Looking from space to lower levels of the food web in Wadden systems

ALWGO project 2019; Utrecht University, Addink, Philippart, Nijland, De Jong, et al.

Background

Tidal flats around the world are of **high ecological importance** (Stutz and Pilkey, 2002; 2011). The Wadden Sea is an ecological treasure along the Dutch, German and Danish coast with international recognition (Ramsar, Natura2000, UNESCO heritage). Barr Al Hikman in Oman has large pristine areas of characteristic tropical intertidal mudflats (Bom et al., 2018a). Shallow seas with large tidal flats serve as nursery areas for fish and staging areas for migrating birds (Wolff, 1983). Their food security strongly depends on the availability of macrozoobenthos (e.g. bivalves, snails, worms and crustaceans; figure 1). Macrozoobenthos form a lower trophic level of the foodweb and their status is a strong indicator for ecosystem health. Biomass of macrozoobenthos is governed by tidal, seasonal, and interannual driving forces and is highly **variable in time and space** (Beukema, 1976; Philippart et al, 2007). Their distribution correlates with environmental factors such as emersion time, sediment composition (median grain size, mud content), and abundance of microphytobenthos (i.e. benthic algae that function as a food source) (Compton et al, 2013).

Physiological tolerances and competitive abilities of many intertidal macrozoobenthic species vary with age and size, resulting in distributional shifts in preferred environmental conditions. Juvenile lugworms, for example, settle at the higher tidal flats characterized by muddy sediments and migrate to the lower tidal flats characterized by more coarse sediments once large enough to survive the competition with adult lugworms (Flach & Beukema 1994). Juvenile bivalves may shift from feeding entirely on microphytobenthos to including more phytoplankton in their diet when growing up (Rossi et al, 2004; Jung et al 2019). **Macrozoobenthos distribution, biomass, and abundance are therefore affected by both environmental changes and life-cycle related mobility.**

Global warming leads to higher temperatures affecting species distribution (Philippart, 2018; and references herein) and may impact the frequency of extreme events such as storm surges, heat waves, and toxic algae blooms (Khedhri et al, 2017). It is likely that sea-level rise will exceed the rate of upsilting of the mudflats (Haasnoot et al, 2018). Hence, **environmental changes will occur, and monitoring is essential** (Waddensea-Secretariat, 2020).

Current monitoring of macrozoobenthos relies heavily on field sampling (Bijleveld et al, 2018). In-situ sampling efforts (e.g. sampling of sediment cores to determine species composition of macrozoobenthos, chlorophyll content and sediment characteristics) are very time consuming and costly. Deployment of this approach is not always possible, e.g. in less accessible coastal systems (Biber, 2013; Bijleveld et al, 2018). Even the most extensive monitoring programs (e.g. the SIBES program where 4500 samples are taken each year; Bijleveld et al, 2012) are, therefore, generally restricted to one sampling period per year. This means that there is **no information available on seasonal variation in population dynamics**, such as possible shifts in the timing of recruitment (Philippart et al, 2007) and periodic mass mortality events (Burdon et al, 2014), which is needed to mechanistically understand the observed year-to-year variation in macrozoobenthic communities.

Economic interests in the tidal systems, like fisheries and gas extraction, are large but may interfere with ecological integrity. Tidal flats are under intense pressure from coastal development, sea-level rise, coastal erosion, reduced sediment fluxes from rivers and subsidence and compaction of coastal sediments (Murray et al, 2019). Information on seasonal variation in intertidal benthic communities is essential for informed policy and decision making. Understanding and forecasting impacts of environmental stressors such as climate change require information on high spatial and temporal resolutions for the different functional groups of these organisms. Such information can only be gathered by deploying techniques which are able to capture high resolution in time and space such as satellite images. **Research and monitoring are key components** especially when coastal management aims **to achieve a sustainable balance** between protecting nature and allowing multiple human uses. Robust information on the proper scale and resolution provides an effective platform for decision-making toward sustainability.

Figure 1. (Signs of) macrozoobenthos. Left to right: *Pirenella arabica* (marine gastropod), *Arenicola marina* (lugworm), *Peringia ulvae* (mudsnail), *Scopimera cabricauda* (sand bubbler crab). Sources: staticflickr.com *(Am)*, wikimedia.org *(Pu),* photos Addink (*Pa, Sc*).

Remote sensing has a high potential to provide information with continuous coverage, also for inaccessible areas. Murray et al (2019) mapped the global distribution of tidal flats using Landsat data. Kromkamp et al (2006) predicted sediment chlorophyll concentration from hyperspectral data. However, examples on applications with macrozoobenthos are scarce, which is likely due to the low spectral variation of tidal flats next to the small size of the benthos. Van der Wal et al (2008) did an extensive study with four field surveys over two years and in two seasons in the Dutch Western Scheldt. They looked at total benthic biomass, species richness, biomass of functional groups, and biomass for four selected species in relation to microphytobenthos response models in a per-pixel approach. Their best prediction (which was found for species richness based upon NDVI and median grain size) explained 43% of the deviance. Choi et al (2011) looked at species distribution at a Korean tidal flat. They collected field data, image data and morphological data to predict potential macrozoobenthos habitat. The data was acquired within a 10-year period. They used a probabilistic model and obtained reliable maps. However, they did not map actual presence of species. However, they did not map actual presence of species. So, although **remote sensing** has been used in these spectrally poor environments for macrozoobenthic mapping, its **performance so far does not allow to map nor monitor individual species or functional groups. Neither did previous efforts take the full potential of remote sensing into account**, **by ignoring additional information on texture and spatial patterns.**

In a first pilot study, we used object-based image analysis (OBIA) on a Sentinel-2 image to predict distribution, biomass and abundance of ten different macrozoobenthos species, together with overall biodiversity (total number of species present at a location) (De Vries et al, 2019). With object-based image analysis (OBIA) contiguous groups of pixels rather than single pixels form the spatial units for analysis (Addink et al, 2012). This offers the possibility to use spatial variables describing the local texture next to spectral characteristics. We used OBIA together with Random Forests (Breiman, 2001) for distribution, and with Ridge Regression (a shrinkage regressor) (Hastie et al, 2001) for biomass and abundance. Distribution maps were rather accurate (60-90%). The biomass of *Ensis leei* (American razor clam) was predicted with an accuracy of 75%, while results for other species were not satisfying yet. Main conclusions on the methodology were 1) It is **important to determine the optimal prediction scales for distribution, biomass and abundance separately**; 2) it is **crucial but difficult to identify relevant, independent variables** as the list of potential object variables is long; and 3) **variable selection in the statistical analysis should be improved**.

In 2019 we did a second pilot with student projects including field sampling and UAV image collection at Texel. They showed that the **associations of macrozoobenthos and environmental conditions change over the seasons**; UAV images have a **prediction accuracy of 85% in median grain size**; the **optimal prediction unit is ~4m^2**; and **texture variables are more important than spectral values.**

<u>The overall aim</u> of the current project is to exploit **the potential of object-based remote sensing to map and monitor macrozoobenthos in intertidal wadden systems** under temperate and tropical conditions. We will work at different spatio-temporal scales and provide a fundament for systematic monitoring. We will expand the ability to capture surface patterns and obtain relevant predictor variables using deep-learning convolutional neural networks (LeCun et al, 2015). We develop the methods in the Wadden Sea and test the transferability in Barr Al Hikman, Oman. Our assumption is that while **macrozoobenthos are not directly visible at the surface, the spatial surface patterns at the tidal flats are strong predictors for their presence underneath the surface**. In the project we aim to:

1) enhance information extraction from images in this spectrally poor environment by deep-learning;
2) map macrozoobenthos distribution, abundance, biomass and habitat from images; and
3) capture dynamics of macrozoobenthos and their habitat.

Figure 2. Left: In situ sampling by NIOZ on a mudflat in the Wadden Sea (Photo Roelant Snoek). Right: Field excursion to Barr Al Hikman (Photo Roeland Bom).

Study sites

The main study site will be in the Dutch part of the Wadden Sea, which stretches for over 500 km along the North Sea coast. This site represents an outstanding example of development of a temperate-climate sandy barrier coast under conditions of rising sea level in the Holocene. The Wadden Sea is unique in that it consists entirely of a sandy-muddy tidal system with only minor river influences on morphodynamics. The Wadden Sea ecosystem is characterized by tidal flats and a barrier island system with extensive salt marshes and is unique in both scale and diversity. For that reason, major parts of the Wadden Sea Conservation Area were inscribed on the UNESCO World Heritage List (CWSS, 2017).

The tidal flats in the Wadden Sea are extremely rich in environmental gradients and transitional zones, offering many different (micro)habitats that form the basis for ecological specialization under extreme conditions (Wolff, 1983). The size of the Wadden Sea allows the diverse species to survive by spreading over several habitats, or by adopting a series of niches over the course of time. This constantly opens up territory for use by other individuals or species, and accounts for a high capacity to accommodate migratory species. We will work on the Dutch part of the Wadden Sea and will include a small area on a tidal flat near Texel for high-resolution mapping and monitoring.

The second study site to study the robustness of our models is Barr Al Hikman; a mainland peninsula located within the Sultanate of Oman, where team members studied the tropical tidal systems over the past years (Bom et al, 2018a; 2018b; 2018c). The hinterland of the peninsula consists of about 1400 km^2 sabkha (salt areas) where only bacterial and archaeal communities can persist (Vogt et al, 2018). Coastal dunes along with scattered mangrove stands of *Avicennia marina* form a narrow 5–20m fringe between the sabkhas and the intertidal mudflats (Fouda & Al-Muharrami, 1995). The intertidal area consists of about 190 km^2 mudflats and some scattered reefs. Basic ecological research showed that the intertidal and sublittoral area of Barr Al Hikman is an important (nursery) area for marine animals including turtles, whales, shorebirds and shrimps (Bom et al, 2018b; 2018c).

Over the last 50 years, Oman and most other countries in the Arabian Peninsula abruptly changed from a closed and traditional society into a modern economy. Many of the intertidal mudflats in the area suffered from land reclamation, pollution and overfishing (Sheppard et al, 2010; Burt, 2014). Yet, Barr Al Hikman still features many characteristics of a pristine wadden system (Reise 2005). The area lacks extensive dike constructions that characterize many of the 'modern' intertidal areas (Reise 2005), so hydrodynamic and sedimentary processes resemble what is reported about the coastal areas in Europe a century ago (Lotze et al, 2006). The density of shorebirds, who depend on macrozoobenthos for food, was also similar to the densities in other intertidal areas before they decreased in recent decades (Bom et al, 2018b; 2018c).

Methodology

We will process the various images (Sentinel-2, SPOT, PlanetScope, UAV) using the same workflow both in the Dutch Wadden Sea and Barr Al Hikman. We will combine different images with matching ground-truth data to train the algorithms and create maps (figure 3). The images are first transformed into new features by an autoencoder convolution neural network. Object sets are created at different scales to select optimal size, then distribution of selected species is mapped using Random Forests. New object sets are created for locations where presence is predicted to optimize the spatial scale for quantitative mapping. Finally, LASSO regression is applied to create maps of abundance and biomass with the optimal object set. By using images from different dates, temporal dynamics become apparent.

1) <u>Enhanced information extraction</u>

The surface of tidal flats is poor in spectral contrast, so we will develop a method to optimize pattern-information extraction from the images. All imagery will first be radiometrically and atmospherically corrected either through known correction algorithms or the empirical darkest pixel correction. With UAV time series we will use a set of bright and dark reflectors to place on the surface before the flights to ease relative calibration over time. We will use object-based image analysis (Addink et al, 2012) and follow the scale approach (Addink et al, 2007) to optimize prediction accuracy. The optimal object set is likely to differ for each system property, even if the properties seem correlated (Addink et al, 2007). Internal variance steers the object size and by using a range of threshold values on the variance several object sets are created. We model the system property for each set by regression, and select the optimal object set by comparison of the prediction performance.

However, given the low spectral contrast in the original pixel values of the tidal flats, we need a smart optimization. Generally, spectral values of individual pixels determine the objects. Here, we assume surface texture is the key to spot and track the macrozoobenthos, which often live underneath the surface. Hence, we aim to work with features that capture the spatial pattern. From these features, we will then create objects, so the information that we assume relevant, forms the basis of the object sets. **Generating new features describing the image patterns is hence the first major step in the project** (Features (1), figure 3).

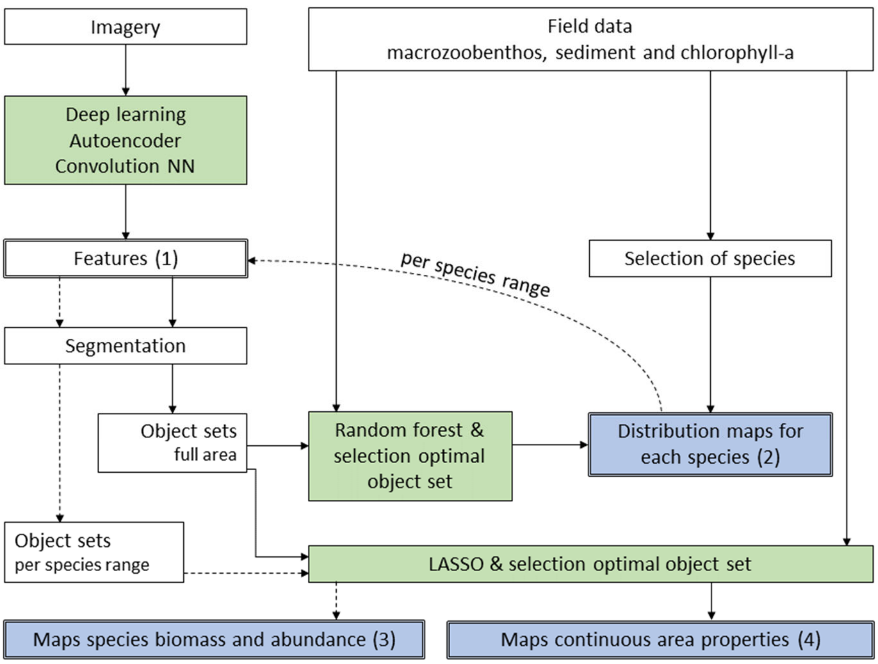

Figure 3. Overview of the method with data analysis (in green) and resulting products (in blue). Dashed lines indicate that the area considered is limited to the range of an individual species. Numbers between brackets refer to project results.

The deep neural network (NN), as a representational learning model, maps input data to target output (LeCun et al, 2015; Schmidhuber, 2015). It creates hierarchical features capturing different levels of information in the input data. A NN is trained using pairs of raw data input and labelled output without preprocessing of the raw data, in our case reflectance values. During training of the NN, forward propagation steers the input data through the network. This consists of a series of hidden layers of nodes connected by edges, where the output of each layer is the input for the next layer. In each of the layers, the edges and nodes apply linear weights and non-linear activations to produce a representation of the input data. The prediction error at the output layer is then sent back to the NN along the edges through backpropagation to guide the update of weights. The weights are considered properly tuned when the NN error is under a set threshold. Each layer of the network then produces meaningful, hierarchical features. The convolutional NN (CNN) can take remote-sensing images into the network as a multi-dimensional data array. The images are internally split into image patches of a fixed size and led through the network. Both spatial and spectral configurations in the images remain (LeCun et al, 2015). The generated features describe different levels of the spatial and spectral patterns of the input image.

We will apply a special type of CNN named autoencoder to generate our desired features (Baccouche et al 2012; Geng et al 2015; Guo et al 2016; Leng et al 2015). The autoencoder can be trained in an unsupervised manner, where the input and output are identical, and without ground-truth data (Hinton and Salakhutdinov, 2006). Thus, it learns representational features at the encoder part so it can restore the input image at the decoder part (Figure 4). The features are derived through filters and the number of features equals the number of filters designed in the autoencoder. For instance, if a set of 32 filters is applied to a 4-band input image patch at the first block, a set of 32 feature maps will be produced to characterize the input image. These feature maps together form a full representation of the patterns in an image. They are ideal for our purpose to describe the texture of the spectrally poor tidal flats. So, by extracting these feature maps we obtain the input for the creation of the object sets.

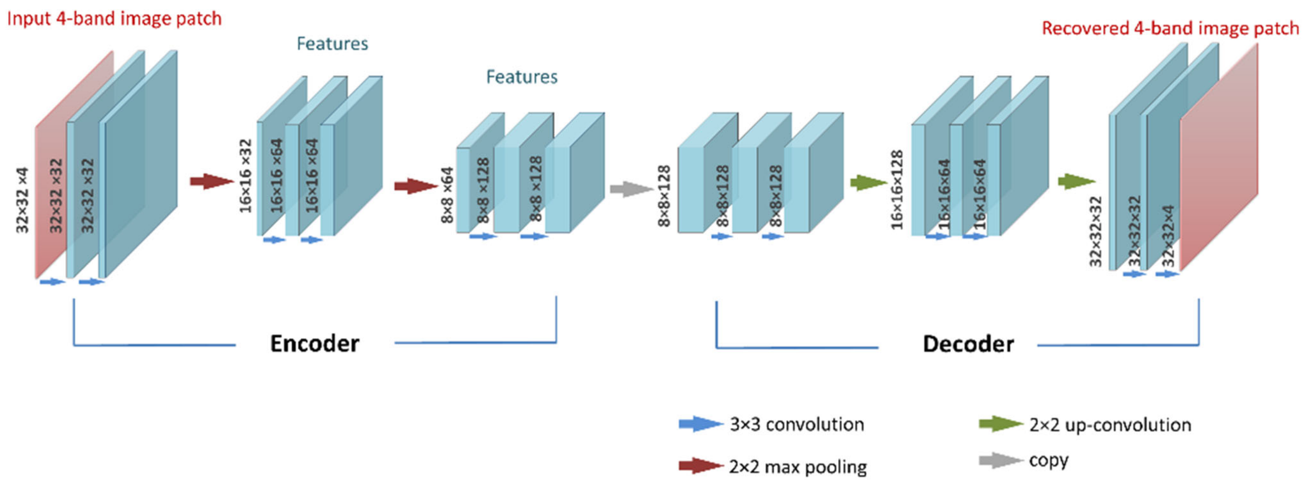

Figure 4. Illustration of Convolution Neural Network autoencoder. The original image is reduced through a set of filters to feature maps from which it can be reconstructed. In red the original image, in blue the blocks with filters. The filters and associated weights on the encoder side are used inversely on the decoder side to reconstruct the original image. Here we are not interested in reconstruction, but in the features from which it can be reconstructed, and which describe the image.

2) *Mapping macrozoobenthos distribution, abundance, biomass and habitat*

From the object sets we will create binary distribution maps for individual species. The object sets will range in median object size to include spatial surface patterns at different scales. We will link the ground-truth data on species occurrence to the object sets and their newly created CNN features. By applying Random Forests (Breiman, 2001) we will create a distribution map for each species and for each object set. Random Forests are a set of multiple classification trees, where each tree is built by a random subset of the training objects and their features. An unknown object will be led through all trees and a majority vote determines which class -here presence or absence- will be assigned. By splitting the ground-truth data in two, we can train on one part and validate on the other part. **The object set performing best on the validation set will provide the species distribution map** (Maps (2), figure 3).

Besides these binary distribution maps, we will create continuous maps on quantitative variables. For total biomass, species diversity, chlorophyll-a and sediment the maps will cover the full study site (Maps (4), figure 3). For species abundance and biomass, the range of the specific species will determine the spatial extent within the study site (Maps (3), figure 3). For the latter two, new object sets will be created for the range of each species. Besides this spatial distinction, the procedure for Maps (3) and (4) is identical. We will link the object sets to quantitative ground-truth data. For each object set and each variable we will run LASSO (Least Absolute Shrinkage and Selection Operator) (Tibshirani, 1996) and create maps. LASSO is a shrinkage-regression method limiting the size of the coefficients to avoid overfitting. This is particularly relevant for the species-specific maps, as the number of observations may be low which leads to increased sensitivity for overfitting. For each variable we will produce a map for each object set. **By validating the different maps, we can select the optimal object sets for chlorophyll-a, sediment, and species/total abundance and biomass**.

Both Random Forests and LASSO provide the relative importance of the features. When returning to the object definition, new object sets can be created by only including relevant features. This will make the method more generic and allows predicting with tailor-made objects.

3) *Dynamics of macrozoobenthos and their habitat*

Currently, most studies on macrozoobenthos distribution collect data in a single season and look at environmental conditions for the different species within that season (e.g. Compton et al, 2013). Over the seasons, species develop though and might require different conditions for optimal functioning like the lugworm move to coarser sediment and the bivalves include phytoplankton in their diet next to microphytobenthos (Flach & Beukema, 1994; Rossi et al, 2004; Jung et al 2019). By collecting field data in the different seasons and applying our methodology (figure 3) using images with different spatial resolution, we can create maps over time, capturing seasonal and annual dynamics at different scales (figure 5). We will have full coverage maps on species distribution and will study the dynamic relation between species and environmental factors. This will provide unique ecological insights in the dynamics of macrozoobenthos and their habitat.

Implementation

Image data

The methodology described is in potential applicable to any image in combination with field data. To capture the fine-scale patterns of macrozoobenthos distribution, we will limit the use of images with a spatial resolution ranging from 5cm (UAV), 3m (PlanetScope), 5m (SPOT) to 10/20m (Sentinel). With the increasing spatial resolution, we can study the effect of spatial detail and produce maps for the Dutch Wadden Sea and Barr Al Hikman. The different images will represent specific surface textures. Besides, the spectral information content increases with decreasing spatial resolution. We will explore how these effects affect the mapping and monitoring.

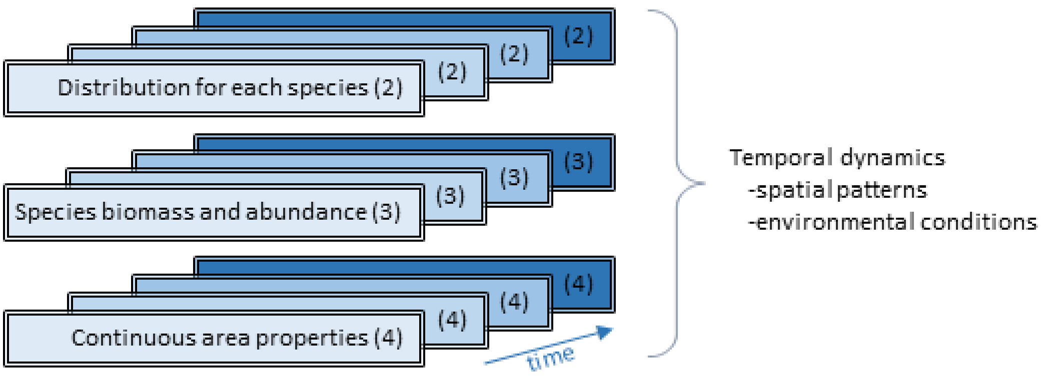

Figure 5. Monitoring dynamics. Mapping over time provides insight in changing spatial patterns and the shifting relations between species and environmental conditions. Numbers correspond to those in figure 3.

Sentinel-2 imagery (ESA, 2019) will be used as its extent provides an overview of a large area. Images are available since 2015. The optical and Near-Infrared (NIR) bands with 10 and 20m resolution will be used. The revisit time of Sentinel-2 is five days, but as wadden systems are submerged twice a day, image acquisition should coincide with both cloudfree conditions and low tide. This reduces effective image collection to a few times per year. Next, we will use Planetscope data (Planet, 2019); first available in 2015. These are collected on a daily base, have a pixel size of 3.1m for the ortho-images and come in tiles of 25x25 km^2. The daily acquisition significantly improves the hit chance of both cloudfree and low-tide conditions. Besides Sentinel and Planetscope, we will check Rapid-Eye and SPOT6-7, which have 6m pixels and are available since 2008 resp. 2012. This offers additional input to the range of spatial resolutions and adds to the temporal component as well. We will check their archives to identify cloudfree and low-tide images. The exact location and extent of the macrozoobenthos maps will be steered by the availability of imagery.

Field data

Ground truth data for this study will be collected on Texel and Barr Al Hikman together with UAV image acquisition. Sample data from the Wadden Sea is available from the Synoptic Intertidal Benthic Survey (SIBES) database collected and managed by NIOZ. It is built from an annual spatially comprehensive monitoring campaign, starting in 2008, within the Wadden Sea (the Dutch Wadden Sea and recently also an adjacent part of the German Wadden Sea) (Bijleveld et al, 2012; Compton et al, 2013; Christianen et al, 2017). The SIBES program covers the entire intertidal area and consists of gridded samples taken at 500 m intervals and additional random samples (~4500 samples per year). At each point sediment samples are taken from the surface to determine chlorophyll-a concentration and particle size distribution. For macrozoobenthos sediment cores (25 cm depth, core surface of 0.018 m^2) are sieved on a 1-mm^2 sieve in the field for counting and identification. Samples are identified to species level or the finest taxonomic level possible at the Netherlands Institute for Sea Research (NIOZ, Texel, The Netherlands) and per species biomass (ash free dry mass; AFDM) is determined.

Higher sample point density is required for the UAV area. Fieldwork is here split in two parts. First, UAV data are collected to avoid effects of foot prints on the tidal flat on spatial patterns in the UAV images. Photos are collected with 80% overlap and taken at nadir and at 70˚ forward looking for optimal orthophoto creation. Second, samples are taken at fixed points along transects. Each point is traced back by a hand-held GPS, after which its exact location is determined by dGPS. This way, repeated sampling at exactly the same spot is avoided as this has an unknown impact on the macrozoobenthos.

For Barr Al Hikman UAV and ground data are collected using a similar protocol; images are recorded before accessing the tidal flats for sampling.

Species selection

Diversity of macrozoobenthos species in the study area is large and all species are identified and processed from the samples, but for the species-specific maps (maps 3, figure 3) we will work with a selection. Species are selected to represent each functional group with several species having 25+ observations and a distribution ranging between 20 to 80% of the observation points.

Rationale for using space infrastructure

Remote sensing provides spatially continuous information from which we can derive the distribution and seasonal dynamics of macrozoobenthos. This cannot be achieved by fieldwork as tidal flats are vast and inaccessible, and fieldwork is expensive.

Innovative aspects

- We develop a novel method to map and monitor macrozoobenthos from remote sensing images, both in temperate and tropical climates. Macrozoobenthos form the intermediate level of the food web on tidal flats and are essential for fish and birds. Their status is indicative for ecosystem quality, but so far, no information on their presence and dynamics is available.
- Detailed information on macrozoobenthos distribution and dynamics will contribute to an improved understanding of tidal-flat ecosystem functioning.
- Deep-learning methods provide image features normally not accounted for in remote-sensing analysis. We leverage their potential to create indicators of surface patterns which are essential for mapping macrozoobenthos in our spectrally poor environments.

Scientific significance and impact

Successful completion of the project yields optimized remote-sensing methods to map and monitor macrozoobenthos in wadden systems in both tropical and temperate regions. We learn how much ground truth is required, how seasonal variation affects the algorithms, what the effect of spatial resolution is, and if the algorithms can be transferred between different regions. We will use the information obtained from our method to help inform policy makers on activities affecting wadden systems and in the monitoring of these systems. This is a major step to preserve these ecological treasures.

7b. Literature references

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