SATELLITE DERIVED BATHYMETRY FOR MONITORING NEARSHORE DYNAMICS

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INTRODUCTION

Research on the physical, ecological, and environmental processes in the coastal zone traditionally rely on the availability of accurate seafloor topography (bathymetry) information. This information becomes increasingly important as coastal environments are under pressure by climate change and anthropogenic developments. Nonetheless, the bathymetry of shallow nearshore waters is only marginally monitored by cost- and time-intensive survey techniques that are dependent on in-field environmental conditions. Here, Satellite Derived Bathymetry (SDB) offers a valuable alternative to enrich available bathymetric data in both data sparse and data rich environments (see Figure 1), reducing the need for in-situ measurements in the future. The high spatial and temporal resolution of satellite imagery yields a more comprehensive understanding of our coast and its dynamics. Yet, consistently mapping temporal change is still challenging, as the majority of currently available empirical SDB algorithms are heavily dependent on in-situ data for calibration purposes. In this study we present a methodology for assessing nearshore horizontal morphodynamics using the uncalibrated reflectance signal from satellite sensors while focusing on the Friese Zeegat, a tidal inlet of the Dutch Wadden Sea.

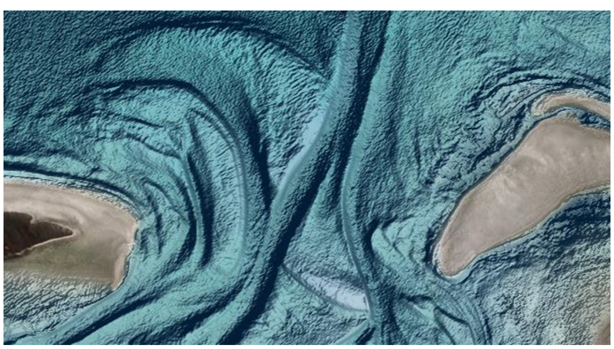

Figure 1 – Satellite Derived Bathymetry (2019) for the Friese Zeegat, a tidal inlet between the islands Ameland and Schiermonnikoog (Wadden Sea), The Netherlands.

BACKGROUND

Space-borne remote sensing potentially provides a tool for global bathymetric mapping with frequently recorded data, albeit at lower resolution than multi-beam sonar or airborne lidar surveys (Burgers, 2020). Obtaining SDB from optical sensors has been extensively studied since the 1970's (Lyzenga, 1978). The spatiotemporal resolution of optical imagery has since increased significantly, for example with the launch of Sentinel-2 satellites. Multispectral imagery from this mission is publicly available with a revisit time up to five days and a spatial resolution of ten meter for its visible and near-infrared bands (European Space Agency, 2015). Data from space sensors also becomes more easily accessible for instance through services such as the Google Earth Engine (GEE, Gorelick et al., 2017). Furthermore, SDB is not limited to a certain spatial extent, allows for monitoring at higher temporal scales, is less costly, less time consuming and not (directly) dependent on in-field conditions.

Estimation methodologies that obtain bathymetry from spectral information vary from empirical to (semi-) analytical models. Analytical approaches simulate the propagation of light through the atmosphere and the water column by inversion of radiative transfer models (Hedley et al., 2009 and Lee et al., 1999). Although analytical models require no in-situ data for calibration, these approaches are strongly dependent on knowledge of the optical properties of the ocean and the characteristics of the seafloor (Gao, 2009 and Hedley et al., 2009). Empirical approaches derive a relation between the intensity of a spectral image and in-situ depth data, for which methods vary from simplified models (Lyzenga, 1978) to extensive Machine Learning techniques (Sagawa et al., 2019). In any case, most bathymetry estimation methodologies are heavily dependent on in-situ data, whether these are measurements of optical water properties as input for analytical models or depth data to train empirical models.

The ability of SDB to supplement in-situ data also has other limiting factors. Emitted sunlight cannot penetrate the water column infinitely and hence SDB is restricted to a certain water depth (i.e. nearshore areas). This depth is further reduced by in-water characteristics like turbidity and algae. Besides, cloud (shadow) cover and sunlight intensity prohibit the use of optical satellite imagery in its entirety for certain periods of the year (mostly in winter).

METHODS

To exploit the uncalibrated reflectance signal (called depth proxy) from Top of Atmosphere (TOA) images from the Landsat-8 (NASA) and Sentinel-2 (ESA) missions, we make use of the compositing technique explained in Donchyts et al. (2016). Compositing allows to reduce local and high frequent noise from drivers of inaccuracy such as clouds and waves. The depth proxy (D) is computed as the log-scaled weighted-average of the inverse-depth relation, where the weights are derived from the spatio-temporal variability of reflectance (see eq. 1 and 2).

$$D = E[d] = \sum d * w(f_{clouds}, x, y, t) \quad (1)$$
$$d = \log(\rho - \rho_{deep}) \quad (2)$$

Accessing single images within each depth proxy composite enables to assess the validity and feasibility of using the method to compute bathymetric information. Newly generated insights in the sensitivity of amongst others the cloud frequency threshold and the composite window allow to tune the depth proxies accordingly for regional and local applications.

By concatenating the depth proxies over time and subsequently computing its maxima and minima per pixel, we derived the so-called Depth Proxy Heat Maps (DPHMs, see Figure 2). The heat maps indicate historical seabed mobility levels at nearshore areas for various time windows and allow to qualitatively inspect morphodynamics possibly anywhere in the world.

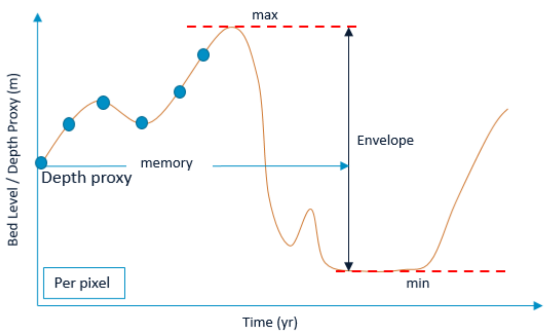

Figure 2 - Schematic pixel-based visualization of the method to create Depth Proxy Heat Maps.

On top of that, a 2DV-tool is developed to assess the morphodynamic behaviour of various coastal features over time quantitatively. Along a transect, depth proxies are detrended by means of linear regression to remove the bias induced by the Darkest Object Subtraction (DOS) in the compositing procedure. Whenever the signal to noise ratio is sufficiently large, distinct coastal features become apparent. Applying 1D cross-correlation allows to compute quantitative characteristics like migration rate and direction. The tool is applicable for the detection of migrating sand bars / waves, sand banks or shoals, flats, channels and / or local depressions and could also be supplemented with validation data for calibration or interpretation purposes.

RESULTS

Figure 3 gives insight in the available satellite images within the Friese Zeegat area (see Figure 1) between 2015 and 2022. Here, green lines (298) represent all single images included in the depth proxy composites. The composite window is set at 2 years and the cloud frequency threshold is equal to the MODIS sensor mean annual cloud fraction in the area of interest. The transparent blue and purple lines (578) indicate the cloud-filtered Sentinel-2 and Landsat-8 images respectively. The outcome is in line with the fact that on average about 60 to 80% of the Netherlands is covered with clouds annually, although seasonally there is quite some variation. The seasonality in cloud cover is indicated by the monthly green-boxed numbers at the bottom of Figure 3. The winter and autumn months contain about half the usable images of the spring and summer months. The influence of the Sentinel-2 mission is also clearly visible as the number of usable images (green-boxed vertical numbers) picks up from mid-2017 onwards (after Sentinel-2B became operational). This number peaks at 62 in 2018, caused by an anomaly in cloud cover, after which it stabilizes to around 50 usable images per year. The recent launch of Landsat-9 will increase the number of usable images in the analysis even more; however, this mission is not yet incorporated into the workflow.

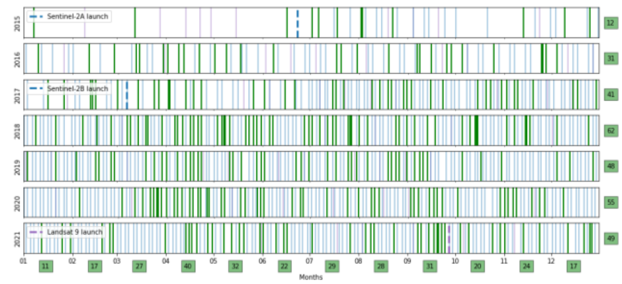

Figure 3 - Available Landsat-8 and Sentinel-2 images for the period between 2015 and 2022. Transparent blue and purple lines represent all satellite images for the Friese Zeegat, green lines represent the remaining images after filtering cloudy images. The green-boxed numbers on the bottom and right represent periodic counters.

The computed DPHM for the Friese Zeegat is visualized in Figure 4. This (static) heat map indicates historical seabed mobility levels over the complete timespan of available satellite data (2015-2022). The bright yellow / orange colours indicate highly mobile areas whereas the darker purple / black colours indicate static or deep seabeds. The map can be browsed interactively for the complete Wadden Sea area in a beta-version web viewer (GEE app) available through the following link: https://etiennekras.users.earthengine.app/view/jip-calm-depth-proxy-heat-map. This viewer, which is still under development, is stated to represent a quick assessment tool to explore morphodynamic areas regionally and qualitatively.

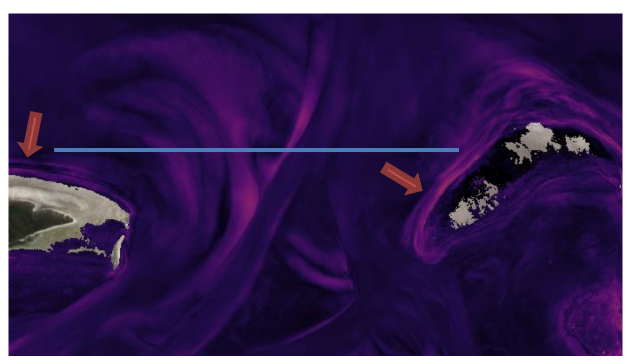

Figure 4 - Depth Proxy Heat Map for the Friese Zeegat. Brighter yellow / orange colours indicate dynamic, darker purple / black non-mobile or deep areas. The blue line (transect) is used by the 2DV-tool for a quantitative assessment of horizontal dynamics. The red arrows indicate dynamic shore-parallel sand bars.

Figure 4 shows that the tidal inlet and ebb-tidal delta consist of some highly dynamic coastal features (bright colours) such as shoals and channels. Here, highly dynamic refers to large horizontal displacements, as vertical changes are not traceable (only made insightful) because of the usage of uncalibrated depth proxies. The shore-parallel sand bars in front of the island Ameland (left) and the sand bank 'Het Rif' (right) also show dynamic behaviour (indicated with red arrows).

The 2DV-tool allows to assess local horizontal dynamics (migration rate and directions) of various coastal features in the nearshore area over time. Figure 5 explores the dynamics along the blue transect shown in Figure 4. As seen from the legend, the local assessment uses a composite interval of 1 year. This deviates from the standardized regional-scale 2-year composite interval used in the web viewer. By decreasing the composite window, we inherently include more noise but do not smooth out some very fast-moving features. At this location, it was found to be feasible to decrease the composite window while not compromising the quality of the output. The trade-off in the composite window is very much dependent upon system characteristics (i.e. moving speeds & distinctiveness of the features) and environmental parameters (i.e. turbidity & cloud cover).

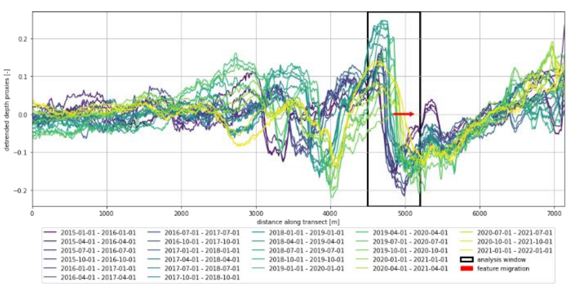

Figure 5 – The 2DV-tool derived morphodynamics along the blue transect in Figure 4. Depth proxies are coloured from historic (purple) to more recent years (yellow). Quantitative information can be derived by setting the analysis window.

The parts from approximately 0 to 2000 and 5500 to 7100 m (see Figure 5) show some very noisy depth proxies over time, where no clear movement of any feature could be distinguished. This is confirmed in Figure 4 where these areas show dark colours and hence indicate either no movement of the seabed or areas too deep to trace seabed movement for. From 2000 to 5500 m, the signal to noise ratio is large. This allows to distinguish three (dynamic) coastal features; two shoals and a channel. The most distinct shoal (see analysis window in Figure 5) is found to be moved 274 m in eastward direction, leading to a change rate of 46 m/year. This is indicated by the red arrow. The channel (2900 to 4500 m) is found to have an average but decelerating change rate of 122 m/year, while the shoal (5200 to 5500 m) is stable (i.e. change rate is close to 0 m/year). These satellite-based quantifications of horizontal dynamics are found to be comparable to the dynamics derived from assessments using solely in-situ (Vaklodingen) data for the same area.

CONCLUSION, IMPACT AND DISCUSSION

A combination of the here-presented DPHMs (web viewer) and 2DV-tool allows to quickly obtain insights and accurately assess the horizontal dynamics (migration rate and directions) of various coastal features like sand bars / waves, sand banks or shoals, tidal flats, channels, and local depressions in the nearshore area. This could potentially be applied anywhere across the world, also in data sparse environments such as Small Island Developing States if in-water characteristics allow. The result is a cost- and time-efficient derivation of first-order insights (including inter-annual variability) to shape system understanding. Horizontal nearshore morphodynamics are relevant for many engineering applications like the planning of cable landfalls and dredging- and nourishment activities as well as to revise the schedule of expensive monitoring campaigns.

In the future it is opted to enhance the outlined methodology with an assessment on in-water characteristics like turbidity or algae. This would significantly improve the quality of composite images, especially in challenging environments.

ACKNOWLEDGEMENT

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