



LPS 2022

Refinement of remote sensing information on the coast using verification data via AI

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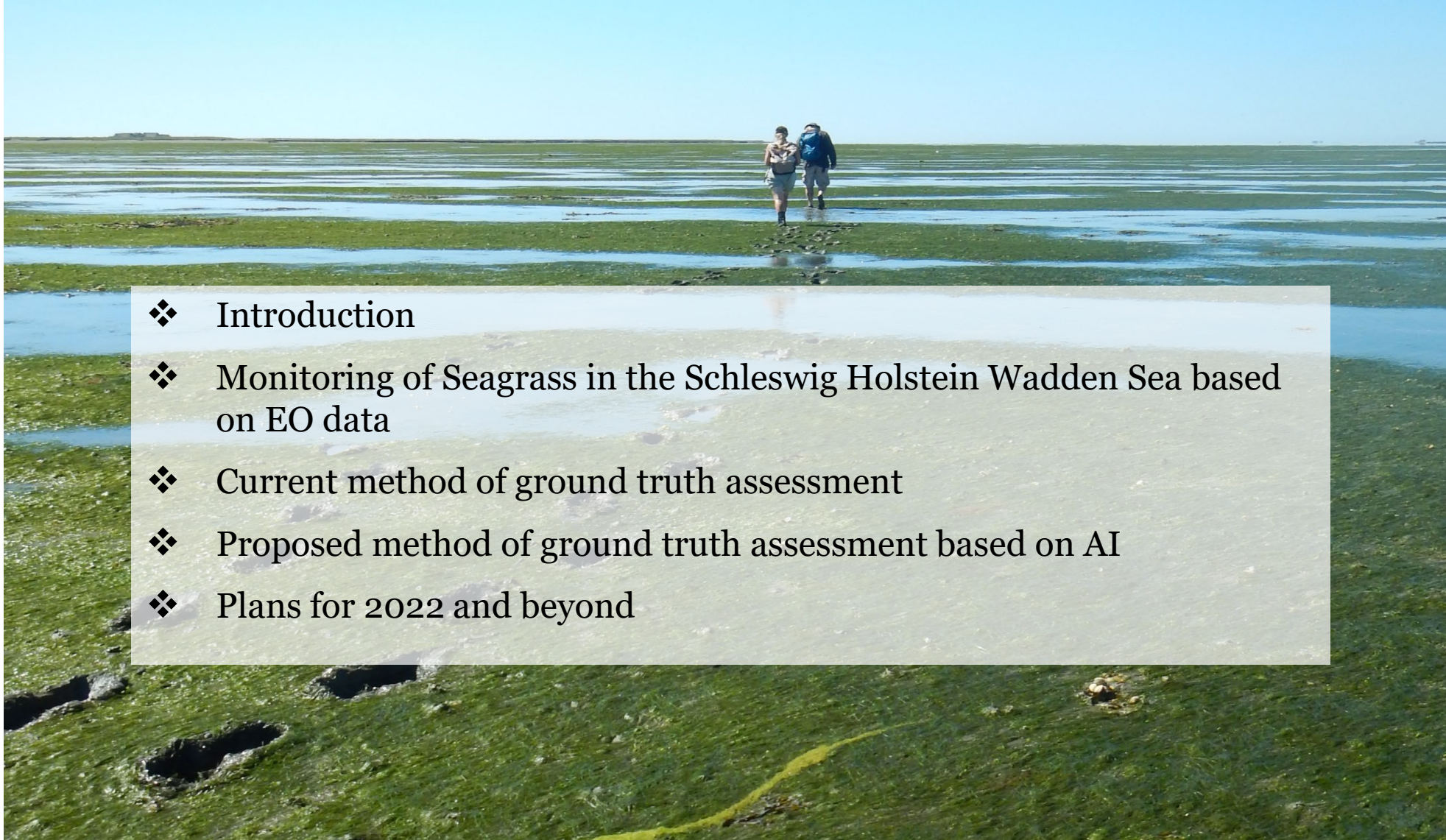
Nationalpark
Wattenmeer

SCHLESWIG-HOLSTEIN




BROCKMANN
CONSULT GMBH

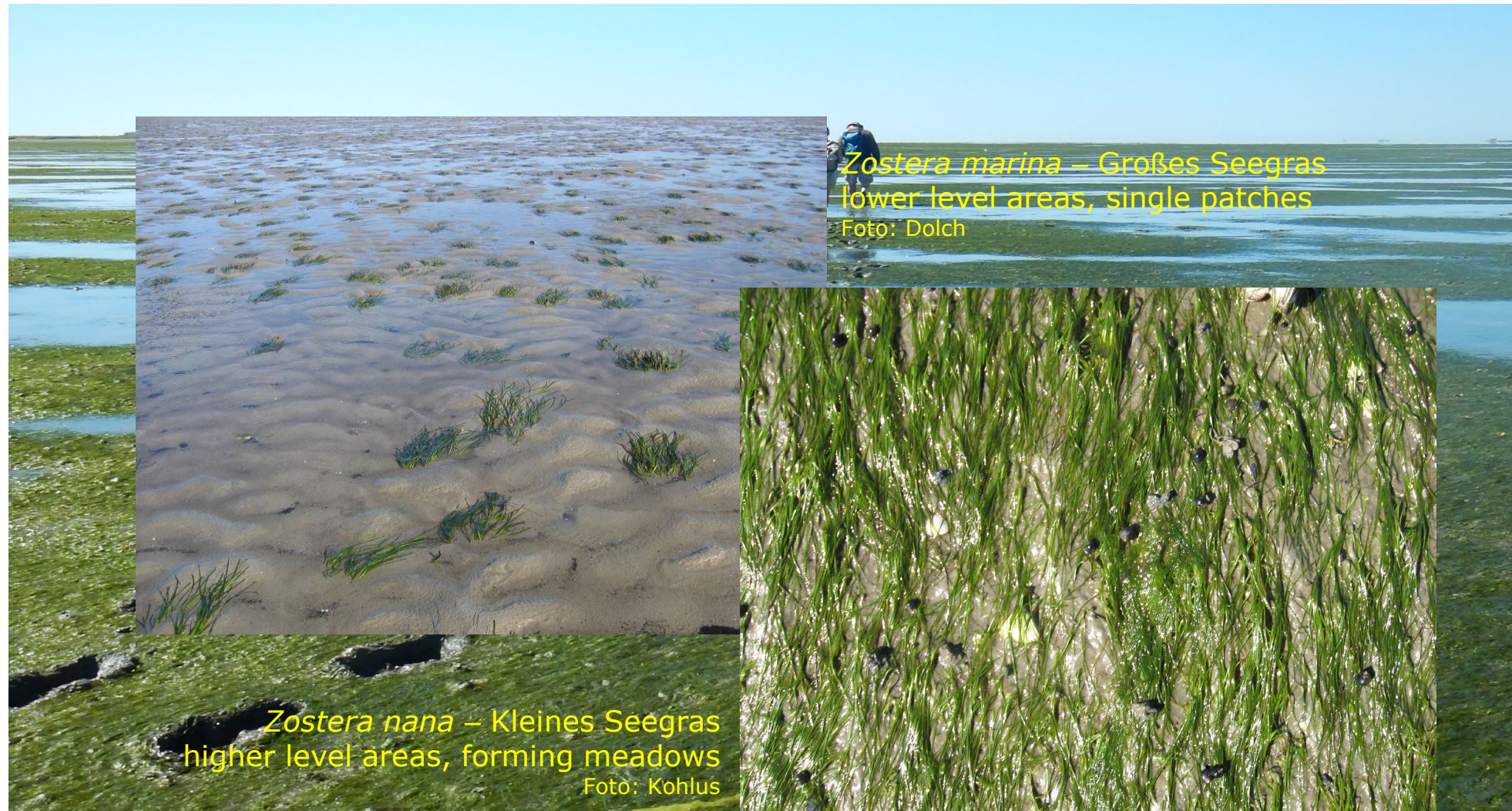
Overview



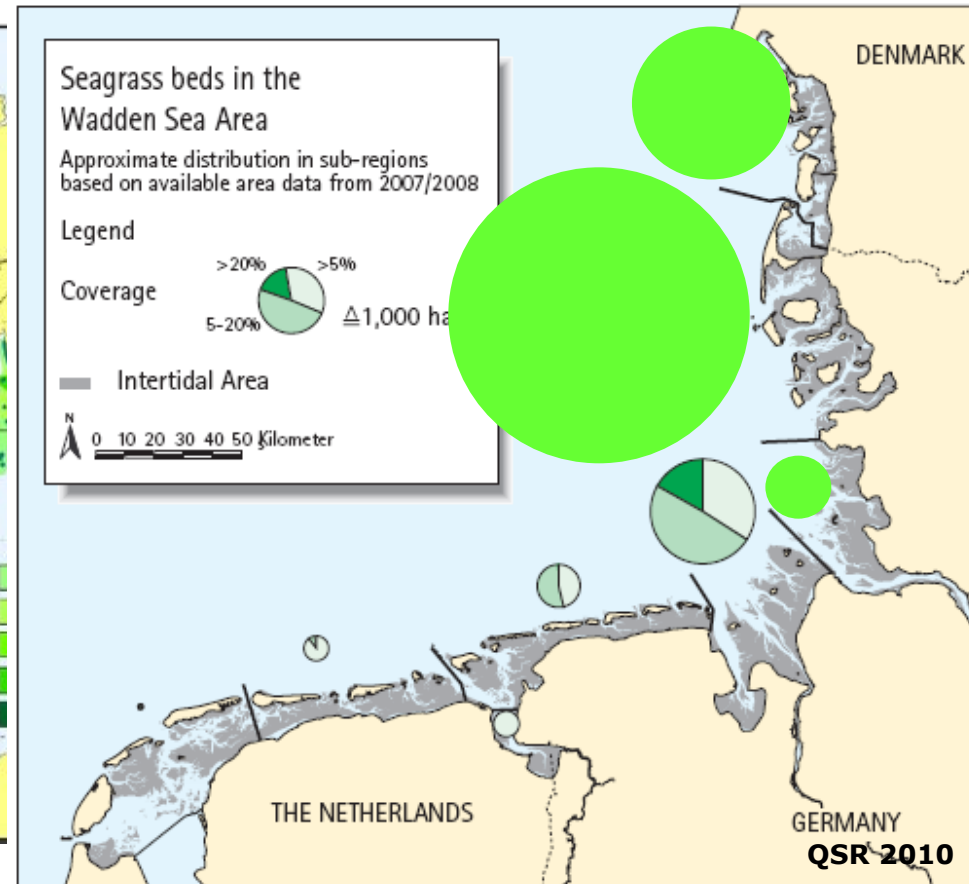
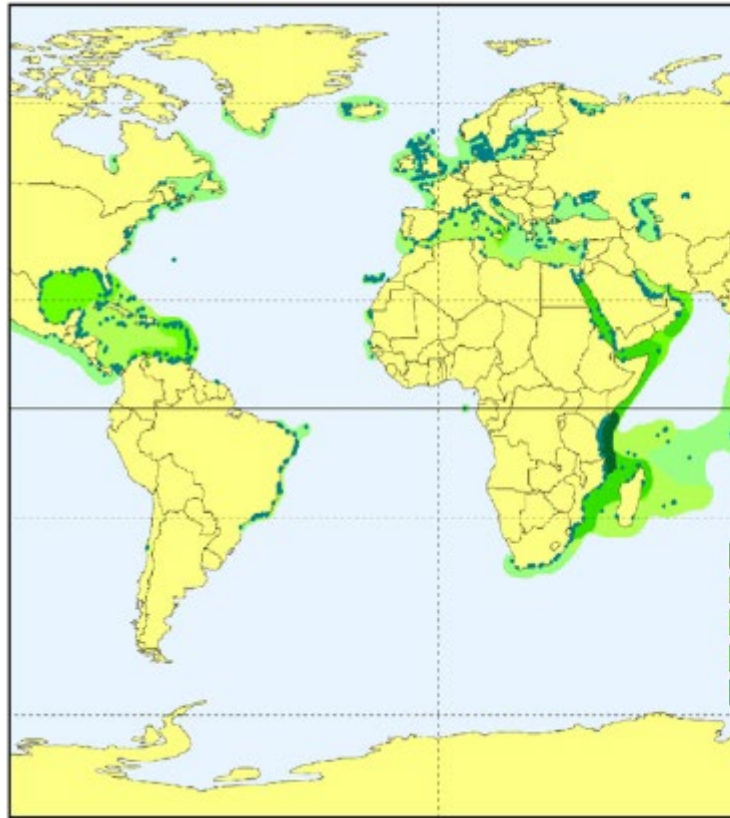
- ❖ Introduction
- ❖ Monitoring of Seagrass in the Schleswig Holstein Wadden Sea based on EO data
- ❖ Current method of ground truth assessment
- ❖ Proposed method of ground truth assessment based on AI
- ❖ Plans for 2022 and beyond



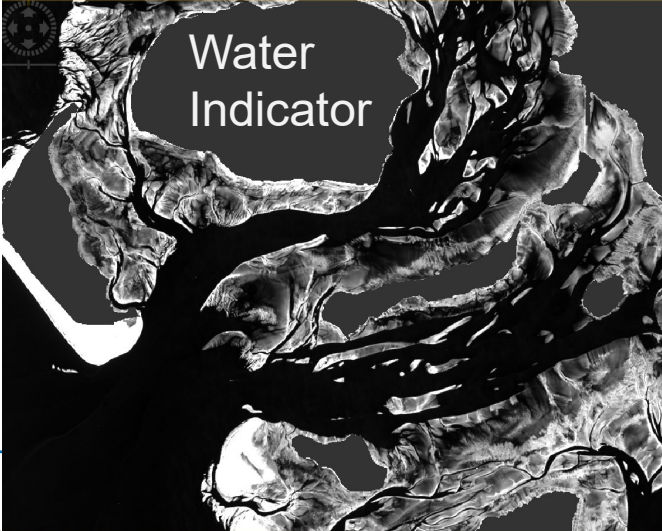
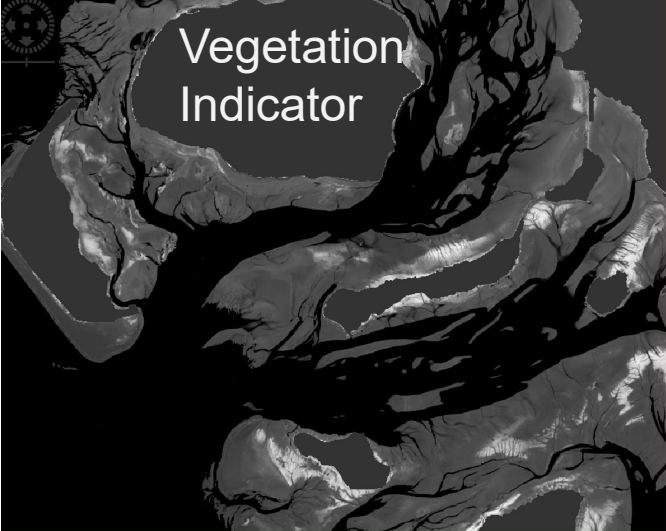
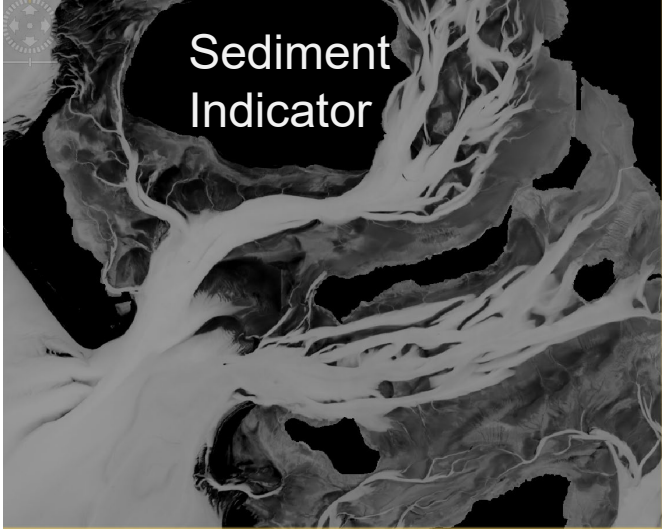
Seagrass meadows in the Wadden Sea



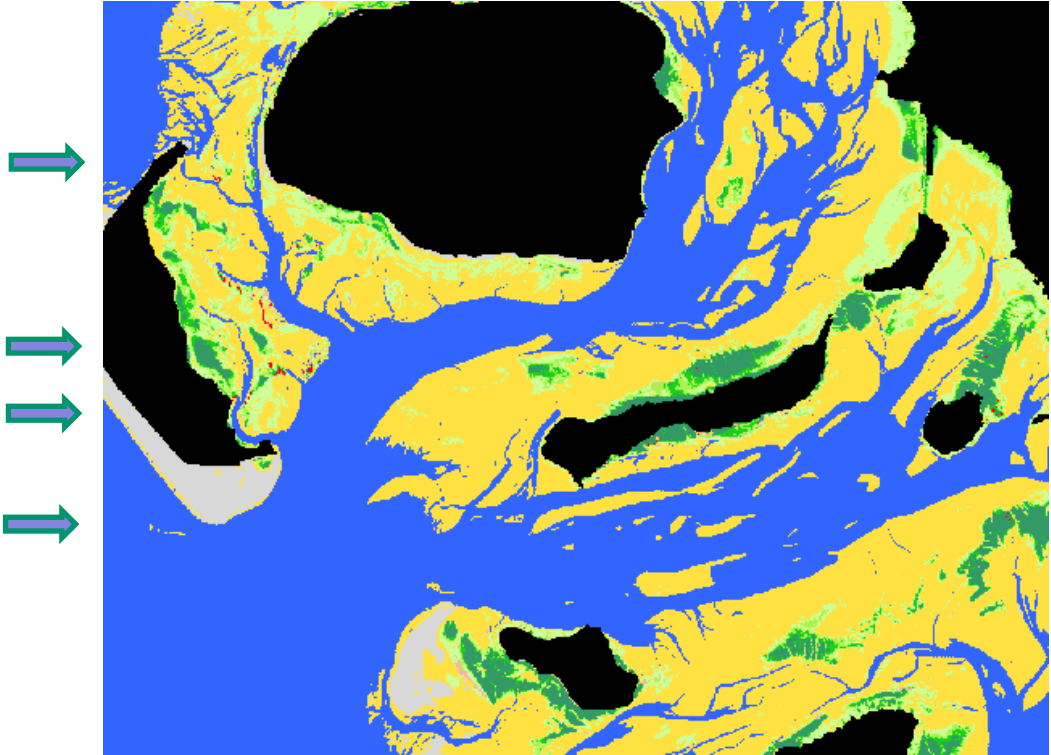
Seagrass occurrence



EO classification system seagrass



Classes of seagrass density



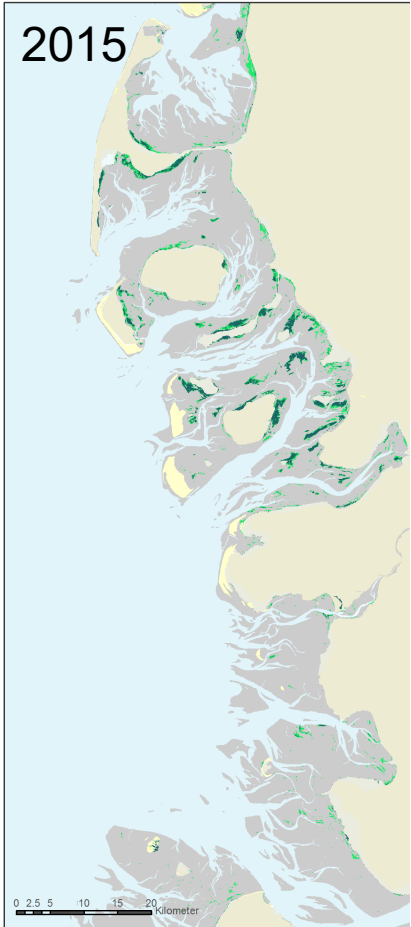
- 5-10%
- 10-20%
- 20-60%
- >60%



Monitoring of Seagrass with EO data since several years

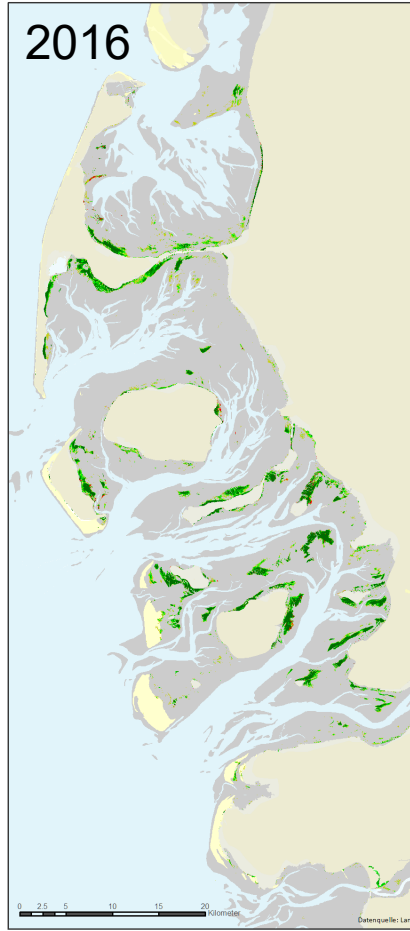
Seegrasvorkommen auf der Ba
- Schleswig-Holsteinisch

2015



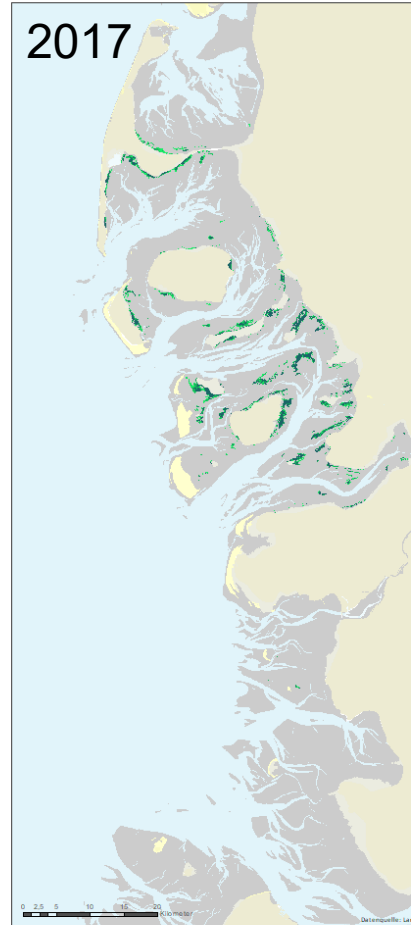
Seegrasvorkommen auf der Ba
- Schleswig-Holsteinisch

2016



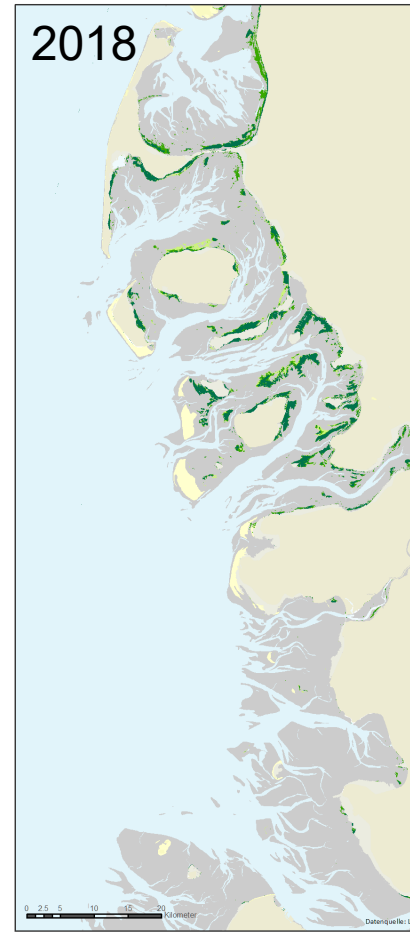
Seegrasvorkommen auf der Ba
- Schleswig-Holsteinisch

2017



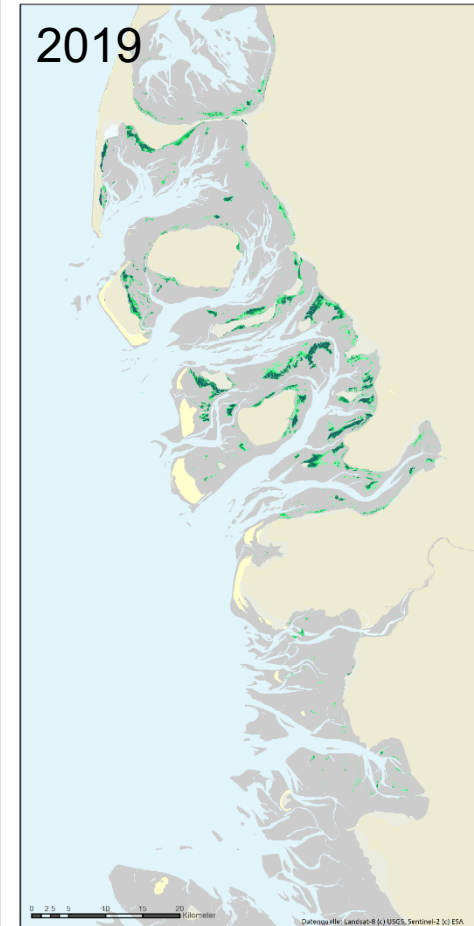
Seegrasvorkommen auf der Ba
- Schleswig-Holsteinisch

2018

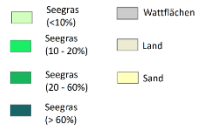


Seegrasvorkommen auf der Basis von Satellitendaten
- Schleswig-Holsteinisches Wattenmeer -

2019



Legende



Beschreibung

Die Karte der Seegrasvorkommen im Schleswig-Holsteinischen Wattenmeer basiert auf der Analyse von Satellitendaten. Hierfür wurden zwei Aufnahmen des Sentinel-2-Satelliten und eine von Landsat-8 verwendet. Die Aufnahmen stammen vom 26.08.2019 & 22.09.2019 (S-2) und vom 03.10.2019 (L5-8).

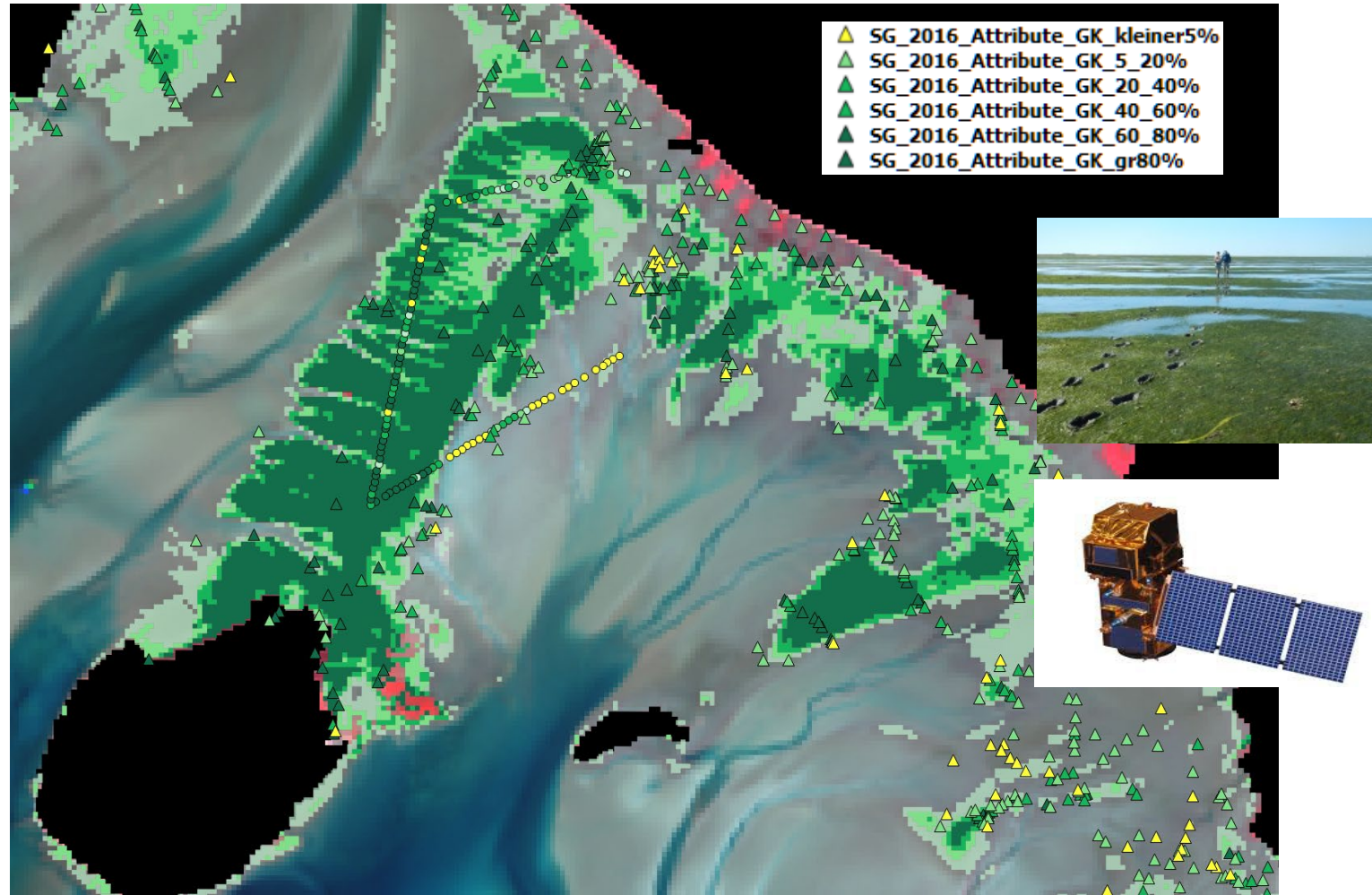
Die spektralen Eigenschaften der Wattoberflächen dienen als Informationsbasis für die Datenanalyse. Die Einteilung der Seegrasvorkommen erfolgte durch eine Kategorisierung des Aufnahmesignals in verschiedene spektrale Klassen, die den Seegrassklassen <10%, 10 - 20%, 20 - 60% und > 60% entsprechen.

Datenquelle: Landsat-8 (3) USGS, Sentinel-2 (3) ESA
Aufnahmedatum: 26.08.2019, 22.09.2019 & 03.10.2019
Thema: Klassifikation von Seegrassflächen
Projekt: Seegrass NPV
Projektion: UTM, 32N, WGS-84
Bildbearbeitung: Brockmann Consult GmbH



Seagrass classification verified with ground truth measurements

- Ground based assessment of the density of seagrass coverage
 - Monitoring program mapping seagrass meadows on ground
 - Dedicated transects assessing the seagrass density
- Assessment of seagrass density performed by experts
- Categories of seagrass density not harmonized between programmes

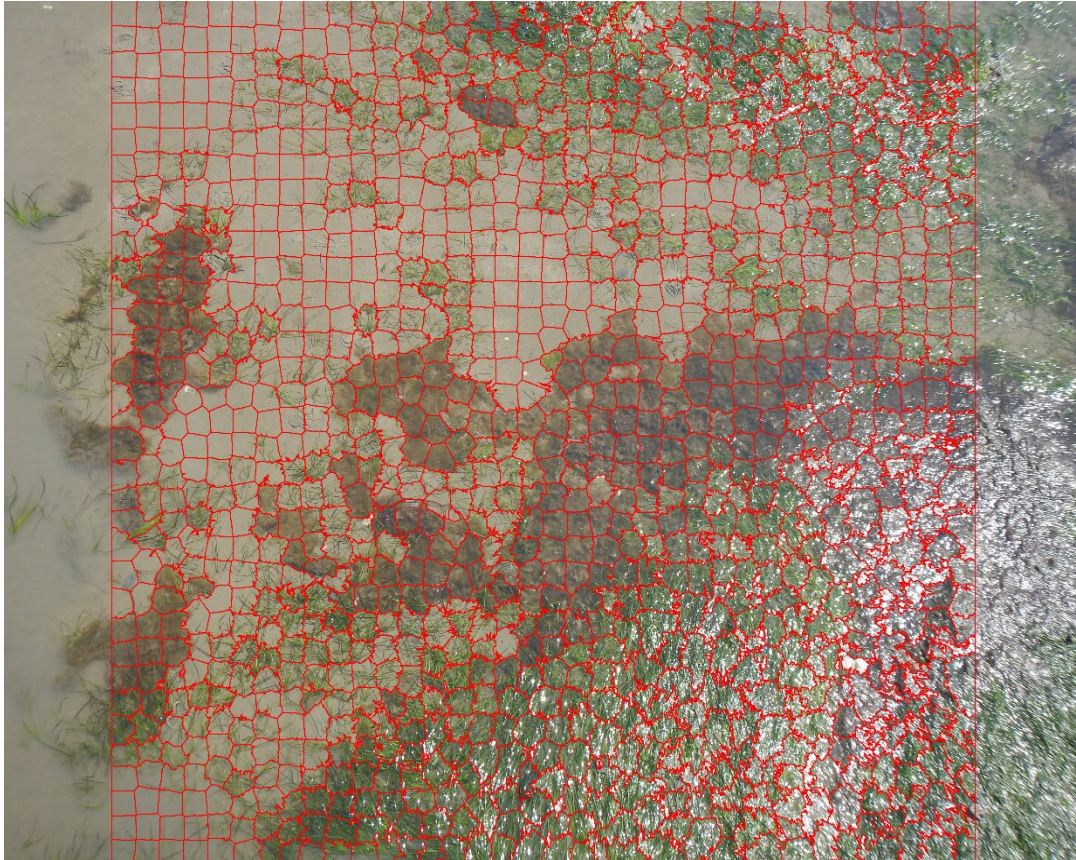


Current ground truth assessment

- Currently, ground based truth coverage data is done via transect or raster surveys
- This may lead to errors or reduced reproducibility due to
 - Fatigue
 - Changing environmental and light conditions
 - Changing personnel
 - No standardization between campaigns
- Need for a more objective measurement
- Ansatz: AI-based coverage estimate on images taken in the field



AI-based estimate: approach



- Segmentation of original image
- Classification of segment images by a neural network



- Calculation of area and coverage of the classes
- Estimation of the uncertainties
- Average calculation from individual images as result for the transect point

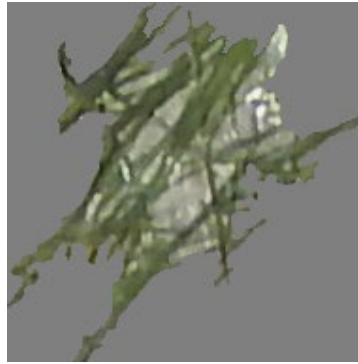


AI-based estimate: Classification by a neural network

- Allocation of segment images into seagrass (scant, medium, plenty) and non-seagrass classes by hand for training
- Random split of dataset into training, validation and test (80%, 10%, 10%)
- Usage of transfer learning (InceptionV3)
- Optimization on the Area Under the Curve of the Receiver Operating Characteristic (ROC AUC) with Early Stopping
- Implementation in Tensor Flow



AI-based estimate: coverage calculation

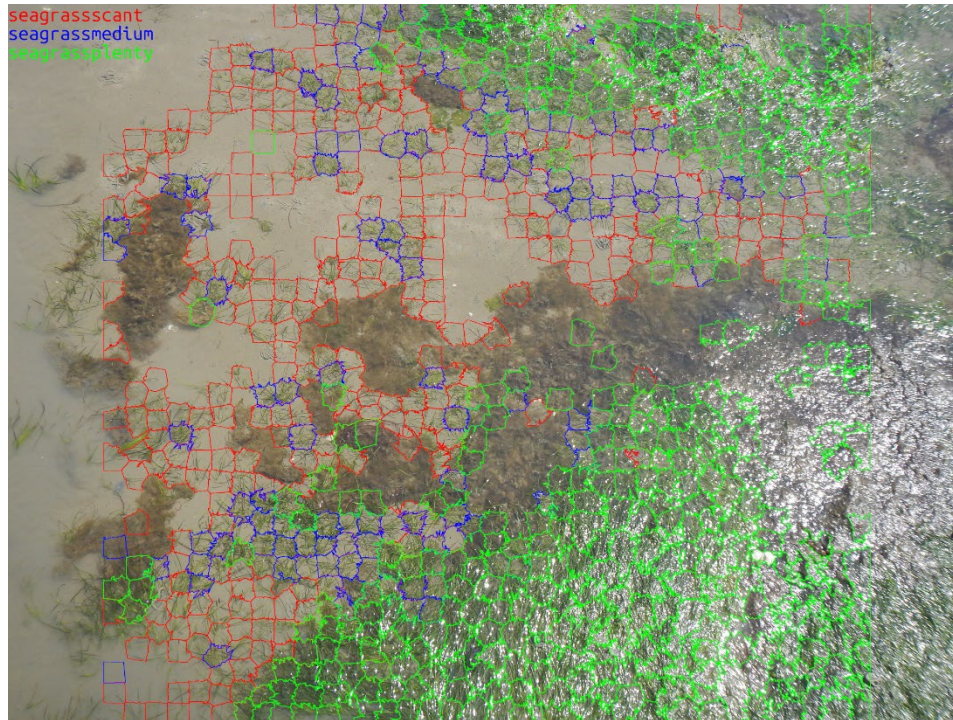


- Wanted: calculation of seagrass ground coverage in percent
- But: segments do not always contain 100% coverage
- Different methods tried to determine the coverage:
 - „Simple“: Allocation of flat coverage (10%, 50%, 90%) to the different seagrass classes (scant, medium, plenty)
 - „GLI“: Green Leaf Index; RGB-approximation on the infrared characteristics of vegetation
 - „Otsu“: finding the valley between peaks to divide between light and dark areas



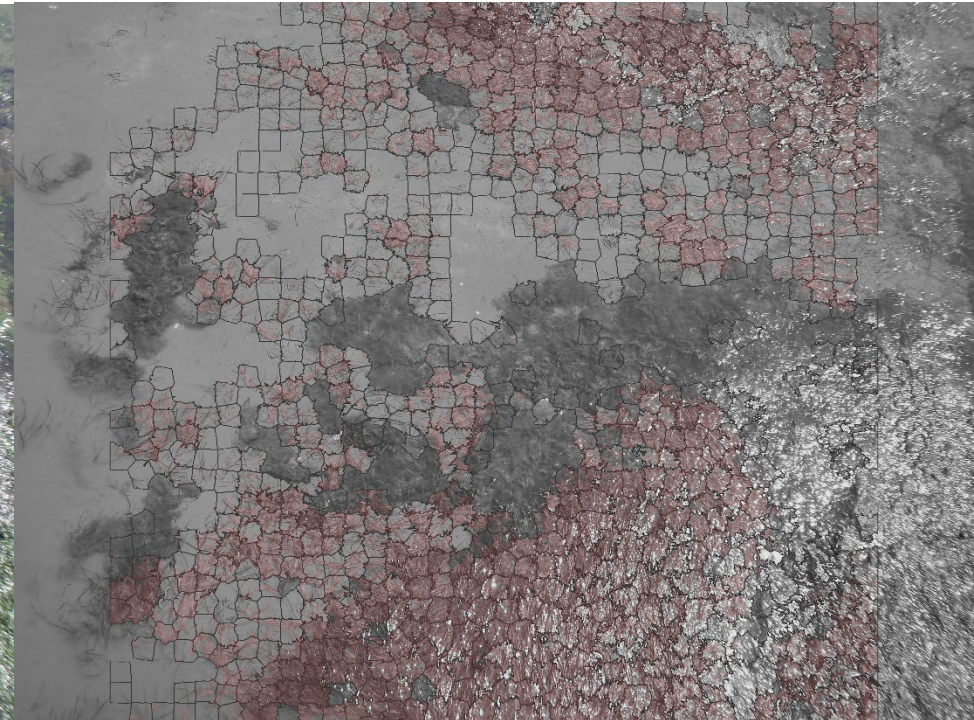
AI-based estimate: coverage calculation example

Simple



37 (err: + 3 - 3) %

GLI



30 (err: + 7 - 5) %



AI-based estimate: Uncertainties

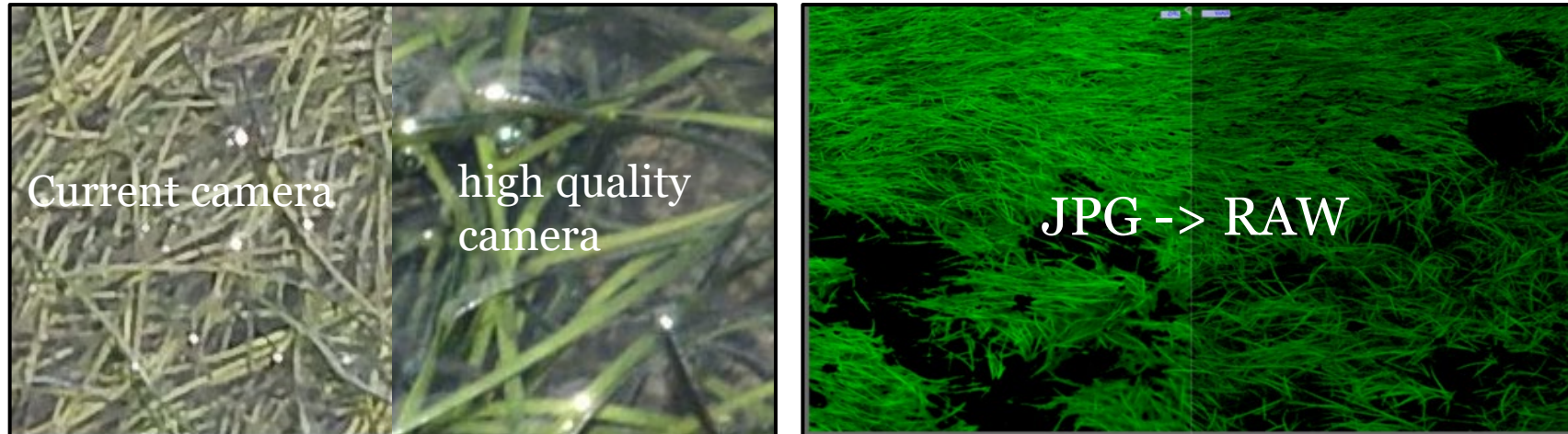
- Classification uncertainty by using Monte Carlo Dropout (100 runs)
- Uncertainty of area calculation by variation of the opening angles of the camera, the image taking height and the inclination of the plane
- Uncertainty for „Simple“ und „Otsu“ by flat 10% uncertainty per segment; for „GLI“ variation of the threshold value.
- Uncertainties on the individual segments are neither fully correlated (linear combination) nor fully uncorrelated (quadratic combination) -> mean value from both
- Uncertainty on the result of the transect point by error propagation from the individual images



AI-based estimate: BOLKI2Fly

Improvements by usage of higher quality images

- Collection of data with a higher resolution and evaluation of new performance
 - Usage of polarization filter to reduce reflections
 - Possible usage of RAW instead of JPG format



- Evaluation of feasibility and benefit in the field
- Provision of an interfaces for running and managing of training by the LKN
- Testing of the procedure on drone images



AI-based estimate: data taking via drones

Planned for
2022

- Few images per transect point needed
- Challenges in the wadden sea:
 - Frequent high wind speeds -> sufficiently large drone needed
 - Several hours of data taking -> large drones have small range
 - Starting an landing in the wadden sea problematic
- Incorporate this objective ground truth data into EO production process will improve the whole process.



Source: „Spatial assessment of intertidal seagrass meadows using optical imaging systems and a lightweight drone“, Duffy et al.





Thank you

for your attention



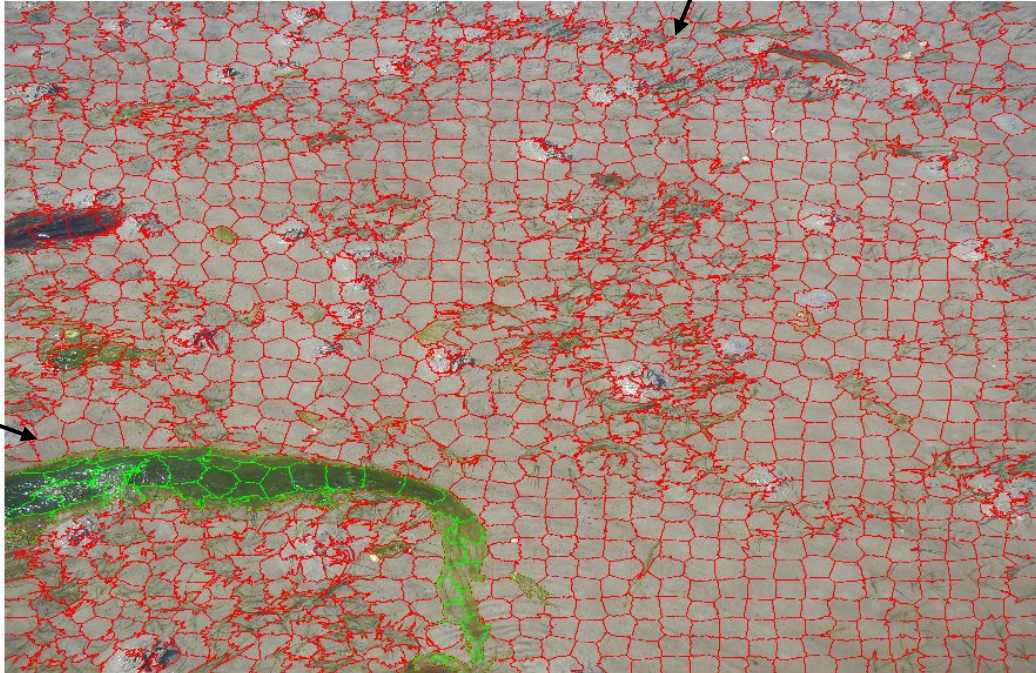
AI-based estimate: labeling tool

Labeled images will be saved in a format immediately usable by Tensor Flow

Zoom by mouse wheel

Multiclass Labeling Projekte Bilder

Bild labeln



Choose segments and label them in bulk

Labels

soil	löschen
greenalgae	löschen
brownalgae	löschen
clam	löschen
shoe	löschen
reflection	löschen
worm	löschen
seagrassplenty	löschen
seagrassscant	löschen
seagrassmedium	löschen
skip	löschen
Skip Remaining	

label

Create and delete classes



AI-based estimate: training data

- Efficiency calculation on test data
- Quality probably slightly overestimated since calculated on segments easily assessed by eye

Class	Number of images	Efficiency [%]
Soil	8319	95
Brown algae	215	29
Green algae	524	42
Shell	95	56
Reflection	103	30
Seagrass (scant)	4213	82
Seagrass (medium)	2500	68
Seagrass (plenty)	6194	94
Lob hill	1129	79



AI-based estimate: misidentification examples

- Misidentification by neural net
- Smearing by non optimal threshold setting (GLI)
- Overselection by Otsu

