Rapid cloud-based temporal compositing of Sentinel-1 radar imagery for epibenthic shellfish inventory

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ABSTRACT

Delineation of shellfish beds through field surveys is time consuming. Remote sensing can help in detecting the location and boundaries of shellfish beds. This can be achieved through the use of aerial photographs and optical satellite sensors during cloud-free and low-tide conditions. Cloud penetrating radar is an alternative, but still requires careful selection of low tide imagery. Manual selection becomes cumbersome for large areas, such as the entire Dutch Wadden Sea. We therefore developed a method that automatically combines dense time series of Sentinel-1 radar imagery into a useful mosaic that allows for effective delineation of shellfish beds. The method consists of temporal compositing many images in the cloud-based Google Earth Engine. We evaluated different combinations of 1) compositing options (average backscatter and various percentiles), 2) temporal periods for compositing, 3) different polarizations, and 4) imagery from ascending versus descending satellite paths. The resulting composite images were visually compared with in-situ records to identify which composite visually best allowed for shellfish bed delineation. Although the average VH-polarized backscatter for one full year provided effective demarcation, an RGB color composite containing three average VH images for four months each provided improved visibility of the shellfish beds. We then quantitatively compared which compositing option was most effective in separating pixels with shellfish beds from those without. For this purpose, the unsupervised classification approach of K-means clustering was applied to the different composite images, and outcomes (i.e. selected classes) were compared with field data derived from the annual in-situ survey. The multi-season image composites (i.e. Jan–Apr, May–Aug, and Sep–Dec) that were made by combining VH image acquisitions of only descending and of combined ascending and descending paths resulted in higher accuracies than other compositing options tested. The producer and user accuracy of the multi-season descending composite were respectively 40% and 70% for the full Dutch Wadden Sea, against 59% and 73% for a smaller subset. These accuracies are similar to what is previously achieved for small study areas with carefully selected radar images acquired around low tide. Moreover, our approach could identify various shellfish beds that were initially missed by the in-situ surveys, but for which later the presence was confirmed (so the actual producer accuracy would increase to about 82%). The composite images can be created on the fly with Google Earth Engine shortly before a field campaign and used as a base for sampling design.

1. Introduction

Bivalve shellfish play an important role in the functioning of marine and estuarine ecosystems (Dame, 1996). By adding structural complexity, epibenthic bivalve reefs increase habitat heterogeneity, thereby offering food and shelter to many different species and increasing local biodiversity (Troost, 2010). Through their grazing activity they form a strong link between pelagic and benthic production (Prins et al., 1998), as is the case with all dense aggregations of bivalve filter feeders. In the Wadden Sea these reefs consist of the indigenous blue mussel (Mytilus edulis) and since 2002 also of the Pacific oyster (Crassostrea gigas). The Pacific oyster was introduced in the Dutch Wadden Sea in the late 1970s (Troost, 2010) and was first recorded in an intertidal mussel bed in 2002. The Pacific oyster expanded rapidly, forming dense beds that are often mixed with mussels.

Since 1995, annual monitoring of mussel beds (and since 2002 also...
Extrapolation of a field inventory with remotely sensed images might be a cost efficient approach, similar to terrestrial surveys. The location and boundaries of shellfish beds can be obtained from aerial photographs (Herlyn, 2005) and optical (satellite) sensors (Brockman and Stelzer, 2008). However, the distinction inside a bed between shellfish patches and areas without shellfish can be seen only on very detailed (scale > 1:5000) aerial photographs and the density within patches cannot be derived from aerial photographs (Herlyn, 2005). Visual aerial photo-interpretation from different years has shown to be a good tool for monitoring (Dolch and Reise, 2010; Folmer et al., 2014). However, cloud and water cover severely limit the potential for detection of shellfish beds from aerial photographs and optical sensors (Herlyn, 2005; Brockman and Stelzer, 2008). Because of a limited daytime window of simultaneous cloud-free and low-tide conditions, suitable optical images are rare (Gade et al., 2014). For that reason, cloud penetrating radar imagery is used for the detection of shellfish beds for selected areas (Choe et al., 2012; Adolph et al., 2018), sometimes in combination with optical data (Gade et al., 2014; Jung et al., 2015; Müller et al., 2016), but only for selected small areas. Higher accuracies in radar-based mapping of shellfish beds can be achieved using multi-frequency or multi-satellite data. Multi-temporal radar analysis provides valuable input for more accurate mapping and monitoring (Gade et al., 2014; Gade and Melchionna, 2016).

For radar imagery to be effective in getting a clear signal from shellfish beds, water above those beds should be absent (Müller et al., 2016). Several authors therefore selected suitable images within an hour or so around low tide (Gade et al., 2014; Jung et al., 2015; Gade and Melchionna, 2016). Because the Dutch Wadden Sea has a temporal difference of low tide conditions of 4.5 h between east and west, it is a time consuming challenge to select and mosaic optimal low-tide imagery over the entire area.

We designed a rapid low-cost operational method with Google Earth Engine (GEE) to create a mosaicked image from many radar images without need for manual selection. This resulting composite image effectively visualizes shellfish beds and can serve as a base for fieldwork design. Because the satellite data can be directly accessed through GEE, image acquisition and downloading are not required and there is no need for dedicated software. We tested multiple temporal compositing options, and examined the effect of using different polarizations and satellite overpass directions. Besides a visual assessment of the resulting composite images, we compared automatic classifications of our resulting images with existing field inventories to establish the mapping accuracy. Based on this we selected the optimal method that allows for the best distinction of shellfish beds in the Dutch Wadden Sea.

2. Method

2.1. Study area

The Dutch Wadden Sea (Fig. 1) consists of the southernmost part of the Wadden Sea that stretches from Denmark to the Netherlands along the coastline of the North Sea, behind a series of barrier islands. It is one of the world’s largest systems of intertidal sand and mud flats (Reise 2005; Reise et al., 2010). The area contains a mosaic of intertidal sandbanks and mudflats, drainage gullies and deeper inlets and channels. The tidal amplitude in the Dutch part ranges between 1.5 and 3.0 m. The tidal wave runs from west to east, resulting in a time difference of 4.5 h. The total surface area of intertidal flats is 111,882 ha (Ens et al., 2009) of which between 2,000 and 3,000 ha is covered by beds of mussels (Mytilus edulis) and/or Pacific oysters (Crassostrea gigas) (Folmer et al., 2014; van den Ende et al., 2016; van der Meer et al., 2018).

2.2. Satellite data

We used time series of Sentinel-1 Synthetic Aperture Radar (SAR) images to map the shellfish beds. The Sentinel-1 constellation presently

Fig. 1. Multi-season composite of Sentinel-1 VH data from descending passes acquired in 2016 covering the Dutch Wadden Sea (Red = average Jan–April, Green = average of May–August, and Blue = average of September–December). All three average composites are linear stretched with from –40 to –17. The green line represents the Wadden Sea boundary (extracted as described in Section 2.5). The red rectangle is the subset A boundary (used in Figs. 3 and 5), while the yellow rectangle is the subset B of Fig. 7. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)
and oysters is at least 5% for both the bed is considered a mixed muscle and Pacific oysters (Crassostrea gigas) is 5% or more. If the cover of mussels are prioritized. The boundaries of visited beds are recorded by marking field survey newly developed beds and beds that appear to have changed beds, and whether large portions of beds have disappeared. During the April -

2.3. Annual field mapping of intertidal mussel and oyster beds

The annual field survey by WMR is carried out in the period April–May. In advance, an aerial inspection flight takes place to assess visually whether the shellfish (mussel and/or oyster) beds mapped in the previous year are still present, whether there are newly developed seed beds, and whether large portions of beds have disappeared. During the field survey newly developed beds and beds that appear to have changed are prioritized. The boundaries of visited beds are recorded by marking waypoints in a hand-held GPS device while walking around the bed. The boundary is determined according to the TMAP (Trilateral Monitoring and Assessment Program) protocol (de Vlas et al., 2005; see also Folmer et al., 2014), i.e. a protocol for the Wadden Sea agreed between monitoring agencies of Denmark, Germany, and the Netherlands. According to the protocol, bare areas within beds are considered as part of the bed if the distance between patches covered by mussels and/or oysters is less than 25 m. Also, 5% is the minimum coverage percentage that is still seen as part of a bed. Lower percentages are classified as “scattered mussels or oysters” and only occasionally mapped as separate contours. Such contours of “scatter” were excluded from this study. A bed is considered a mussel bed if the cover by mussels is 5% or more (assessed visually). Similarly, a bed is considered an oyster bed if the cover by Pacific oysters (Grassostrea gigas) is 5% or more. If the cover of mussels and oysters is at least 5% for both the bed is considered a mixed mussel/oyster bed. The three weeks that are available to carry out the field survey are usually insufficient to visit all beds each year, especially in years following a large spatliff of mussels (i.e., the settlement of larva and subsequent metamorphosis into juvenile mussels, by which new mussel beds are formed (Gosling, 2003)). The overall percentage of beds surveyed in the field lies between 40 and 95% for the entire time series. For beds not visited it is assumed that the contour is the same as in the preceding year if the aerial survey confirmed their presence. When a bed is visited in a following year the contour in the missing year is estimated on the basis of the contours before and after the missing year. Sometimes, beds are missed in the aerial inspection flight and subsequent field survey. If these beds survive longer than 1–2 years they may be detected in subsequent years, in which case their age is estimated and the bed contours are projected backwards in time accordingly. Occasionally newly formed beds may not be detected at all, especially if they disappear quickly, as is often the case with mussel seed beds (van der Meer et al., 2018).

2.4. Temporal compositing and visual analysis

The Sentinel-1 imagery were accessed and processed in the cloud, using Google Earth Engine. This enabled us to automatically select and use a large number (hundreds to thousand) of images without the need of downloading them. Besides an internet connection, no other specialized software for image analysis is required. In this way, we could create a temporal composite out of about thousand images in less than 5 min.

Based on visual comparison between the temporal Sentinel-1 composites for 2016 and the WMR 2016 polygons, we examined which polarization (VH or VV), satellite overpass path direction, and temporal compositing approach (average, minimum, maximum, 25th, 40th, 50th, and 75th percentiles) visually resulted in the clearest identification of known shellfish beds. When taking percentiles for each pixel all available satellite data where considered; because this is automatically done on a pixel-by-pixel basis, no manual selection procedure is needed and the process automatically accounts for different timings of low water. The logic of using percentiles is that we favor observations during specific conditions. For example, because in radar imagery open (smooth) water causes low backscatter due to specular reflection away from the satellite sensor, low percentiles correspond to higher tide conditions when shellfish beds are covered by water. We also tested different lengths and periods for calculating averages, i.e. per year, per month, as well as three or four months combined. In addition multi-season images, in which three different periods are visualized in red, green and blue were compared against single layered (grey levels) temporal composites.

Some options resulted in a very similar visibility of the shellfish beds, thus not allowing for a clear judgement of one best option. In these cases image classification of the 2016 radar composites was performed for the different options and an accuracy assessment was effectuated by comparing the “shellfish bed” clusters with the 2016 WMR polygons (more detail in Section 2.5 and 2.6). Analyses were performed for the entire Dutch Wadden Sea, and also for a subset with a relatively high density of beds (see Folmer et al., 2014).

2.5. Classification

In order to quantify the agreement in radar detected beds with the field maps, classifications of retained radar composite images of 2016 were performed. For the different options, the single layer annual composite was classified as well as multi-season composite consisting of three layers (with each layer being a composite of four months of radar data). In order to classify these composites, the temporally-aggregated Sentinel-1 images were downloaded from GEE at 30 m resolution for the entire Dutch Wadden Sea area. The multi-season images were stacked in the remote sensing software ERDAS Imagine 2018.

To avoid backscatter from land objects contributing to the classification results, land areas had to be excluded. This was done by creating a polygon surrounding the areas with open water and temporary water cover, excluding land. We used a full year (in this case we used 2018 data, although the results were close to identical for the other years) of Sentinel-1 VH backscatter observations, because the VH backscatter is very low for open water (or flooded surfaces). While this is also true for VV polarization, we found that VH was more effective in differentiating land and water. With GEE, we calculated for each pixel the 25th percentile VH backscatter value over all 2018 Sentinel-1 observations as an optimum value to obtain a single mask of areas that have regular land and water. We used a full year (in this case we used 2018 data, although the results were close to identical for the other years) of Sentinel-1 VH backscatter observations, because the VH backscatter is very low for open water (or flooded surfaces). While this is also true for VV polarization, we found that VH was more effective in differentiating land and water. With GEE, we calculated for each pixel the 25th percentile VH backscatter value over all 2018 Sentinel-1 observations as an optimum value to obtain a single mask of areas that have regular water presence in this tidal landscape, thus also including shellfish beds. Values below the 25th percentile resulted in inclusion of larger parts of the coastline and inland water (which are sometimes flooded), whereas larger values excluded many shellfish beds that we wanted to retain in our mask. Following the percentile calculation, we applied a threshold of ~28 dB; i.e. values with a 25th percentile VH backscatter below this threshold were retained in our mask. While the masking procedure is incorporating both Wadden Sea and North Sea; we removed the North Sea part from our mask by drawing straight lines between the islands and/or island and main land. To reduce edge effects in classification of land water boundaries a 100 m buffer inside was selected. However, areas within the 100m buffer containing WMR polygons were retained in our mask.

Unsupervised k-means clustering (ERDAS Imagine 2018) with 100
The majority filter was applied (Westinga et al., 2013). The effect of applying the majority filter was used on the binary classification result. Three consecutive times a $3 \times 3$ majority filter was applied (Westinga et al., 2013). The effect of applying the majority filter was evaluated for the best compositing option. The surface amount of removed classified beds by applying the majority filter, was calculated in and outside the WMR polygons.

### 2.6. Accuracy assessment

The filtered classified images were then converted to polygons and the projection transformed to the Dutch RD coordinate system (EPSG: 28992) in ArcMap 10.6. The classified polygons were crossed (Union) with the WMR inventory. Polygons with very small area size were subsequently removed, as these were caused by slivers. This procedure is similar to other shellfish beds mapping efforts (e.g. Jung et al., 2015).

Here we used the smallest mappable unit (Westinga et al., 2020) at 1: 10 000 scale, which corresponds to an area of 2,500 m$^2$.

The surface area of the polygons was summed in order to get all four binary class combinations of the bed presence/absence for both the radar-based classification and the WMR survey. Based on these totals, the overall, producer and user accuracy were calculated. The overall accuracy is the sum of true positive areas (i.e. actual shellfish beds that are classified as such) and true negative areas divided by the total area.

We note that due to the relatively large size of true negative areas, the overall accuracy will be very high, and consequently the other accuracy measures may be more informative about the effectiveness of shellfish bed detection. The producer accuracy (or sensitivity) is the true positive areas divided by the total amount of WMR beds (or the sum of true positive and false negative areas). The user accuracy (or precision) is the true positive areas divided by the total area of classified beds (or sum of true positive and false positive). Given that ultimately a high user and producer accuracy is desired, we also averaged both metrics to obtain the average accuracy (e.g., Vrieling et al., 2007). The accuracy assessment was performed for the entire Dutch Wadden Sea and for subset A (see Fig. 1). While the selection of composites and accuracy assessment focused on the year 2016, we additionally applied the best compositing option to the years 2017 and 2018 to demonstrate that the method can be effectively transferred to other years.

### 2.7. Comparison at fine spatial detail

Although the WMR polygons were used as field validation, these are also an interpretation of reality. The level of detail of the polygons is determined by the protocol used. As a means to aid in the interpretation of the radar composites in comparison with the WMR polygons we carried out a small-scale comparison with aerial photographs in combination with field validation visits. Based on aerial photographs of 2017, a design was made for a field validation campaign as part of an MSc study in 2017 (Nasimiyu, 2018). These aerial photographs have a 25 cm spatial resolution, were commissioned by the Dutch government, and are made available through Esri Nederland Content via ArcGIS online [https://geodata.nationaalgeoregister.nl/luchtfoto/rgb/wms?request=GetCapabilities&service=WMS](https://geodata.nationaalgeoregister.nl/luchtfoto/rgb/wms?reuest=GetCapabilities&service=WMS). To make the best use of the limited budget and available time in the 2017 field campaign, field visits were restricted to seven locations accessible from land. Selection of these seven locations was based on the 2016 WMR inventory and aerial photographs of 2017. In advance, detailed photo interpretations were made of the seven beds. For field validation of the photo interpretation, sections of bed contours were recorded using a hand-held GPS and mapped using ArcPad 7 software on an IPAQ 2700 pocket PC. In addition, waypoints were recorded with Locus Map Pro on a mobile phone. At each waypoint a visual estimation of the shellfish bed cover was made. The time available for measurements per visit was restricted by the tides, and ranged from approximately 2 to 3 h. The recorded field data of 2017 and polygons of WMR 2016 were then overlaid on aerial photos of 2017 and on the radar composite image in ArcGIS to evaluate if the radar composites allowed for effectively capturing the fine spatial detail of the shellfish bed contours.

### 2.8. Change detection

To demonstrate the potential for change detection the optimal radar composites for 2016, 2017 and 2018 were combined in one multi-annual RGB composite image for subset B (Fig. 1). This was overlaid with polygons of WMR inventories of 2016, 2017 and 2018. Based on this overlay we visually examined to what extent the multi-annual image corresponded with the WMR polygons.

### 3. Results

#### 3.1. Visual comparison of temporal radar composites

We first evaluated visually if VV or VH, and descending or ascending passes, resulted in a clear composite that allowed to depict shellfish beds. The average of all VV acquisitions of one year (2016) revealed clearly discernible gully patterns, but shellfish beds could hardly be distinguished from the mudflats. The average of VH clearly showed the beds in descending and ascending orbit. Descending VH showed slightly less speckle than ascending VH and was therefore chosen to further evaluate different percentiles and temporal compositing periods.

Fig. 1 displays a multi-season Sentinel-1 VH composite image for the entire Dutch Wadden Sea. It shows a few clear vertical lines over the water areas, which corresponds to the transition from one satellite swath to the next. The amount of speckle increases from east to west within a swath, visible as lighter areas in Fig. 1.

When comparing different temporal compositing approaches (Fig. 2) the minimum of VH descending satellite radar data of 2016 showed a completely black image over the Wadden Sea area with no backscatter of shellfish beds at all; this is likely due to the fact that the minimum backscatter corresponds to inundated (high tide) conditions when most radar backscatter is away from the satellite sensor because of specular reflection. Similarly, also the 25th percentile gave an almost entirely black image for the Wadden Sea area, because it still selects moments of high water. The 40th percentile looked similar as the average and the beds showed a clearly distinct backscatter on the images. The 50th percentile (median) had a similar appearance as well, but with slightly more speckle. The 75th percentile showed all beds, but also considerably more speckle, and the maximum had an even higher degree of speckle. This speckle can be observed as small-scale variation in grey levels, which is due to the combination of constructive and destructive interference of radar waves. This interference is larger for surfaces that are rough on the scale of the wavelength (i.e., 5.6 cm for Sentinel-1), resulting consequently in more speckle for low water conditions with higher exposure of sand banks, shellfish beds, and gully sides. Also waves cause a spatial variability in backscatter and increased speckled appearance of the image.

Given that the average backscatter produced good results, we used this temporal measure to now evaluate the best time period for temporal averaging. We found that on the average composite image for the whole year more shellfish bed area is visible than on composite images of a single month or of a period of several months. However, combining information from multiple time periods into a single RGB composite
image (Fig. 1) provides a slightly better visual differentiation of shellfish beds. To illustrate this in more detail, Fig. 3 shows a spatial subset of the same image in Fig. 1, although stretched differently to better discern the shellfish beds.

For visual interpretation of the shellfish beds the optimum linear stretch is from $-30$ to $-10$ dB (Figs. 2, 3 and 6B). The beds have values in the range of $-27$ to $-24$ dB and appear in greyish tones, while mud and water are black. Land surfaces have many different colors. The beds visible in the radar composite in Fig. 3 are mostly contained in the WMR shellfish bed polygons. Four large areas (>1 ha) are visible which are not inside a polygon and are indicated with a green rectangle in Fig. 3. An explanation is given in Section 3.2.

### 3.2. Classification and accuracy assessment of temporal Sentinel-1 composites

Given that radar composites from ascending versus descending passes gave a similar visual result, we used image classification to decide which pass direction would result in higher accuracies. Temporal radar composites from each individual pass direction were downloaded, classified and compared with the WMR polygons. In addition, ascending and descending paths were also combined in two different ways. First, the average was taken of all combined VH acquisitions (ascending + descending), and second, a two-layered composite was made with one layer containing the composite of all scenes from ascending, the other of scenes from descending paths. For the four options (i.e. ascending only, descending only, ascending + descending in a single composite, ascending + descending in a two-layered composite), we calculated both the average over the full year 2016 and a multi-season composite (January–April, May–August, September–December). The results of the overlay with the 2016 WMR polygons is presented in terms of overall, producer, user, and average accuracy (Table 1).

The ascending composites (i.e. annual and multi-season) have the lowest average accuracy among all options (Table 1). For the remaining
composites, the average accuracy of classifications based on the multi-season VH images (combining multiple composites within one year) are higher than for the annual VH images. This is predominantly due to their higher user accuracy, which indicates that a larger portion of the classified beds are actual beds.

Although the six-layer multi-season composite that combines the averages of all VH (descending and ascending paths) has the highest average accuracy (Table 1), the multi-season VH descending is preferred for the visual interpretation because only three layers can be visualized in a single image. When repeating the same classification approach to the multi-season VH descending for 2017 and 2018 and comparing these with the WMR polygons for those years, we obtained an average accuracy of 51.93 and 52.52, respectively. The similar accuracy values suggest that our classification approach is robust over the years. The classification of the VH descending multi-season image of the entire Wadden Sea (Fig. 1) is presented in Fig. 4. Two classes were separated; beds and no beds. The cluster corresponding to the shellfish beds had an average backscatter of about $26\text{ dB}$ for all three time periods of the year, with a standard deviation of approximately $1.5\text{ dB}$. In order to visualize the comparison with the WMR polygons of 2016, this data is presented for the subset A in Fig. 5. Most of the radar-based detection of shellfish beds in the study area (Fig. 5) correspond with the WMR field inventory. Within subset A the overall accuracy for the multi-season VH descending composite is 97.64%, the producer accuracy 59.13% and user accuracy 72.58%.

Along the coast the reflection of poles (groynes) is visible in Fig. 3 and classified as beds in the form of lines perpendicular to the coast (Fig. 5). These land reclamation poles occur between the white line in Fig. 5 and the coast. Given that these are well-known structures that are not directly related to shellfish beds, visual interpretation would rapidly discard these areas as potential shellfish beds. The total classified areas within the white line and the coast amounts to 6.8 ha.

From the four large areas classified as beds and not contained in the polygons two are proven mussel beds in the 2018 WMR inventory. Area 1 (4.5 ha) was mapped in the field in the spring of 2017. At that time the mussels present were estimated to be more than two winters old, which means the bed must have been already present in the spring of 2016. Area 2 (7 ha) was mapped in the field in the spring of 2017, when it mainly contained seed mussels and a scattering of older mussels. The seed mussels likely settled in the summer of 2016, and the bed structure had become visible by eye in the course of the summer, and was obviously picked up by the radar composite. Area 3 (5 ha) was recorded in the field in spring of 2018. At that time it consisted mainly of older Pacific oysters, meaning the bed had already been present for at least a couple of years. Area 4 (17.5 ha) was not validated in the field, due to its poor accessibility (extremely muddy). The aerial photo of 2017 suggests there may be a bed present, but whether it is actually a live bed or shell rubble with perhaps a scattering of oysters and/or mussels cannot be established until a further field visit. Excluding the areas along the coast within the white line (Fig. 5) and accounting the four areas (34 ha) as correct the overall accuracy increases to 97.94%, the producer accuracy to 61.67% and user accuracy to 82.08%.

**Table 1**

Overall, producer, user and average accuracy of the 2016 average VH images as compared with the 2016 WMR polygons. The composites are sorted on average accuracy.

| Composites used                                      | No. of layers | overall accuracy | producer accuracy | user accuracy | average accuracy |
|------------------------------------------------------|---------------|------------------|-------------------|---------------|-----------------|
| Multi-season ascending and descending                | 6             | 99.31            | 37.73             | 72.48         | 55.10           |
| Descending multi-season                              | 3             | 99.31            | 40.30             | 69.71         | 55.01           |
| Multi-season ascending and descending combined       | 3             | 99.30            | 40.47             | 69.22         | 54.85           |
| Annual ascending and descending                      | 2             | 99.29            | 40.36             | 67.51         | 53.94           |
| Annual ascending and descending combined             | 1             | 99.09            | 54.64             | 49.41         | 52.03           |
| Annual descending                                    | 1             | 99.15            | 51.58             | 52.39         | 51.99           |
| Multi-season ascending                               | 3             | 99.23            | 33.27             | 63.57         | 48.42           |
| Annual ascending                                     | 1             | 98.22            | 53.09             | 25.97         | 39.53           |

Fig. 3. Multi-season Sentinel-1 2016 VH descending passes composite of subset A; each average composite is linearly stretched between $-30$ and $-10\text{ dB}$. The RGB composite contains in red the average VH backscatter for Jan–April, in green of May–August, and in blue of September–December. The inventory by WMR of 2016 is displayed as yellow lines. Green rectangles indicate visible features that are not within the WMR inventory of shellfish beds. The red rectangle is subset C of Fig. 6. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)
The initial classification of the 2016 multi-season VH descending composite had 1753 ha classified as beds, of which 600 ha was removed by applying the majority filter. From these 600 ha 169 ha was inside the WMR polygons and 431 ha outside. Therefore, while the majority filter eliminated some pixels contained within WMR-identified shellfish beds, the main effect of its application is the removal of a substantial amount of noise.

3.3. Comparisons at fine spatial detail

In Fig. 6A and B an aerial photo of 2016 and the average of all VH descending images for 2016 are shown side by side for the sub-area indicated by the red box in Fig. 3. An interpretation of the aerial photo is shown as red lines, and field observations on shellfish density that were made during the indicated MSc fieldwork (see Section 2.6) are written on the figure. The field recorded boundaries coincide with the interpretation. Most of the area is contained in a WMR polygon (yellow line). As can be seen the distribution and density of beds varies considerably within the WMR polygon. The annual 2016 average radar composite (Fig. 6B) shows the beds in light grey and mud in dark grey to black. The number of VH images that were used to make this 2016 composite for this specific area is 145, of which 71 descending and 74 ascending. The aerial photo interpretation coincides with the beds visible in the average radar image.

3.4. Change detection

Changes in bed areas can be visualized by combining the images of three consecutive years (Fig. 7). The images are stretched from −30 to −20 dB to show more detail on the beds. Both radar images and polygon
Lines of each individual year were assigned to a distinct color (2016 red, 2017 green and 2018 blue). Polygons of combined years (e.g. contours present in 2016 and 2017) were given an outline color that matched the combination of the colors of those years (e.g. red and green is yellow). Red areas in the multi-annual composite were only present in 2016 and are not visible since. Green areas were only present in 2017, and blue areas only in 2018. A combination of colors indicates that beds were present during at least two years: yellow areas were present in 2016 and 2017 but were gone in 2018, cyan areas were present in 2017 and 2018 but not before, and white areas in all three years. The WMR polygons are colored in a similar way.

Comparison of the WMR polygons and the radar based images reveals that mostly they have the same color. The white area indicates beds in all three years and have a white polygon line. The greenish area indicates beds in 2017 only. The large green polygon also includes red areas, indicating 2016 only, which is likely due to a redistribution of the mussels within the field contour due to storms and wave action (pers. field obs.). One bright red area can be seen which was not included in the 2016 inventory. This is likely a new mussel seed bed that already disappeared before the field survey.

4. Discussion

Shellfish beds were detected on the average cross-polarized (VH) Sentinel-1 C-SAR images. A previous study by Choe et al. (2012) with RADARSAT-2 for South Korea also indicated that for a single low-tide image, oyster beds were better detected in the VH as compared to VV and HH polarized bands, due to the strong volume scattering and depolarization. When evaluating different options for temporally aggregating the VH imagery, we found that the average resulted in better visual separability of shellfish beds as compared to alternative percentile composites. In addition, best visual results were obtained when averaging the imagery for a full year, rather than focusing on a month or few months.

The overall accuracy is very high as the coverage of beds is limited. Only 0.9% of the Wadden Sea area is covered with shellfish beds,
According to the WMR inventory, the average of descending VH-polarized Sentinel-1 images resulted in higher accuracies than the ascending Sentinel-1 image composites probably because the latter contained more speckle. We selected the multi-season VH descending composite as the optimal for visual interpretation. The overall accuracy of this composite is 99.31%, the producer accuracy 40.31%, and the user accuracy 68.71%. The accuracy levels obtained in this study are similar to those obtained with single selected images during low tide (Jung et al., 2015; Nieuwhof et al., 2015). An analysis that combined single-date TerraSAR-X and RapidEye images gave a similar overall accuracy of 98.25%, a higher producer accuracy of 63%, and a lower user accuracy of 55% (Jung et al., 2015). A classification at two sites of TerraSAR-X VH imagery (Nieuwhof et al., 2015) resulted in slightly lower overall accuracies (94% and 97%), higher and lower producer accuracies (57% and 29%), and lower user accuracies (10% and 42%). For the same areas with HV Radarsat-2 (Nieuwhof et al., 2015) the classification had similar overall accuracies (99% and 98%), slightly higher producer accuracies (48% and 46%) and similar user accuracies (60% and 69%). A study for a German site (Müller et al., 2016) compared multiple satellite sources and reached best classification of shellfish beds using as input a combination five TerraSAR-X images and one Landsat-8 image; they reported a producer accuracy of 79%, but only for the areas within the inventory polygons. That means that the actual shellfish bed cover of the area is 100% and therefore not comparable with our calculations.

We performed image classification for the entire Dutch Wadden Sea, while previous shellfish detection with radar (Choe et al., 2012; Gade et al., 2014; Gade and Melchionna, 2016; Jung et al., 2015; Nieuwhof et al., 2015; Müller et al., 2016; Adolph et al., 2018) concentrated on relatively small study areas and in the case of Nieuwhof et al. (2015) contained mainly clearly defined high-density oyster and mixed beds. Therefore we also calculated accuracies for the VH descending multi-season option within a smaller-defined subset area A (Fig. 5) with a comparable mussel bed coverage (Folmer et al., 2014) as the study areas of Jung et al. (2015) and Nieuwhof et al. (2015). The cover of shellfish beds in subset A is 3.7% according the WMR inventory. For this subset area, the overall accuracy of 97.64% was lower, the producer accuracy of 59.13%, and user accuracy of 72.58% were higher than for the entire Dutch Wadden Sea, and also similar or slightly higher than Jung et al. (2015) and Nieuwhof et al. (2015). In addition four classified areas not included in the 2016 WMR inventory, proved to be beds in subsequent in-situ surveys. Taken this into account the overall accuracy in subset A increases to 97.94%, the producer accuracy to 61.67% and user accuracy to 82.08%.

Although our producer efficiency was similar to the other studies, a value of 40.31% can still be considered relatively low. This is likely due to the fact that not all parts within a WMR contour are classified as shellfish bed when applying the k-means clustering to the radar composite. The still relatively low user accuracy to 82.08%.

Based on both the visual analysis and the reported accuracies we can conclude that with our automatically-composited image that does not require manual selection of appropriate-tide images, it is possible to detect shellfish beds just as good as from selected images around low tide. We note that quick implementation of our compositing approach over previously-studied regions in Germany (Gade et al., 2014; Jung et al., 2015; Müller et al., 2016) and Korea (Choe et al., 2012) also resulted in clearly-identifiable shellfish beds, which largely match with the reference data shown in those studies.

We used a quick and easy to use classification method to compare different options and to give a rough estimate of classification accuracy. More sophisticated analysis methods can be applied both for compositing and classification. For example, it is known that windy conditions may result in increased backscatter over water surfaces due to waves (Jung et al., 2015). While this effect is reduced in our cases by averaging over a large number of images, gridded temporal datasets on wind speed could potentially be applied to discard images during strong wind conditions. In relation to classification, visual interpretation may result in higher accuracies as compared to automated classification (Garvis et al., 2020), given that noise and small areas will be removed in the interpretation process.

Our method to create an image from the average of images from a whole year can also be used for monitoring shellfish beds. Accuracies for the different years were similar, indicating that the method is robust. Detecting changes in shellfish beds of 3 years can be based on single multi-annual images (Fig. 7). Field surveys can be concentrated on newly detected beds and older beds that have (partially) disappeared. This method has already been applied in the preparations for the 2020 field campaign by WMR, and has proven to be highly useful in the detection of new and changed beds, rendering the inspection aerial inspection superfluous (which actually could not be carried out due to the Covid-19 crisis).

5. Conclusions

We presented a new method to automatically construct temporal composites from Sentinel-1 data, which allows for effective visualization of shellfish beds over large areas. This process involved the use of the cloud-based Google Earth Engine for accessing, and processing the imagery, and resulted in major time gain with respect to selecting low-tide imagery, downloading, and processing with specialized software. The process can be easily and rapidly repeated by non-experts across the globe using our provided script, given that only a working internet connection and some basic knowledge on how to use GEE is required. GEE is free of charge for scientific, educational, and non-profit usage. As such, our method presents a relevant input for monitoring agencies, for example to better inform field campaigns. The script for creating the multi-seasonal VH composite can be found in the online supplementary material.

Credit author statement

Eduard Westinga: Conceptualization, Methodology, Investigation, Validation, Formal Analysis, Visualization, Writing – original draft, Writing – review & editing Karin Troost: Conceptualization, Validation, Writing – review & editing Lydia Biri Nasimiyu: Investigation Petra Budde: Investigation Anton Vrieling: Methodology, Software, Visualization, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecss.2020.107115.

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