

Detecting hydromorphological structures using AI-based analysis of high-resolution drone imagery to access physical river habitat development



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River habitat development – how to assess?

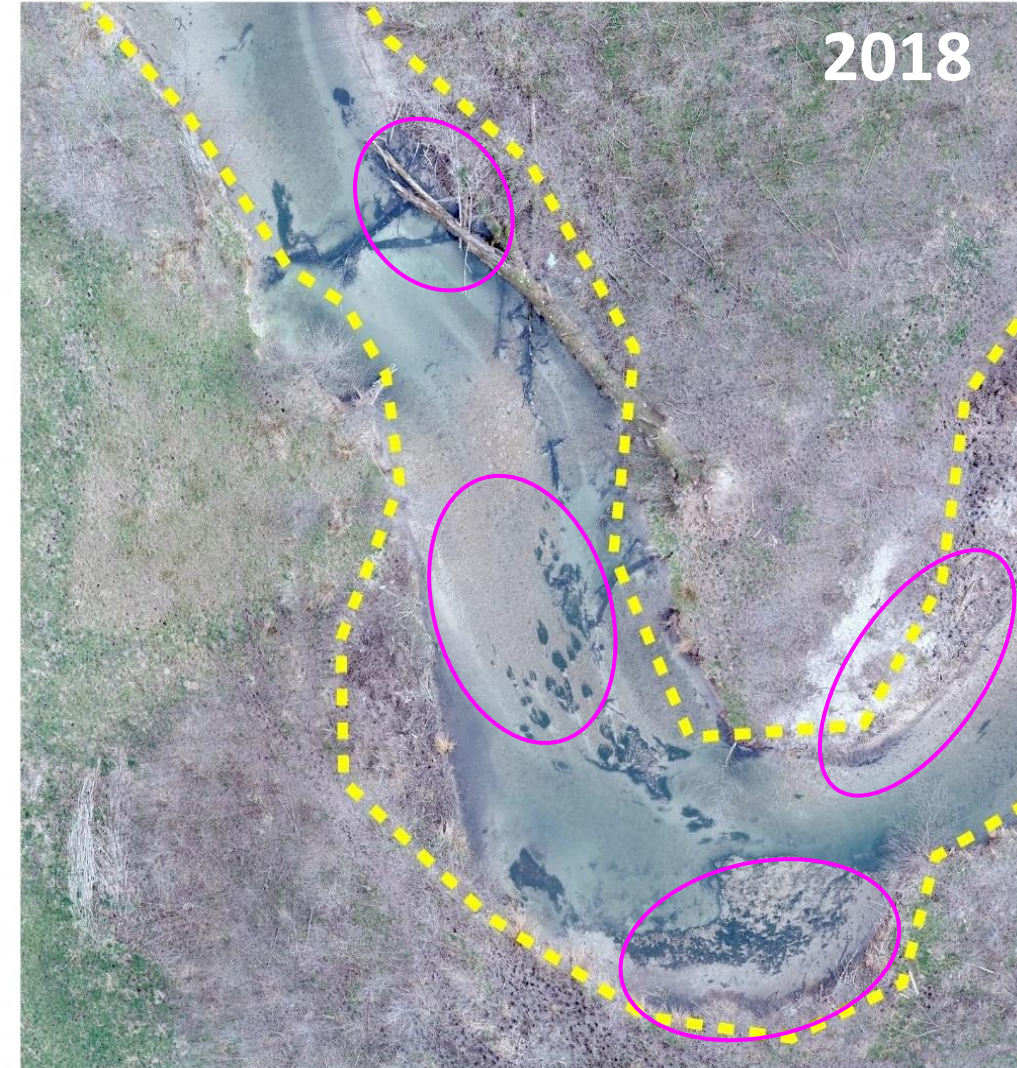


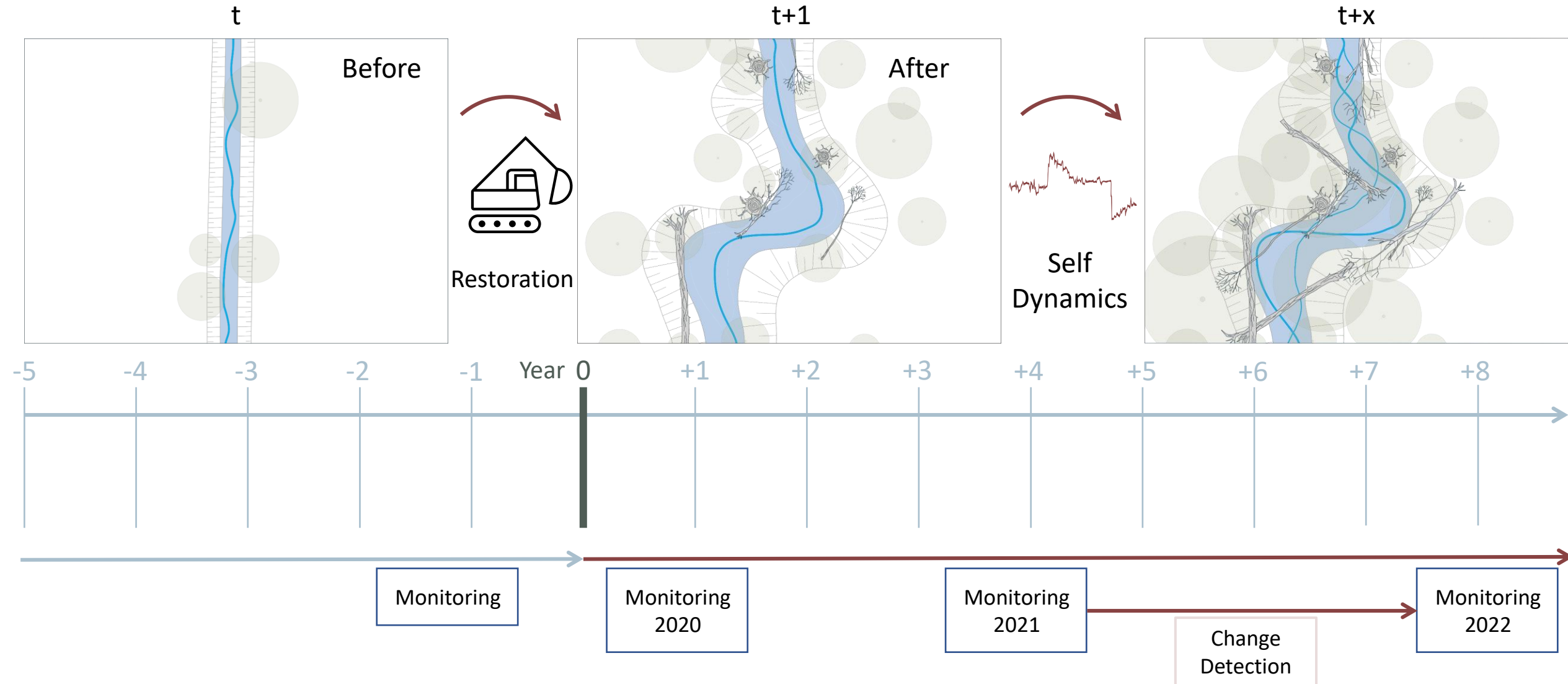
River Lippe

Can river
**hydromorphological
structures** be
quantified?

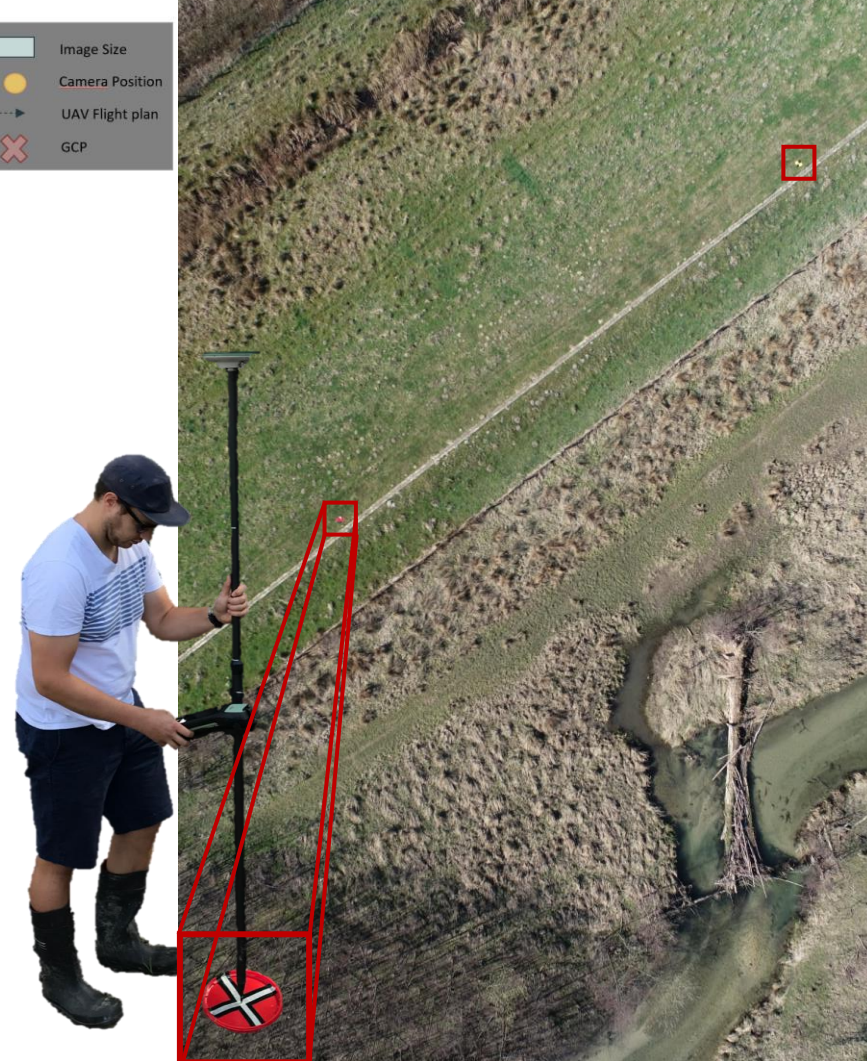
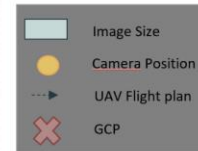
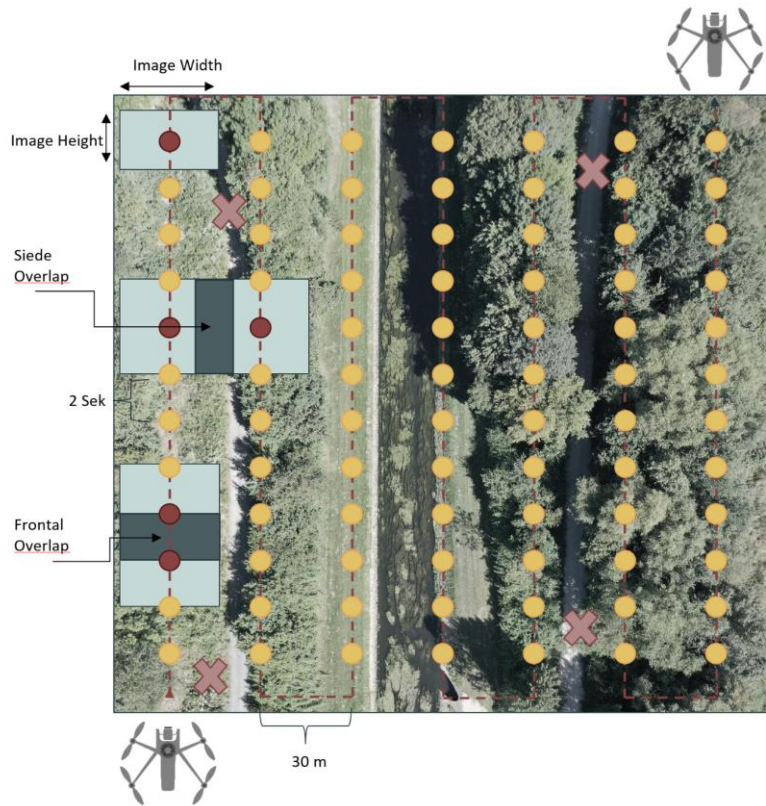


Which **parameters**
should be taken into
account for
quantification?





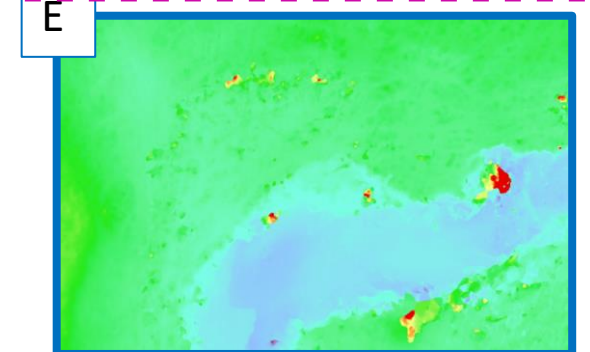
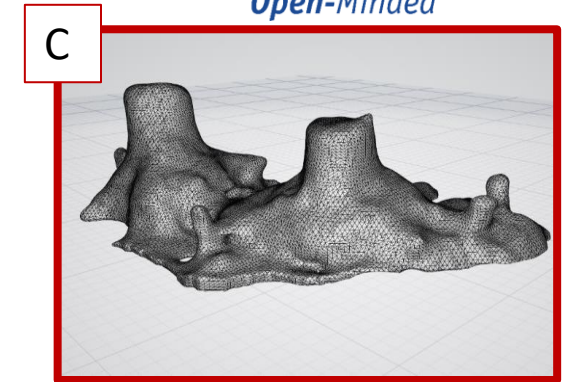
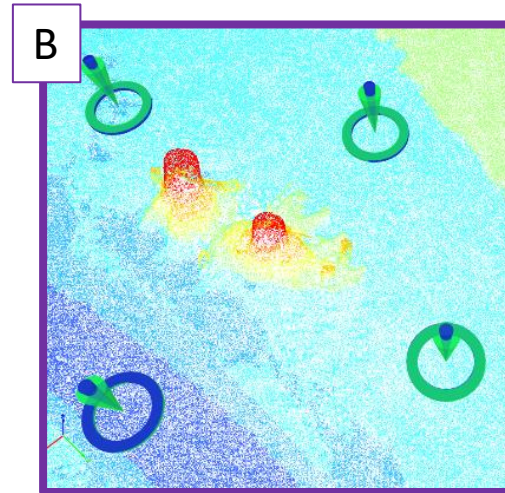
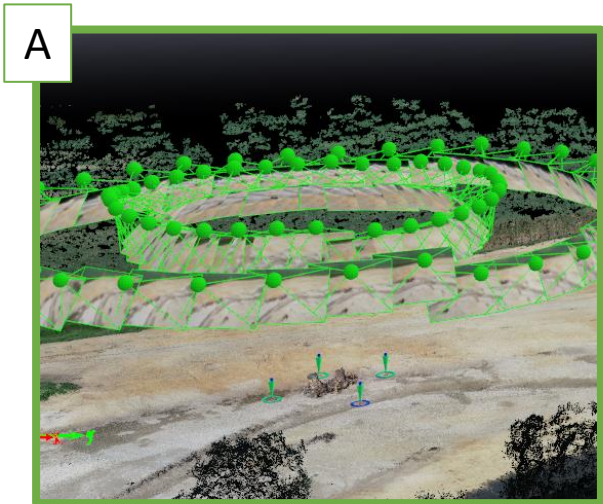
Field survey – Drone & GNSS data acquisition



Date of Survey	Images
20.03.2020	886
17.11.2020	887
16.04.2021	891
25.03.2022	920

Photogrammetry – The basis for spatial analysis

- Field survey of **drone images, image location and ground control points [A]** to create photogrammetric **3D objects [B & C]**
- 3D objects are generated as **3D point cloud** and **3D textured mesh data [C]**



- Based on 3D objects [B & C] high resolution **digital surface model (DSM) [E]** and **orthomosaic (GSD: 0.8 cm/px) [D]** are generated

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The diagram illustrates a workflow for deep learning. It starts with an orange box labeled 'export Training Data for Deep Learning' containing icons for data export and a person at a computer. An arrow points to a central area with logos for TensorFlow, CNTK, PyTorch, and Jupyter. Another arrow points to a blue box labeled 'Model Definition' containing icons for model definition and a person at a computer. Finally, an arrow points to a blue box labeled 'Classify Objects with Deep Learning' and 'Classify Pixel with Deep Learning' containing icons for classification and a person at a computer.

Create Training Data

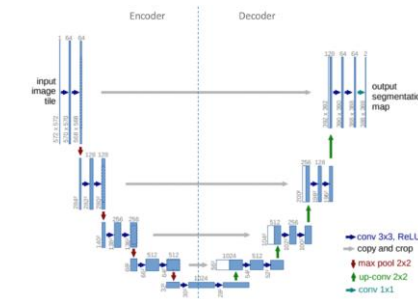
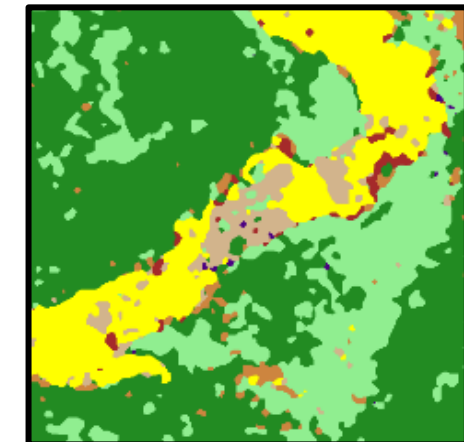
GIS Analysis (GUI)

Built & Train Model
Jupyter Notebook (Python)
Evaluate Model

Apply Model GIS Analysis (GUI & Python)



D

[illegible]

Classify Pixel

Creating Training data

Training Sets (26.03.2020, 16.04.2021)

- Rotation (0)

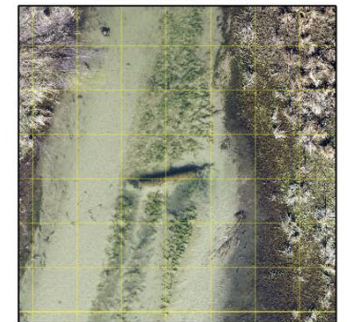
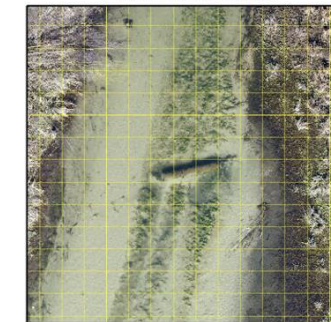
Quelle: esri.de, 2021

- Stride (128)



Tile Size 128

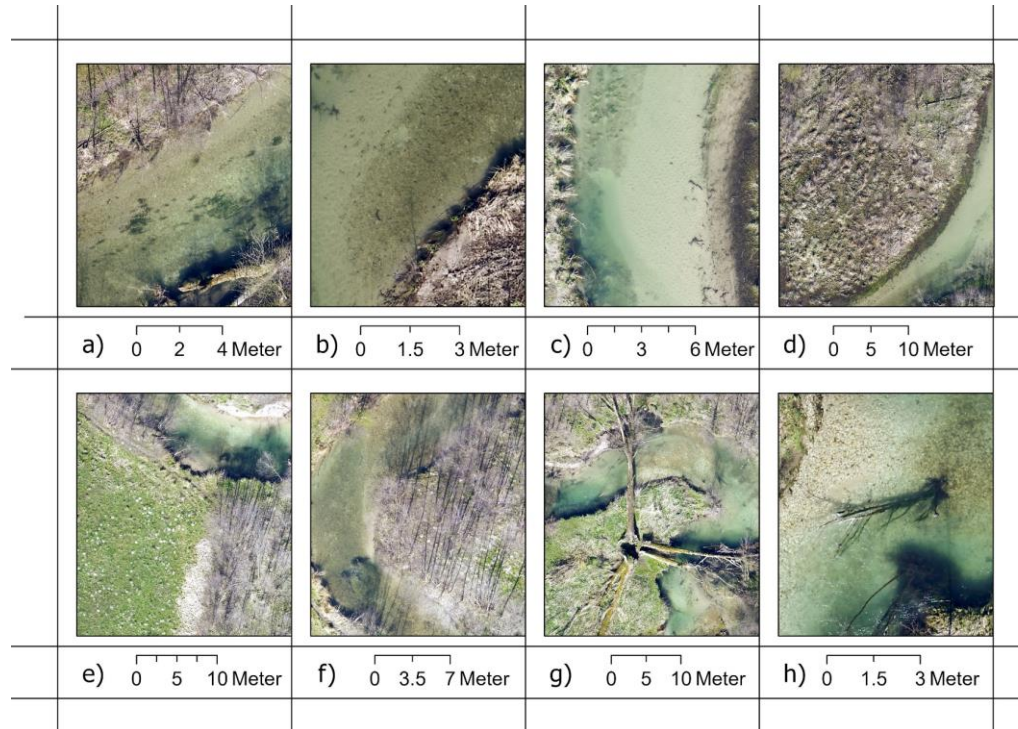
Tile Size 256



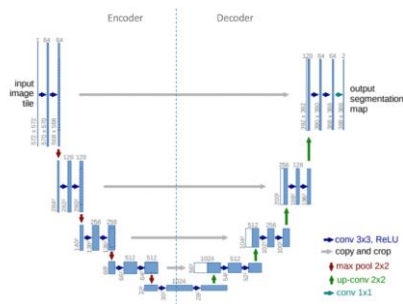
0 4 8 Meter

0 5 10 Meter

- Tile Size (256)



images = 90307*4*256*256						
features =		90307				
features per image = [min = 1, mean = 1.14, max = 5]						
classes = 7						
Land cover	cls value	images	features	min size	mean size	max size
a) Macrophytes	1	2781	3157	0	1,075	5,465
b) Gravel	2	4817	5357	0	1,875	5,465
c) Sand	3	3144	3613	0	1,395	5,465
d) Gras floodplain	6	14472	14678	0	3,87	5,465
e) Gras	7	28103	29608	0	3,735	5,465
f) Trees	8	29878	30275	0	4,07	5,465
g)+h) Wooden debris	5	3342	3619	0	1,9	5,465



Parameter of Trainingdata

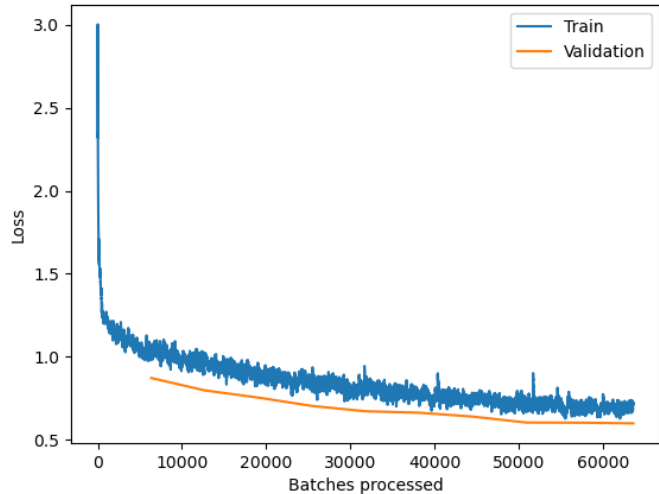
Bands	RGB
Tile Size and Stride	256/128
Rotation	0

Model Setup

Model Type	U-Net
Validation	20%
Backbone Model	ResNet-34
Epochs	10

```
with arcpy.EnvManager(scratchWorkspace=r"A:\Promotion_Dacheneder\01_Untersuchung Lippe\12_temp_GIS\Deep_Learning_Lippe\Deep_Learning_Lippe\scratch\"):
    arcpy.TrainDeepLearningModel(
        in_folder=r"A:\Promotion_Dacheneder\01_Untersuchung Lippe\12_temp_GIS\Deep_Learning_Lippe\imagechips_20200326_RGB",
        out_folder=r"A:\Promotion_Dacheneder\01_Untersuchung Lippe\12_temp_GIS\Deep_Learning_Lippe\classify_26032020_160420",
        max_epochs=10,
        model_type="UNET",
        batch_size=8,
        arguments="class_balancing False;mixup False;focal_loss False;ignore_classes #;chip_size 224;monitor valid_loss",
        learning_rate=None,
        backbone_model="RESNET34",
        pretrained_model=None,
        validation_percentage=20,
        stop_training="STOP_TRAINING",
        freeze="FREEZE_MODEL"
    )
```

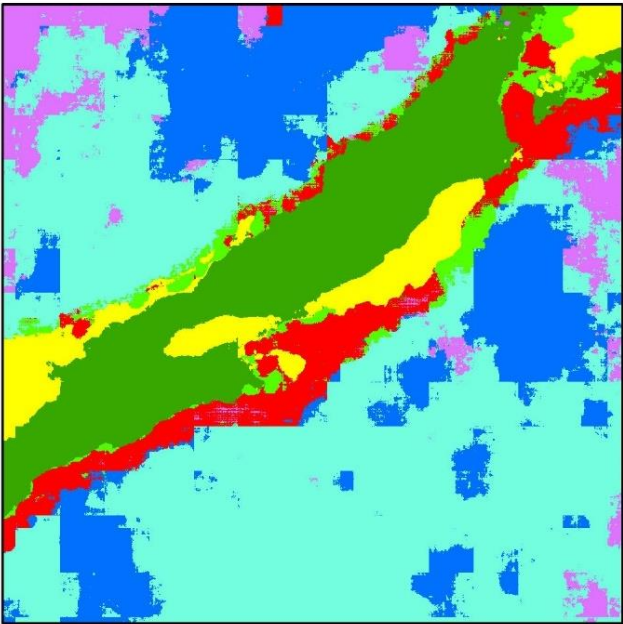
epoch	train_loss	valid_loss	accuracy	dice	time
0	1.078193	0.935739	0.642471	0.587373	2:28:59
1	0.976869	0.801003	0.695521	0.650562	3:49:41
2	0.919197	0.734170	0.720126	0.679072	4:03:31
3	0.854627	0.768757	0.716564	0.680182	3:37:12



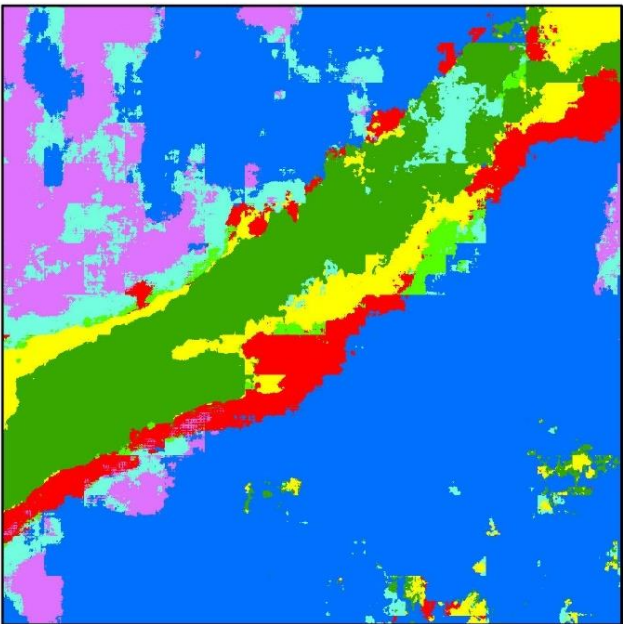
	NoData	Macrophytes	Gravel	Sand	Wooden debris	Gras Floodplain	Gras	Trees
precision	0,73	0,70	0,70	0,70	0,73	0,79	0,75	0,82
recall	0,49	0,31	0,71	0,69	0,45	0,76	0,95	0,92
f1	0,59	0,43	0,71	0,70	0,55	0,78	0,84	0,87

Apply Deeplearning Model for Pixel Classification

2020

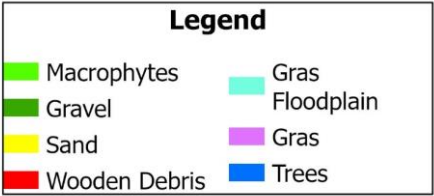


2022

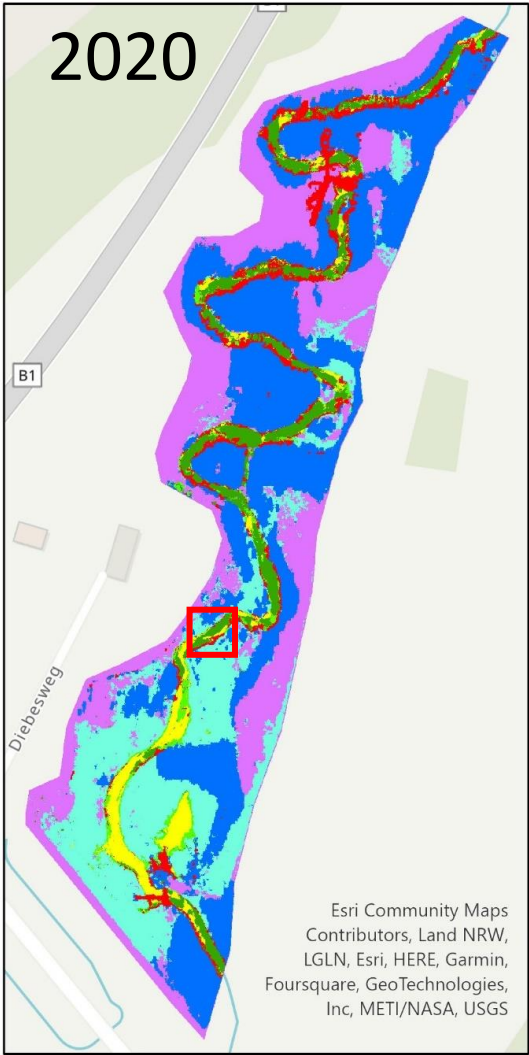


Land cover	2020 Area (m²)	2022 Area (m²)	Difference (m²)
Macrophytes	1191	507	-684
Gravel	2994	3431	437
Sand	1663	2170	507
Wooden Debris	2776	3360	584
Gras Floodplain	10061	4234	-5827
Gras	13607	15681	2074
Trees	17780	32022	14242

0 5 10 Meter

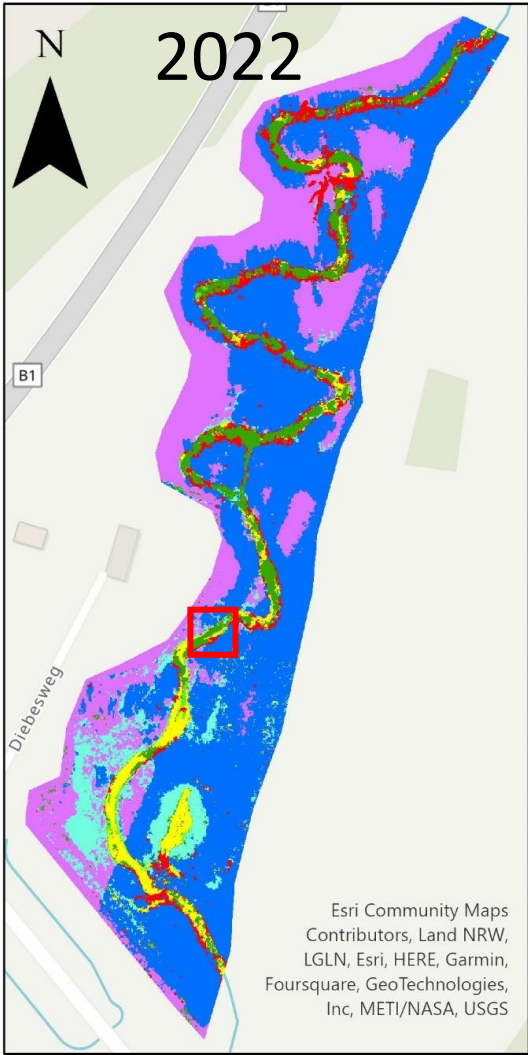


2020



Open-Minded

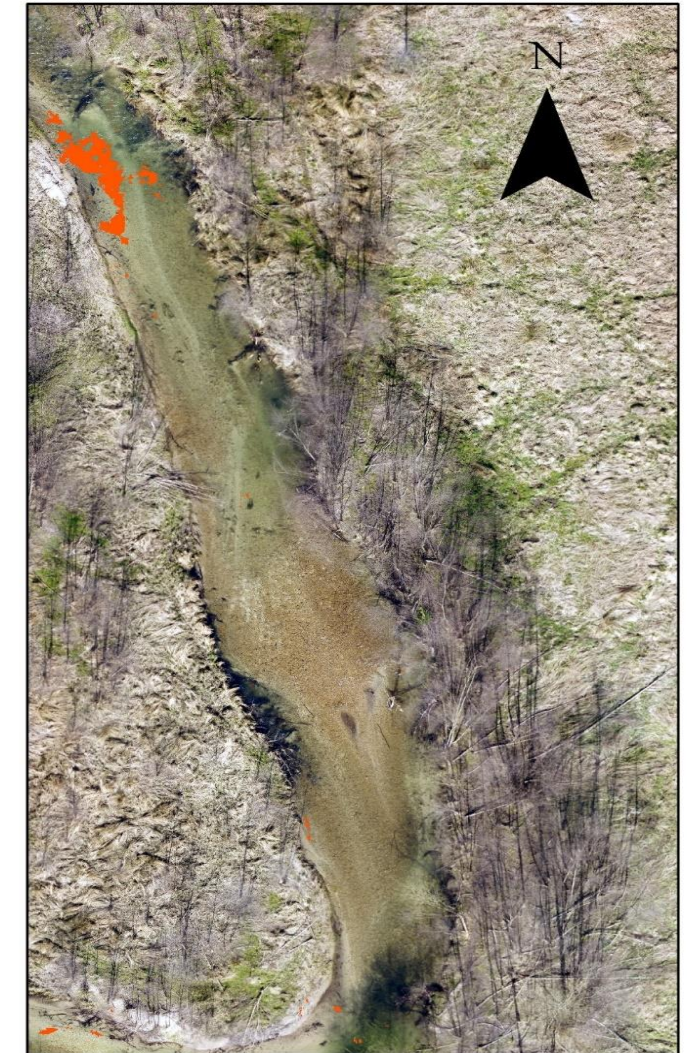
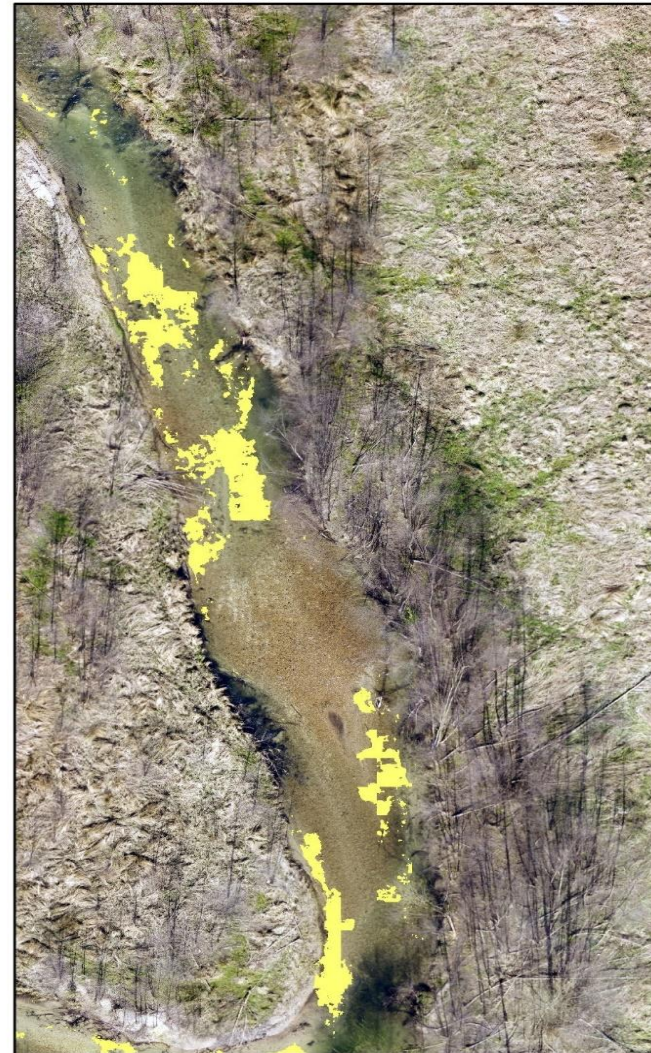
2022



Change detection 2020 to 2022

Land cover	Area m ²
Macrophytes->Gravel	207
Macrophytes->Sand	194
Macrophytes->Wooden Debris	332
Gravel->Macrophytes	48
Gravel->Sand	366
Gravel->Wooden Debris	481
Sand->Macrophytes	112
Sand->Gravel	207
Sand->Wooden Debris	167
Wooden Debris->Macrophytes	66
Wooden Debris->Gravel	302
Wooden Debris->Sand	131
Other	52858
No Change	5945

Legend	
■	Sand->Gravel
■	Gravel->Sand



0 5 10 Meter

Thank you!

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