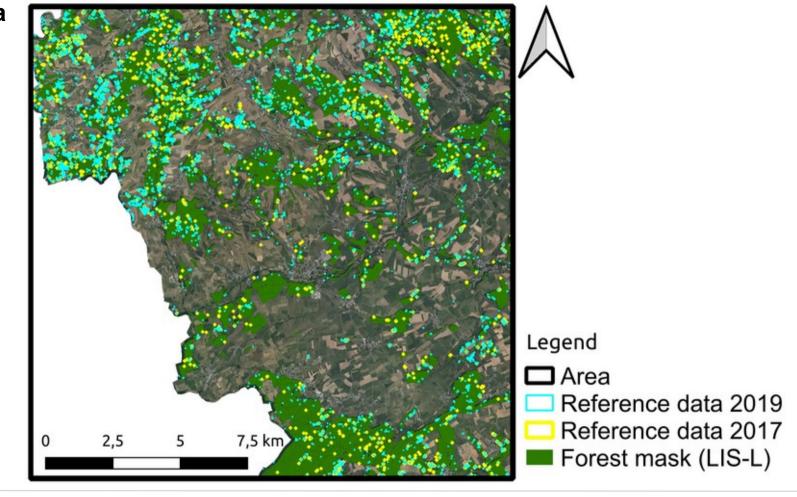
- vector data
- canopy mortality
- 3 classes: conifer, broadleaf, other
- Conifer: 1
- Broadleaf: 2
- training (70%), validation (20%),
- test (10%)

Forest mask 2018

- vector data
- based on LIS-L land use product







	Reference data				
Year	Total (Conifer / Broadleaf)	Training (70%)	Validation (20%)	Test (10%)	
2017	2,309 (2,051 / 258)	1,616	462	231	
2019	12,327 (11,243 / 1,084)	8,629	2,465	1,233	

	Reference data				
Year	Total (Conifer / Broadleaf)	Training (70%)	Validation (20%)	Test (10%)	
2017	2,309 (2,051 / 258)	1,616	462	231	
2019	12,327 (11,243 / 1,084)	8,629	2,465	1,233	

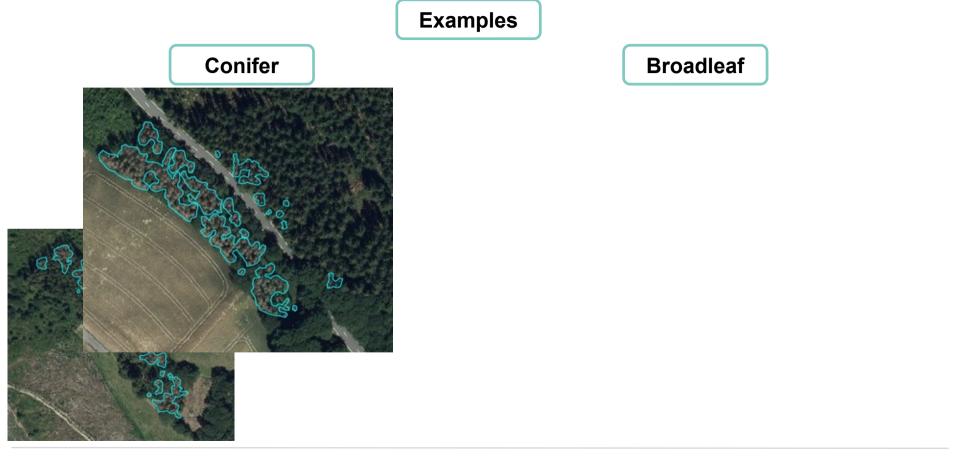
	Reference data					
Year	Total (Conifer / Broadleaf)	Training (70%)	Validation (20%)	Test (10%)		
2017	2,309 (2,051 / 258)	1,616	462	231		
2019	12,327 (11,243 / 1,084)	8,629	2,465	1,233		

Examples

Conifer

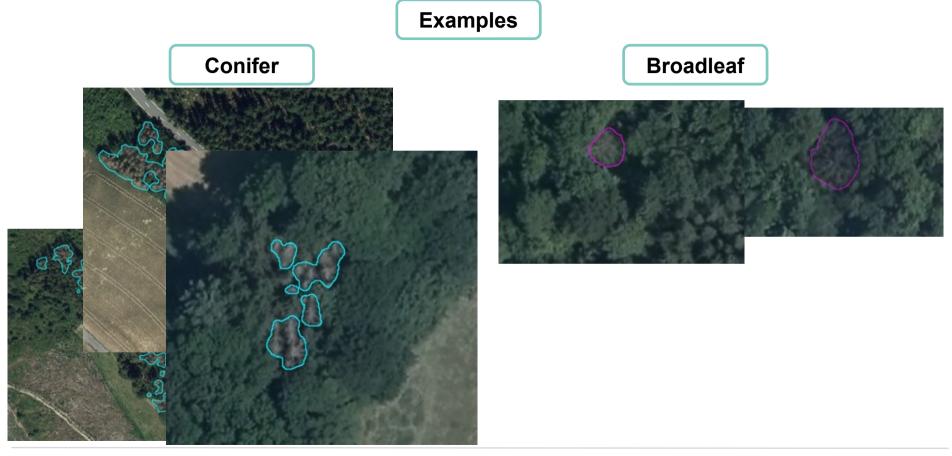
Broadleaf

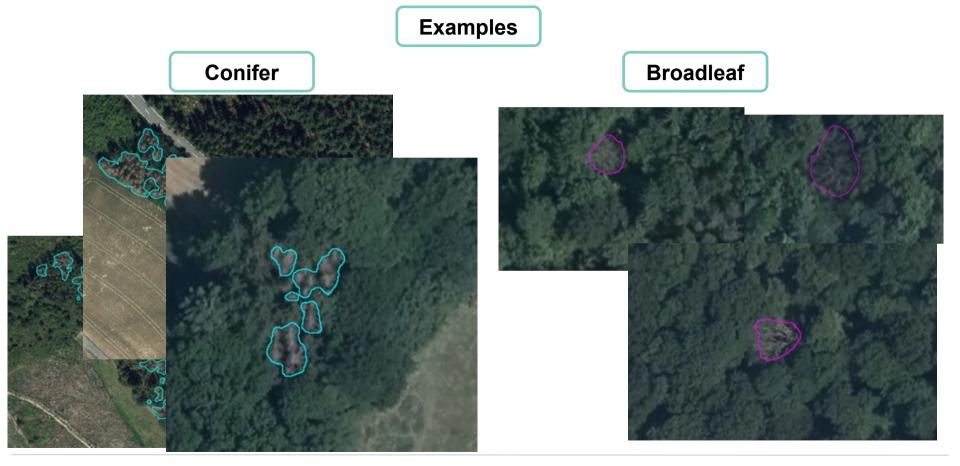






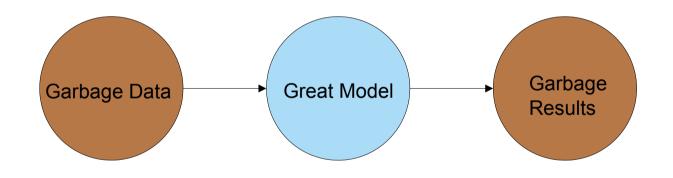


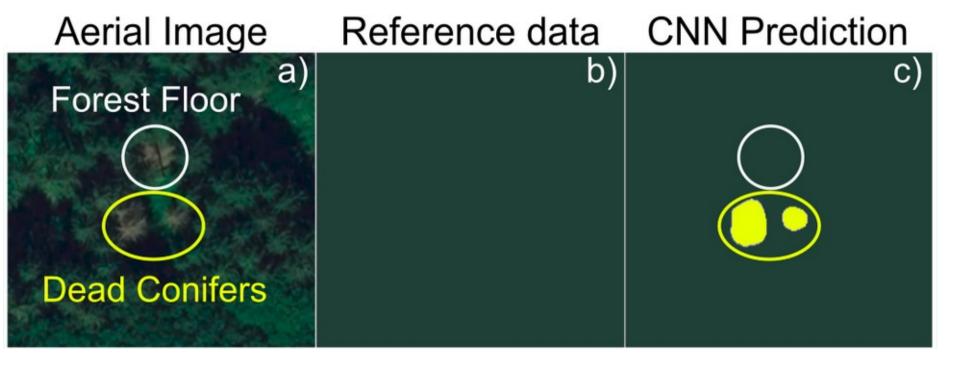


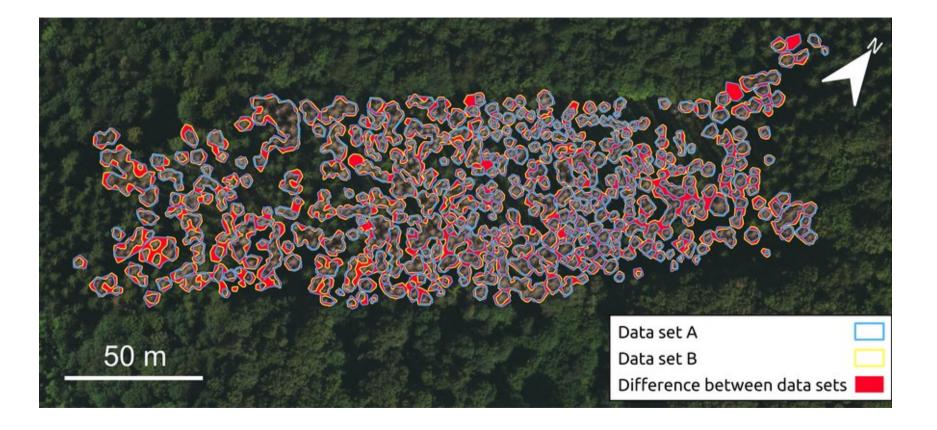


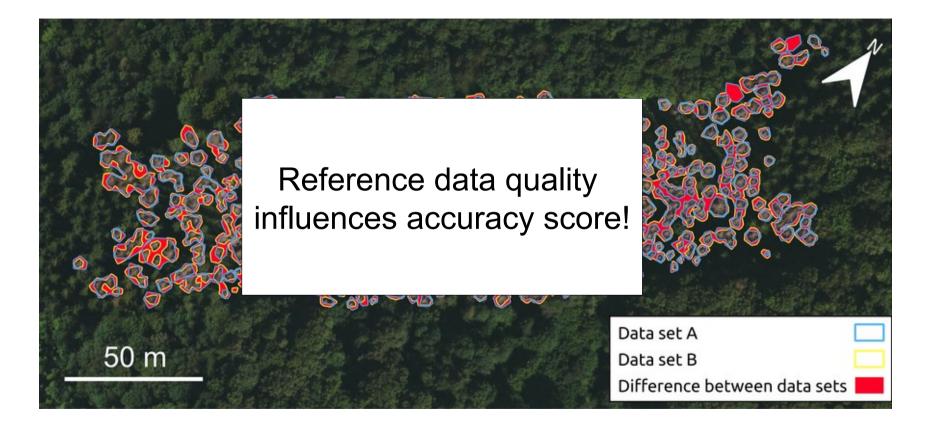


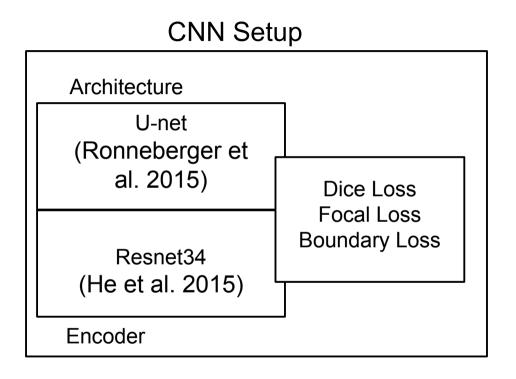
Garbage in = Garbage out?

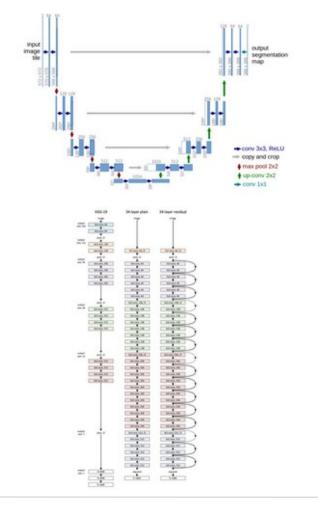






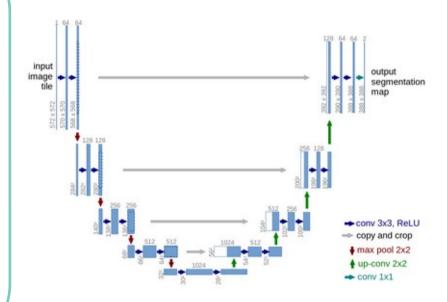






U-net

- Ronneberger et al. (2015)
- Semantic segmentation
- pixel-wise classification
- consist of an encoding and decoding branch
- Encoder:
 - image size reduction with convolution and max pooling operations
- Decoder:
 - image size is gradually increased.
- Skip Connections:
 - connect both paths
 - activations are forwarded to the decoder, providing the spatial identity of the data

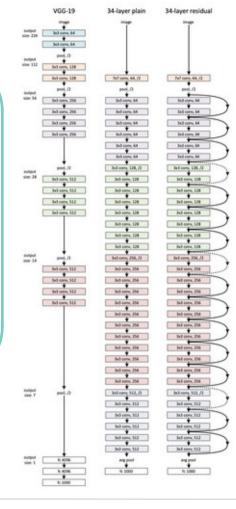


Ronneberger et al. (2015)

– U-net architecture

Resnet34

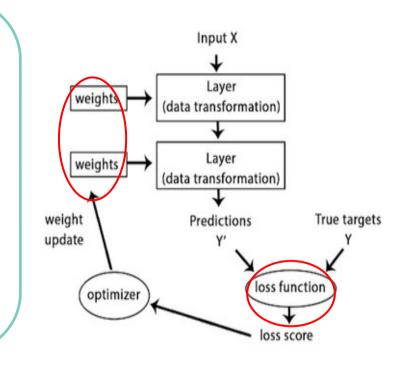
- He et al. (2015)
- Used as encoder
- Image classification model
- Pre-trained on ImageNet
- 34 layers
- Skip connections to jump over layers
 - → avoid vanishing gradients (leads to no change in weights)
 - → avoid accuracy saturation (higher training error)



He et al. (2015) "Example network architectures for ImageNet.". Resnet34 on right

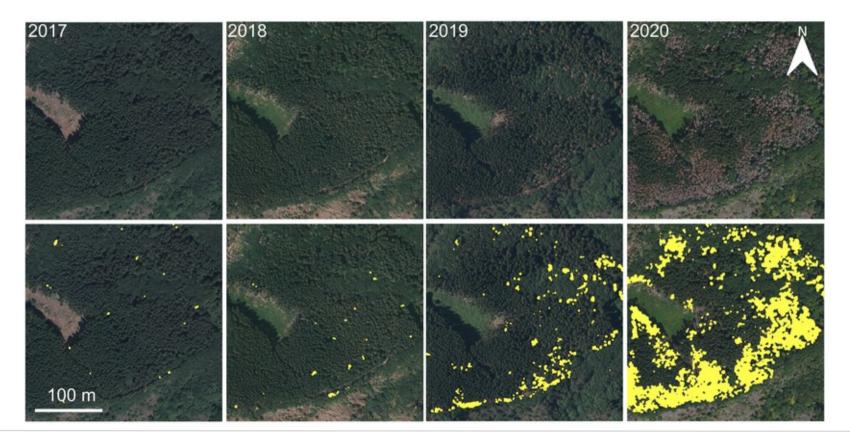
Loss functions

- Dice Loss
 - Based on Sørensen–Dice coefficient
 - Commonly used
 - 0 1 (no overlap perfect overlap)
- Focal Loss
 - Used in imbalanced datasets
 - More focus on misclassified objects
- Boundary Loss
 - grows exponentially with distance from reference data
 - More precise feature delineation



Schematic representation of basic Neural Network Deep Learning with R (2017) by Francois Chollet

Sneak Peak - Results







References



- Schuldt et al. (2020) A first assessment of the impact of the extreme 2018 summer drought on Central European forests
- Silva et al. (2021) Encoder-Decoder Architectures for Clinically Relevant Coronary Artery Segmentation
- Tan & Le (2020) EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks
- Sudre et al (2017) Generalised Dice overlap as a deep learning loss function for highly unbalanced segmentations
- Lin et al. (2017) Focal Loss for Dense Object Detection
- Kervadec et al. (2020) Boundary loss for highly unbalanced segmentation
- Ronneberger et al. (2015) U-Net: Convolutional Networks for Biomedical Image Segmentation
- He et al. (2015) Deep Residual Learning for Image Recognition