Multitemporal land cover classification with Sentinel-2 images for national surveying authorities

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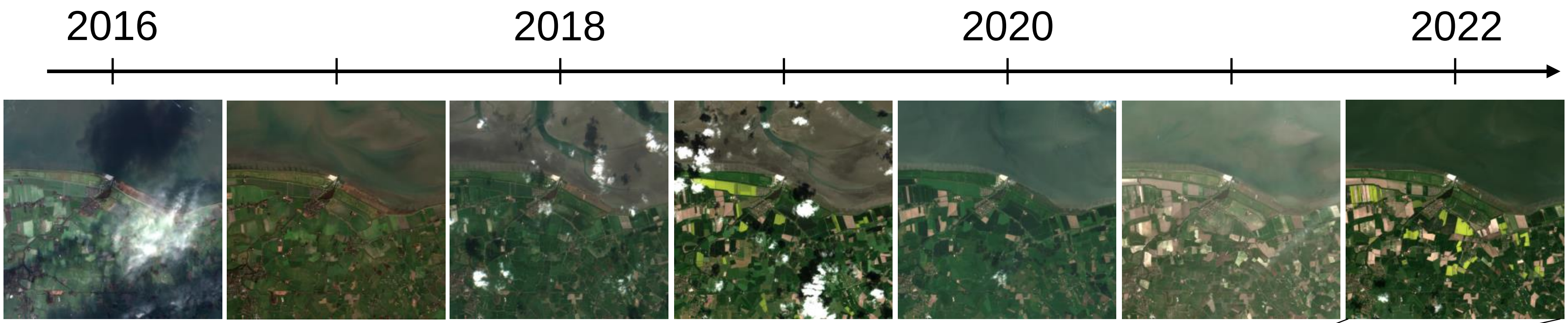
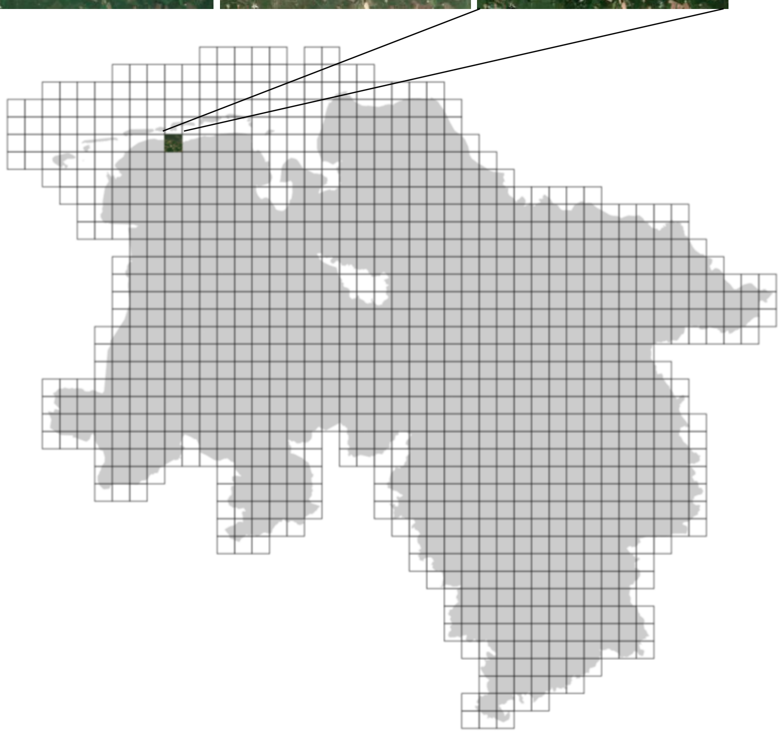
Introduction

- The update of topographic databases is important
  → city planning, navigation, …

	Currently	Project
Update	Manual	Automatic classification, → Changes of objects over time
Turnus	3 years	Potentially real-time (after receiving the images)
Spatial resolution	Few centimeter	10 m (Sentinel-2)
Costs	Expensive	Sentinel-1/2: free Training data: existing geodata of the LGLN

Introduction





- Big Data
  - Satellite image time series
  - Current status of the DB per quarter

→ High temporal resolution

→ Low(er) spatial resolution

Introduction

2016 2018 2020 2022

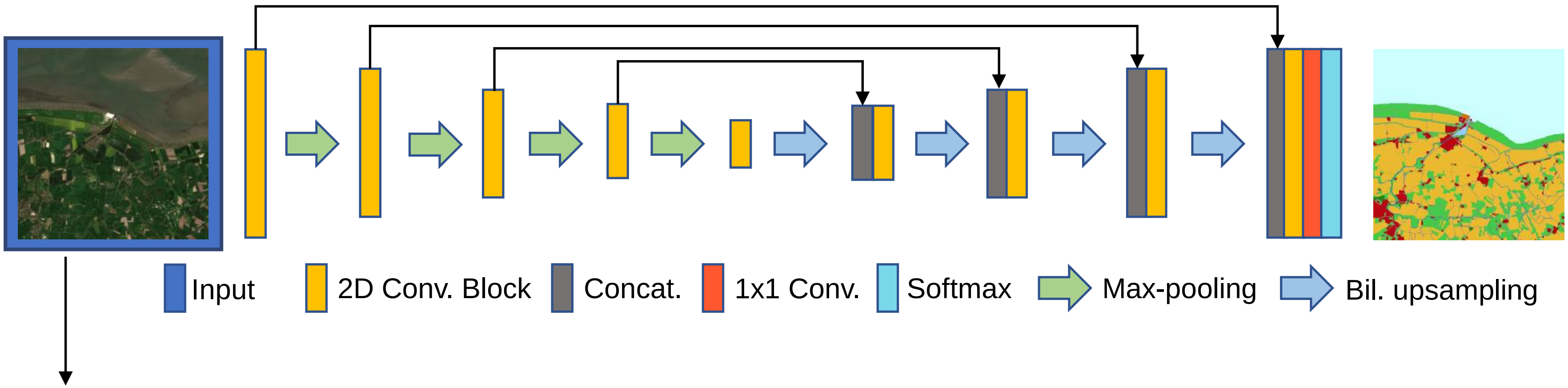
AI

2. Comparison with database
   → Change notes

1. Current land cover
   → derived from satellite images

Method – Land cover classification

Neural Network for pixelwise classification



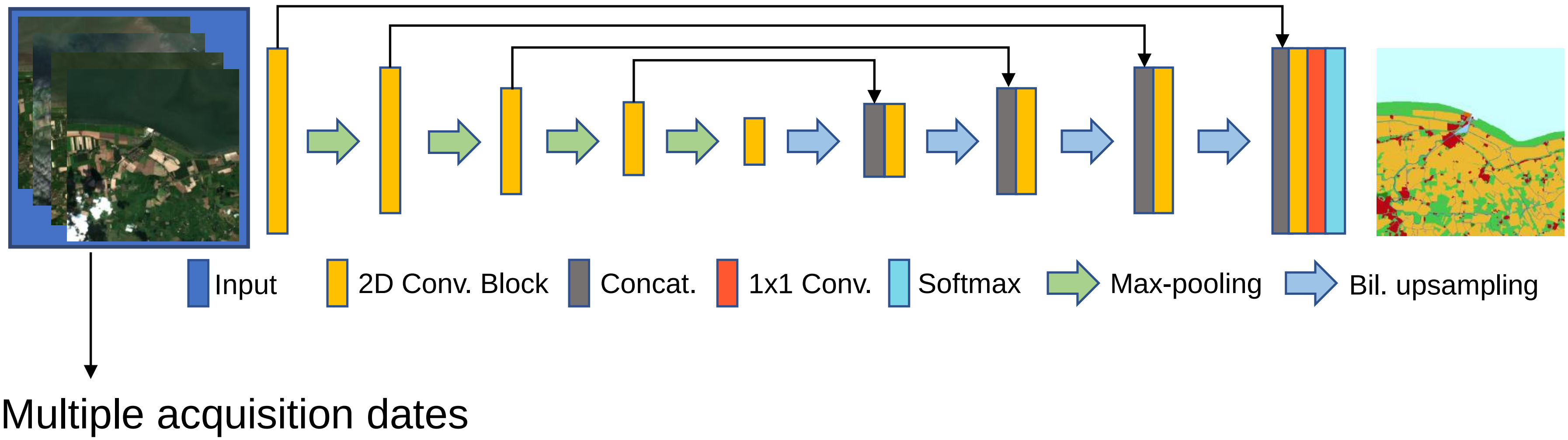
One acquisition date

→ U-Net architecture with monotemporal input image

→ Output: pixelwise classification of land cover

Method – Land cover classification

Neural Network for pixelwise classification



→ Extension: Multitemporal image data as input

→ Various adaptations of the architecture

Class structure

Land cover classes by national surveing authorities:

Landbedeckung

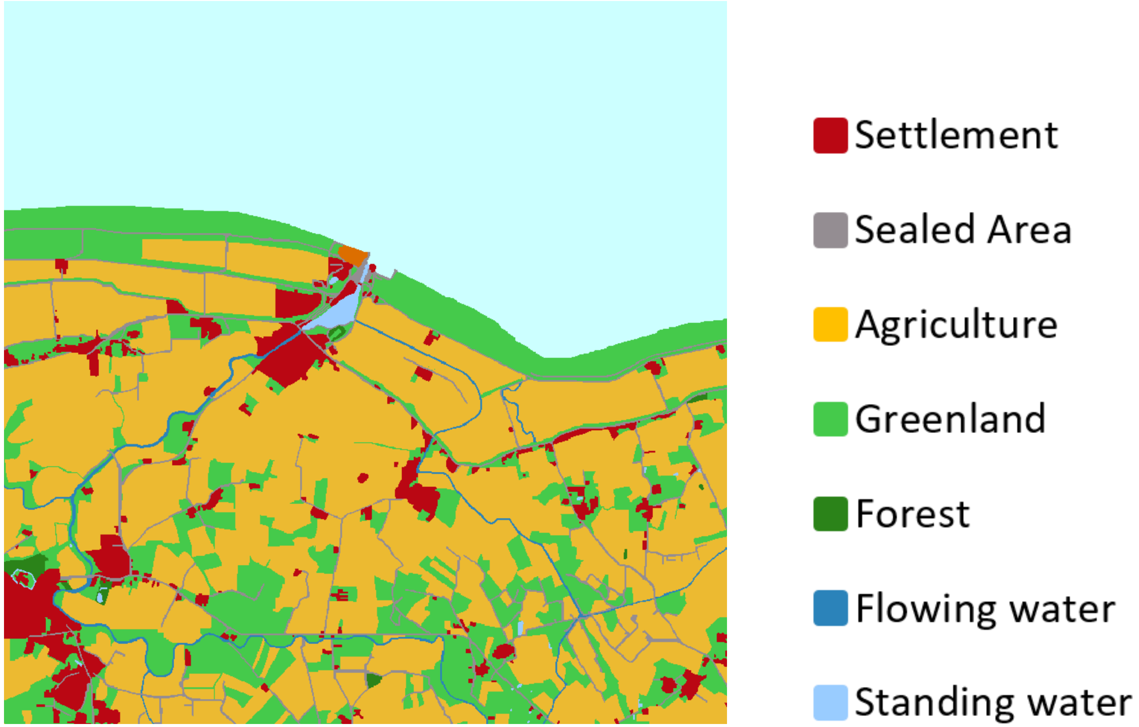
Objektartengruppe	#	Objektart	#	Attribut-/Werteart	#	Attribut-/Werteart	#	Attribut-/Werteart
11000 Bebauung	11010	LB_HochbauUndBaulicheNebenflaechen						
	11020	LB_Tiefbau						
12000 Vegetationslos	12010	LB_Festgestein						
	12020	LB_Lockermaterial	OFM	*oberflächenmaterial*	WST	*wassersättigung*		
			1000	Geröll, Schotter, Kies	1000	ganzjährig		
			2000	Sand, Feinkies	2000	zeitweilig		
			3000	Erdreich				
			4000	Ton, Schluff				
			5000	künstlich				
13000 Vegetation	13010	LB_KrautigeVegetation	VEG	*vegetationsmerkmal*	WST	*wassersättigung*	SST	*salzigerStandort*
			1000	Gras	1000	ganzjährig		boolean
			2000	Röhricht, Schilf	2000	zeitweilig		
			3000	Getreide, Staudengewächse, Farne				
	13020	LB_HolzigeVegetation	VEG	*vegetationsmerkmal*	WST	*wassersättigung*	BLF	*blattform (0..2)*
			4000	Bäume	1000	ganzjährig	1000	Laub
					2000	zeitweilig	2000	Nadel
			5000	Gehölz				
			6000	Büsche, Sträucher				
			7000	Zwergsträucher				
14000 Wasser	14010	LB_Meer	MEA	*meerart*	TID	*tideeinfluss*		
			1010	Watt		boolean		
			1020	Haff, Bodden				
			1030	Priel				
	14020	LB_Binnengewaesser	GWA	*gewässerart*	FLE	*fliesseigenschaft*	WFG	*wasserführung*
			1010	Fluss	1000	fließend	1000	ganzjährig
			1020	Bach	2000	stehend	2000	zeitweilig
			2000	Altwasser, Altarm				
			3010	Kanal				
			3020	Graben				
			4000	Becken				
			5000	See, Teich				
	14030	LB_Eis	EIS	*eisart*				
			2010	Gletscher				
			2020	Dauerschnee, Firn				

Class structure

High construction & ancillary building areas	Settlement
Low construction	Sealed area
Solid rock	Barren land
Loose material	
Grass	Grassland
Wood	
Bushes, shrubs	
Reed	Agriculture
Cereals, perennials, …	
Deciduous trees	Forest
Conifers	
Sea	Sea
Inland waters, flowing	Flowing water
Inland waters, standing	Standing water
Ice	

Class structure

- Trainingdata:
  - Labels from June 2019 + 2020



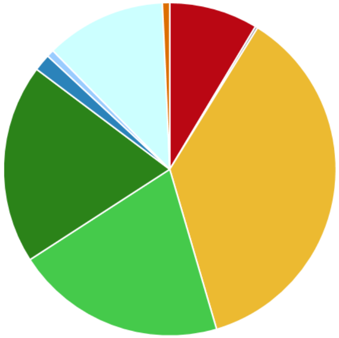
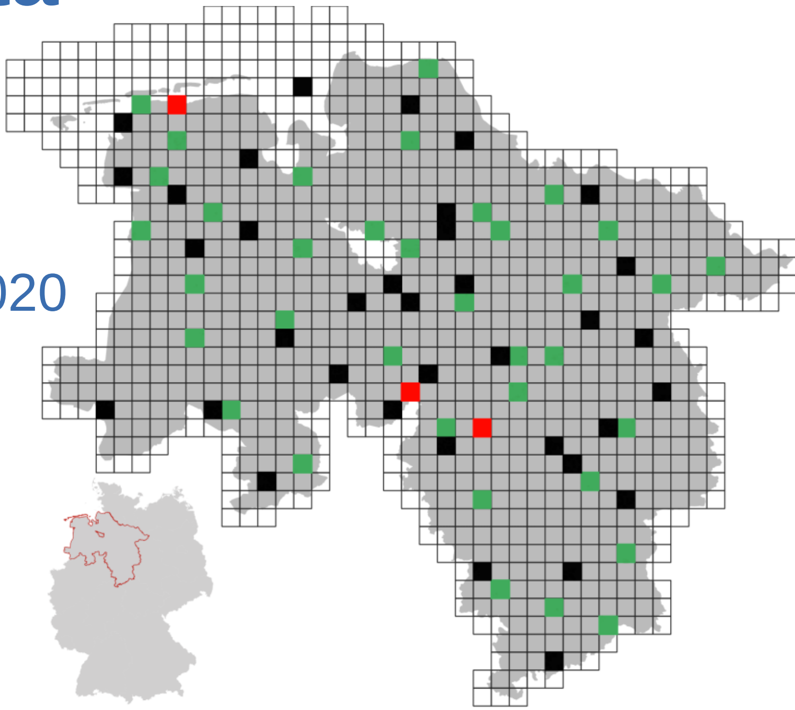


Image data

- Sentinel-2:
  - All cloud free Images covering Lower Saxony (47.600kmm^2) from 2019 & 2020
  - Divided into tiles of 8 x 8 km^2
  - Labels from LGLN database[1]
  - 36 tiles for validation (grün), 39 tiles for testing (schwarz/rot)) 875 tiles for training (grau)
  - 3 manually corrected tiles (rot) → ~18% of pixels were corrected



[1]German Land Survey Office of Lower Saxony

Generation of input data

- Monotemporal trainingdata:
  - Random selection based on all Sentinel-2 images

- Multitemporal trainingdata:
  - Input shall contain t images covering one year
  - Split year into t time intervals
  - Sentinel-2 image acquired most closely in time to the middle of the interval selected

Experiments

- Mono- and multitemporal input data
- Influence of spectral bands
- Application scenario: Peatland classification
- Higher resolution training data
- Fusion of optical and radar data
- Investigation of different architectures / loss functions

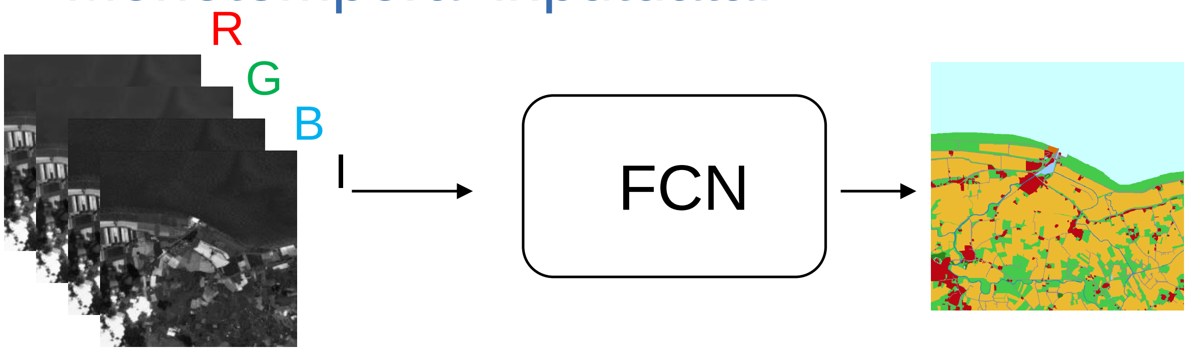
…

Evaluation:

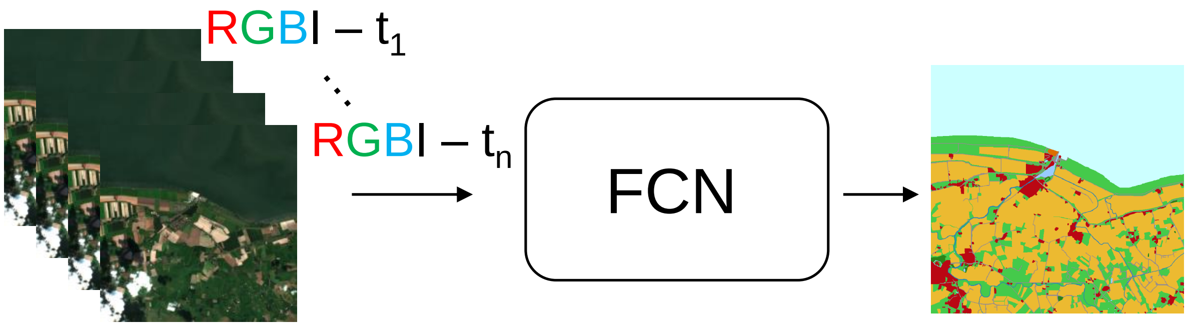
- F1-Scores of all classes, mean F1-Score, Overall Accuracy (OA)

Integration of multitemporal data

- Monotemporal inputdata:



- Multitemporal inputdata:

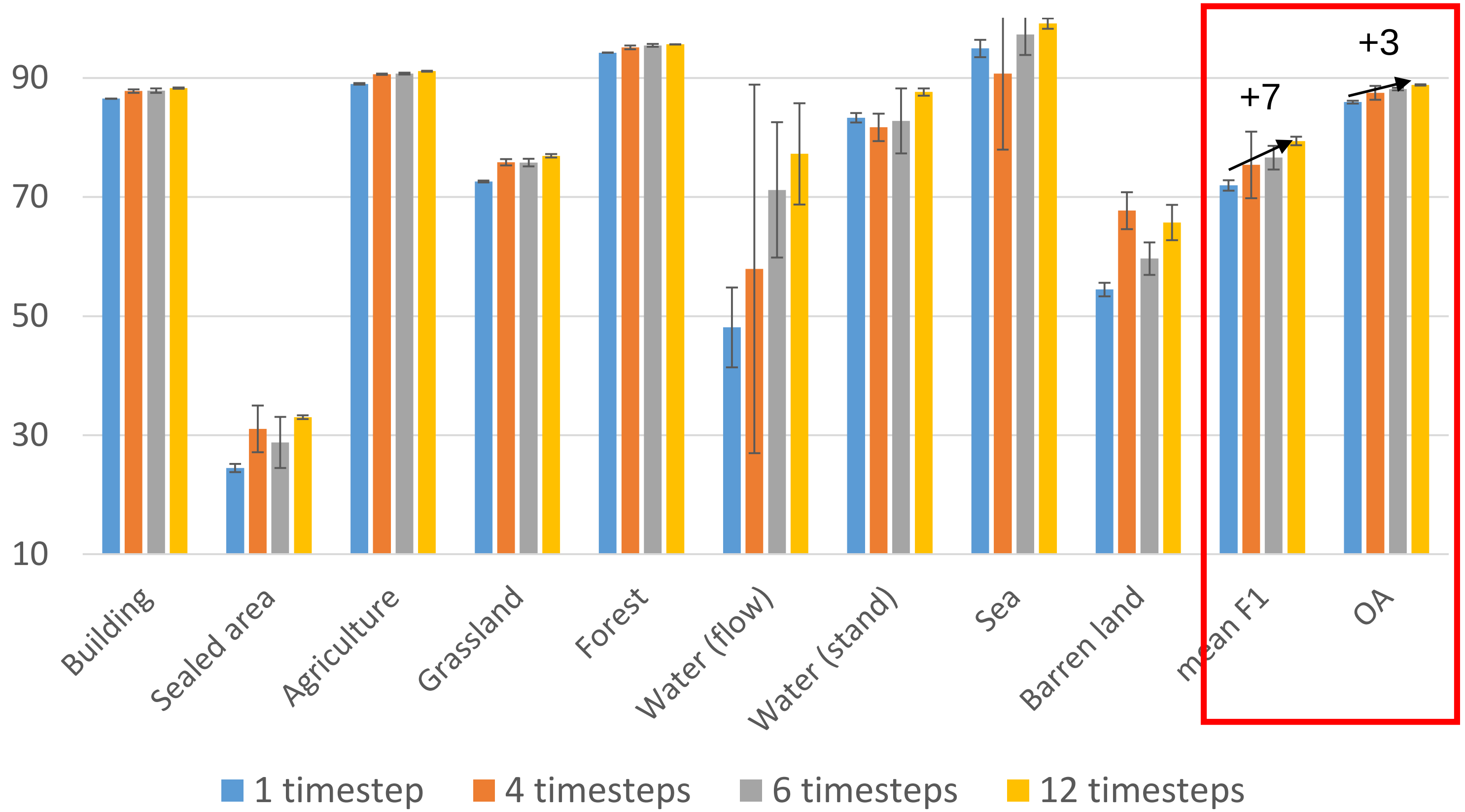


- Stack of different time steps (like additional spectral bands)

- Add an additional dimension (3D Convolutions)

… a lot of other possibilities

Integration of multitemporal data

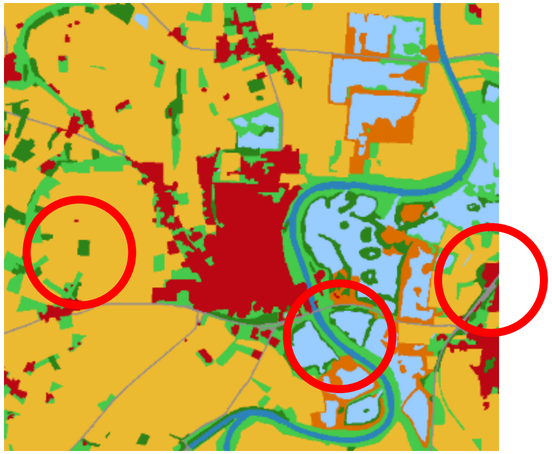


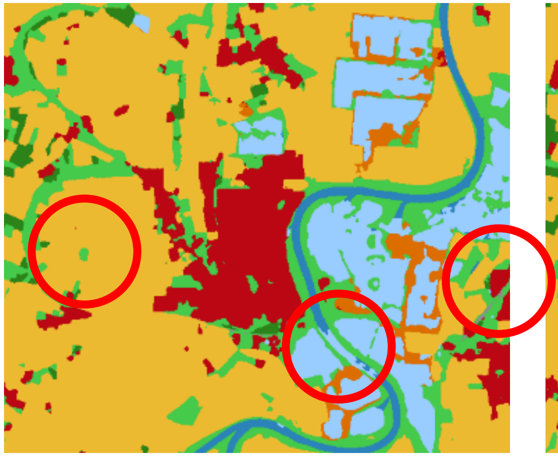
→ Improvement of the F1-scores of all classes

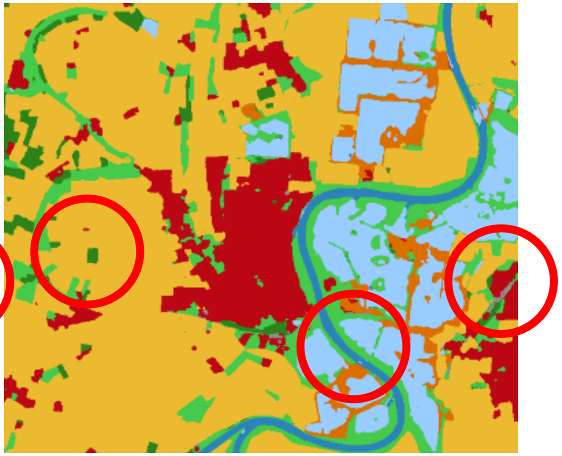
→ Highest improvement for the classes flowing water (+29%) and Barren land (+11%)

Integration of multitemporal data


S2 - RGB


Reference (corrected)


monotemporal


multitemporal

Influence of spectral bands

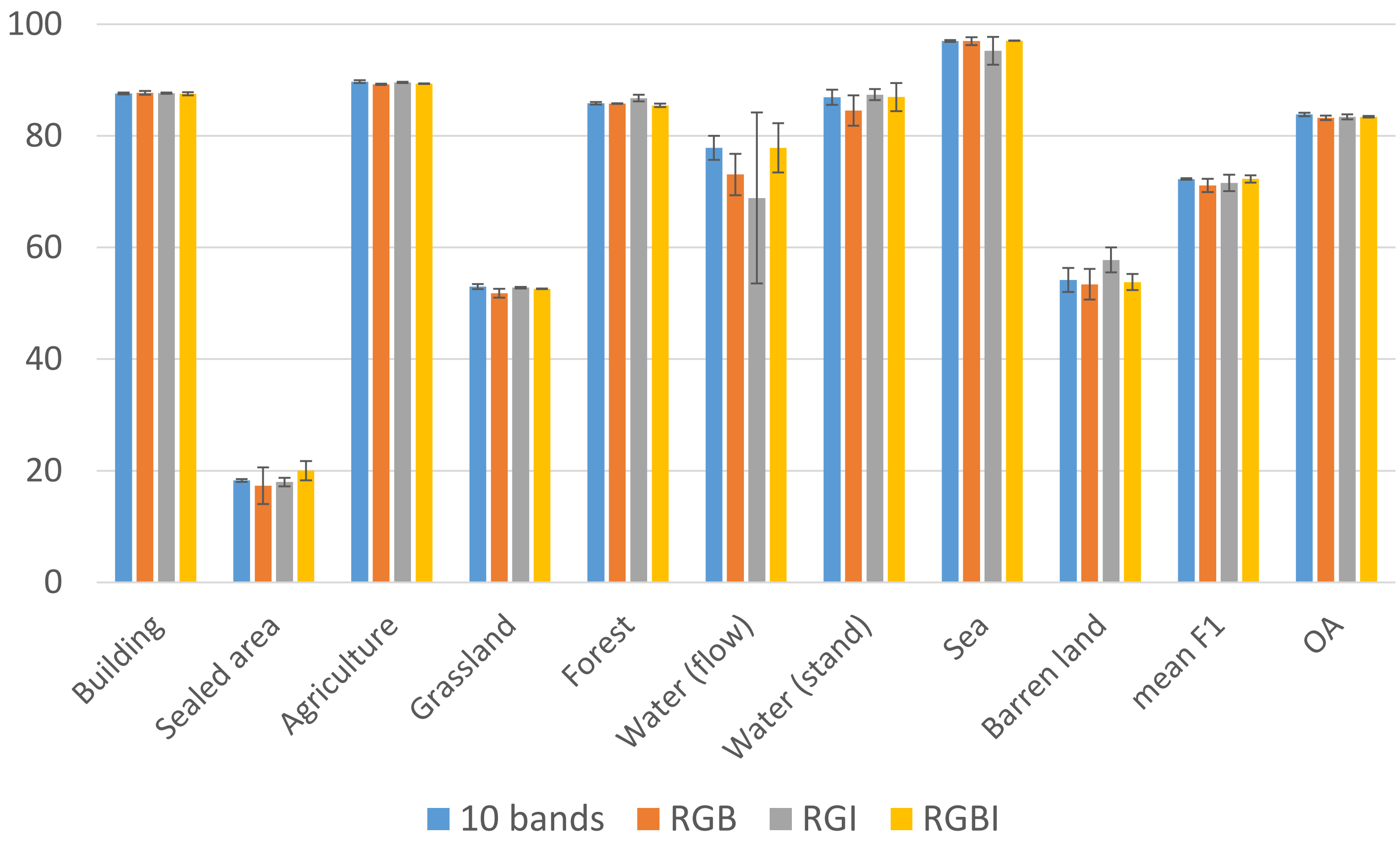
Spectral bands of Sentinel-2:

- 4 bands with 10 m resolution (RGBI)
- 6 bands with 20 m resolution
- 3 bands with 60 m resolution
  → Primarily for measuring atmospheric properties

→ Which channels are best suited for land cover classification?

→ Is it necessary to use them all?

Influence of spectral bands

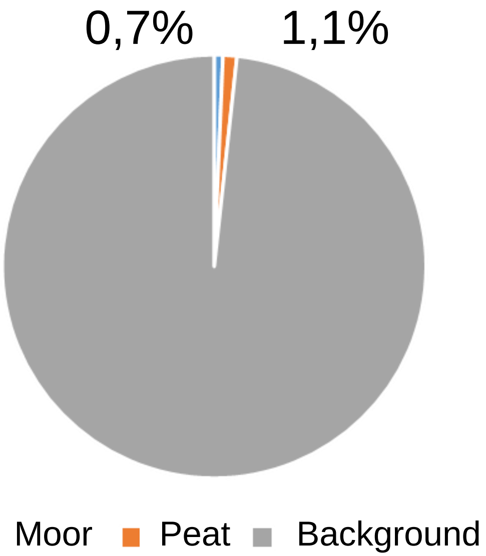


→ The results with RGBI are on the same level as the results with 10 channels.

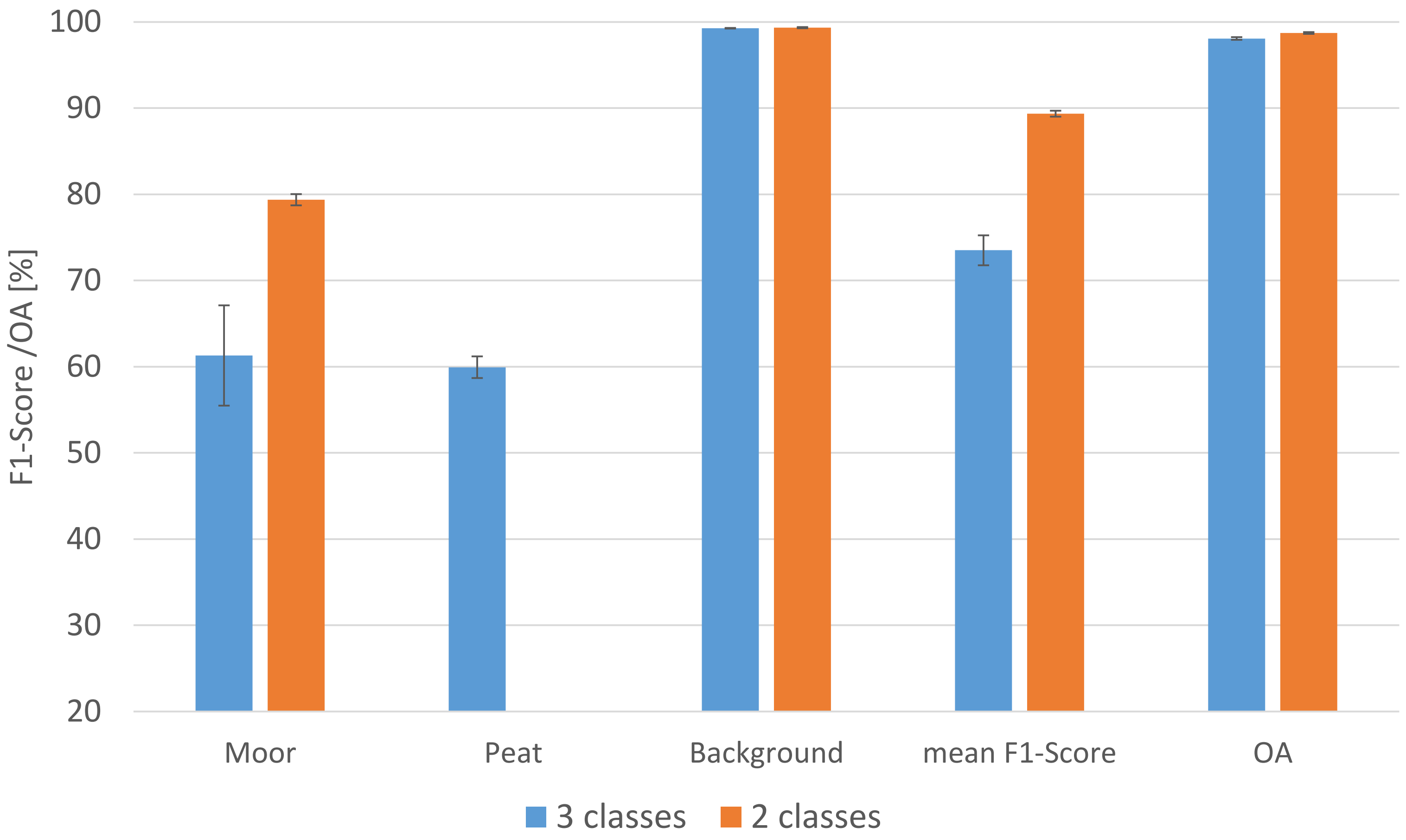
Application scenario: Peatland classification

- Training data:
  - 3 classes: Peat, Moor, Background (Torf, Moor, Hintergrund)
  - 2 classes: Peat + Moor, Background
  - 244 of the 835 tiles contain peat or moor(~30%)

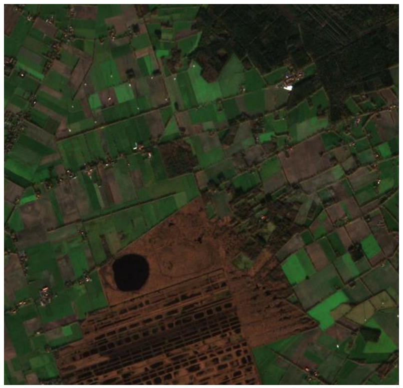
Distribution of the label data within the 244 tiles::



Application scenario: Peatland classification



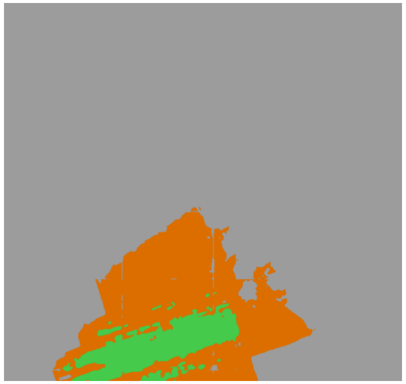
Application scenario: Peatland classification


2020-11-23


2020-08-05


2020-06-01

- Appearance over time varies greatly
- Differentiation between moor and peat (still) difficult

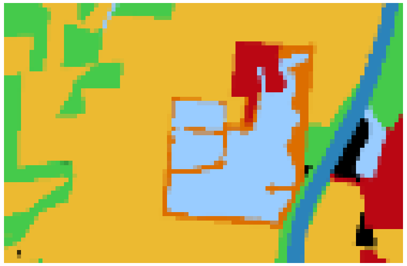

Prädiktion


Label

Summary

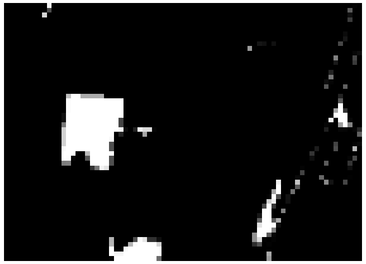
- Successful land cover classification with deep neural networks
  - Accuracies of 84 % OA or 73% mean F1-Score
- Improving results through (a.o.):
  - Larger training data set, multitemporal input data
  - Method: e.g. class-dependent weighting
- Change detection with the help of (manual) post-processing

Database 2019



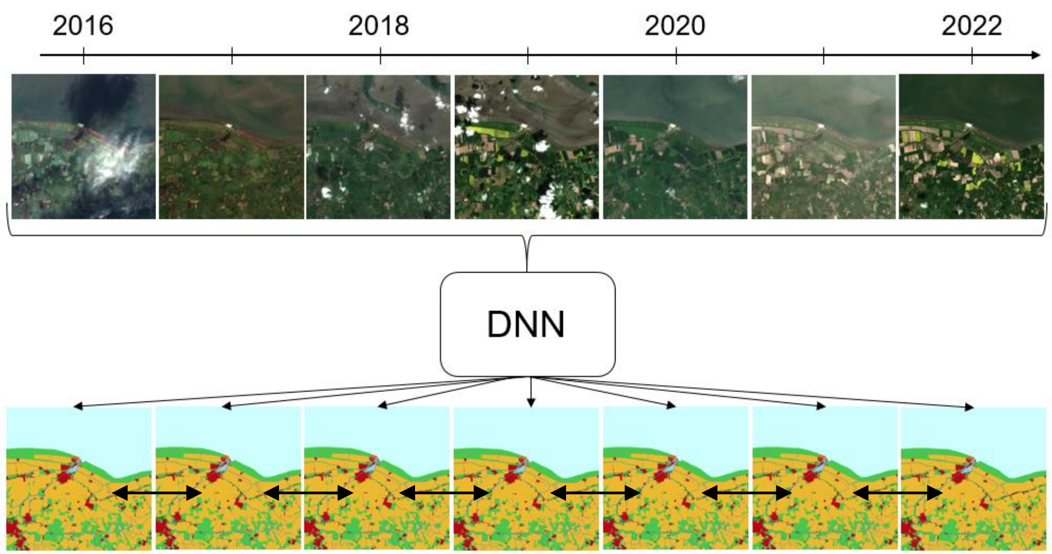
Classification 2020

Note for change



Outlook

- Integrate land cover update in methodology
  - Model land cover development over time
  - Adapt model to multiple outputs
  - Regularize models output (e.g. no back and forth between classes)



→ Update database on these stabilized results

Published Papers

- Voelsen M., Teimouri M., Rottensteiner F., Heipkke C. (2022): Investigating 2D and 3D convolutions for multitemporal land cover classification using remote sensing images. In: ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences V-3-2022, pp. 271–279.
- Voelsen M., Lobo Torres D., Queiroz Feitosa R., Rottensteiner F., Heipke C. (2021): Investigations on feature similarity and the impact of training data for land cover classification. In: ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences V-3-2021, pp. 181–189.
- Voelsen M., Bostelmann J., Maas A., Rottensteiner F., Heipke C. (2020): Automatically generated training data for land cover classification with CNNs using Sentinel-2 images. In: Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci., XLIII-B3-2020, 767–774.

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