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1 **Title:** The application of a radar-based depth inversion method to monitor near-shore
2 nourishments on an open sandy coast and an ebb-tidal delta

3

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15 **Keywords:**

16 - Remote sensing

17 - Depth inversion

18 - X-Band radar

19 - Tidal inlet

20 - Coastal Zone

21 - Nourishment

22

23 **Abstract**

24 Coastal management in the Netherlands has the aim to defend coastal zones by preventing
25 flooding and mitigating erosion. To that end, large-scale nourishments are placed in the
26 nearshore, which are supposed to dynamically preserve the coastal zone over a timescale of
27 years. To assess their effectiveness, these nourishments are monitored over large areas and
28 long durations. As repetitive, in-situ measurements become too expensive, remote sensing
29 offers an attractive alternative, mapping depth and near-surface current fields via depth
30 inversion algorithms (DIA). However, the information that can be derived from remotely-
31 sensed data is subject to improvement. In this study a 3D-FFT based DIA named XMFIt (**X-**
32 **Band Matlab Fitting**) is introduced, which is robust, accurate and fast enough for operational
33 use. Focusing on depth estimates, the algorithm was validated for two case studies in the
34 Netherlands: (1) the “Sand Engine”, a beach mega nourishment at a uniform open coast, and
35 (2) the tidal inlet of the Dutch Wadden Sea island Ameland, characterizing a more complex
36 coast. Considering both sites, the algorithm performance was characterized by a spatially
37 averaged depth bias of -0.9 m at the Sand Engine and a time-varying bias of approximately -2
38 – 0 m at the Ameland Inlet. When compared to in-situ depth surveys the accuracy was lower,
39 but the time resolution higher. Depth estimates from the Ameland tidal inlet were produced
40 every 50 min by an operational system using a navigational X-Band radar to monitor the
41 placement of a 5 million m³ ebb-tidal delta nourishment – a pilot measure for coastal
42 management. Volumetric changes in the nourishment area over the year 2018, occurring at 7
43 km distance from the radar, were estimated with an error of 7%. Depth errors statistically
44 correlated with the direction and magnitude of simultaneous near-surface current estimates.
45 Additional experiments on Sand Engine data demonstrated that depth errors may be
46 significantly reduced using an alternative spectral approach and/or by using a Kalman filter.

47 **1 Introduction**

48 With the extensive urbanization of the coastal hinterland, the role of coastal management in
49 the Netherlands has become increasingly important to ensure flood safety and the protection
50 of recreational and ecological values of the coast. Modern coastal maintenance strives
51 towards a “building with nature” approach (de Vriend and van Koningsveld, 2012), using soft
52 engineering strategies to mitigate long-term coastal recession. Along uniform coastlines,
53 large 1-2 million m³ shoreface nourishments have proved to be an effective strategy (Hamm
54 et al., 2002), and a basic understanding has been established about their behaviour (Huisman
55 et al., 2019; Lodder and Sørensen, 2015). In pursuit of finding the optimal long-term solution,
56 larger nourishment designs have been explored of which the Sand Engine, a beach mega-
57 nourishment comprising 21 million m³ of sand is a famous example (Stive et al., 2013). In the
58 meantime even bigger nourishments have been placed with volumes up to 36 million m³
59 (Kroon et al., 2016). The most recent experiment involved the construction of a 5 million m³
60 nourishment in the outer delta of a complex tidal inlet system at the Wadden Sea island
61 Ameland.

62 To evaluate the success of these innovative coastal management interventions it is necessary
63 to map them and to monitor their evolution. Due to the large nourishment volumes and long
64 lifetime, monitoring with in-situ techniques is expensive and it may be favorable to use
65 remote sensing techniques instead. Such techniques can capture morphological variability at a
66 large spatial scale in high temporal resolution over long periods of time (Bergsma et al.,
67 2019). To be used in an operational setting, remote sensing techniques need to be robust. We
68 define robust as being able to handle variations in environmental conditions and data quality
69 without the need for manual adjustments and costly person hours. Here, we propose to derive
70 bathymetries with a technique that meets these desired requirements and uses already
71 available X-Band radar data from a lighthouse.

72 Marine radars operating in the X-Band range are routinely deployed aboard ships and on
73 marine traffic control towers to detect vessels and other floating objects. In coastal areas,
74 such radars may also be used to monitor waves, currents and water depths. Their benefits
75 over in-situ depth surveys are a high spatial and temporal coverage and lower operating and
76 maintenance costs. However, the spatial resolution of X-Band radars can be coarse and, as
77 sampling frequencies are often low, they have a lacking ability to recognize shorter period
78 waves. Moreover, an inherent uncertainty exists in relating radar image intensities to the
79 observed ocean surface properties, bringing challenges to the analysis of X-Band radar data.
80 Moreover, X-Band radars are expensive instruments, which is why it may be attractive to
81 exploit existing navigational radars in areas of interest.

82 Although considered “noise” for navigational purposes, the wave field leaves a signature on
83 an X-Band radar known as sea clutter. This imprint is produced by radar signal reflection off
84 capillary waves, which are modulated by the underlying surface gravity wave field (Borge et
85 al., 2004; Valenzuela, 1978), the so-called Bragg-scattering (Plant, 1990). Observing the
86 propagation of a wavefield through time offers a possibility to infer information about the
87 waves themselves, but also about currents and depths these waves feel.

88 In particular for the purpose of depth estimation, several depth inversion algorithms (DIAs)
89 have been developed. Most DIAs use wavefield recordings from either radars or beach
90 cameras, but these methods may be used interchangeably between instruments (Honegger et
91 al., 2019). While some DIAs use a sequence of images (i.e. a video of typically 6-12 min) to
92 link wavenumbers to wave frequencies and estimate depths via the linear dispersion
93 relationship (Bell, 1999; Dugan et al., 2001; Hessner et al., 1999; Holman et al., 2013), other
94 DIAs use the average of a sequence of images (i.e. a time exposure) to estimate depths
95 through spatial patterns of breaking intensity (Aarninkhof et al., 2005; van Dongeren et al.,
96 2008). If the area of interest is large, X-Band radars have an advantage above cameras

97 because of their larger field of view. Other advantages are their operability at night and a
 98 smaller sensitivity to rain or sun glare. A large field of view means that depths are estimated
 99 far beyond the breaker zone, therefore a dispersion-based DIA is preferred with a sequence of
 100 images as input.

101 The commonly used dispersion-based DIAs to analyse image sequences from XBand-radar,
 102 employ three dimensional Fast Fourier Transforms (3D-FFTs) to acquire the necessary
 103 wavenumber – frequency relationships. Spatial variations are captured by discretising an
 104 image sequence into smaller domains known as computational cubes (x,y,t) (Trizna, 2001).
 105 These computational cubes are processed separately. A 3D-FFT then converts each
 106 computational cube from the space-time domain (x,y,t) into wave components in the wave
 107 number – frequency domain (k_x, k_y, ω) . This information is used to constrain the Doppler-
 108 shifted linear dispersion shell

$$\omega = \sqrt{g|\mathbf{k}| \tanh(|\mathbf{k}|d)} + \mathbf{U} \cdot \mathbf{k} \quad 1)$$

109
 110 to estimate the water depth, d (m), and the two horizontal current vector components $[u, v]$ of
 111 \mathbf{U} (m/s). The gravitational acceleration is given by g , the wave number vector by \mathbf{k} (rad/m)
 112 with components $[k_x, k_y]$, and ω (rad/s) is the corresponding frequency. The idea to use 3D-
 113 FFTs originally came from the estimation of \mathbf{U} under known d (Young et al., 1985), however,
 114 it could naturally be extended to estimate d as well by keeping d as a free parameter (e.g. Bell,
 115 2008; Hessner et al., 2014; Ludeno et al., 2015; Rutten et al., 2017). The derivation of the
 116 Doppler-shift in the form $+\mathbf{U} \cdot \mathbf{k}$ in equation 1, assumes a depth uniform current equal to \mathbf{U} . In
 117 practice, the current profile is not uniform over depth and the vector \mathbf{U} represents a weighted
 118 average of velocities in the upper layer of the water column (e.g., assuming a linearly sheared
 119 current profile, waves with periods of $T = 5-8$ s travelling in water depths of $d = 5-15$ m feel

120 velocities that occur at 20-45% of the water depth; see eq. 5 in Campana et al., 2016).
121 Therefore, U is commonly also referred to as near-surface current (Young et al., 1985; Senet
122 et al., 2001).

123 Several authors have applied the dispersion relation without Doppler-shift ($+U \cdot k$ in equation
124 1), neglecting the presence of near-surface currents, to remotely sense d from X-Band radar
125 data (Bell, 1999; Hessner et al., 1999). Although conceptually proven, these early
126 developments were applied to limited datasets and lacked quantitative validation. Later,
127 based on two single daily-averaged estimates from Egmond aan Zee (NL) and Teignmouth
128 Pier (UK), Bell (2001) demonstrated that error margins could be within 1 m accuracy for
129 depths up to 12 m, with exception of the breaker zone where errors were approximately 2 m.
130 For the site of Duck (North Carolina, US) with depths up to 6 m, Trizna (2001) reported
131 depth errors of 0 to 4 m depending on the wave-height and suggested that the inclusion of
132 non-linear wave theory improves estimates. This was then disproven by Flampouris et al.
133 (2011) who, for a site near the Wadden Sea island Sylt (GE), reported root-mean-square-
134 errors (RMSE) of at least 1.6 m regardless of the (non-)linear wave theory used.

135 For airborne optical video, Dugan et al. (2001) were one of the first to include the Doppler-
136 shift in equation 1, for the joint estimation of d and U using 3D-FFTs. The extension was
137 subsequently also used in the analysis of X-Band radar data from the Dee Estuary (UK) (Bell,
138 2008). Although near-surface currents could not be validated, it was noted that their inclusion
139 had improved depth estimates, which is consistent with a recent study showing that currents
140 can influence depth estimates significantly (Honegger et al., 2020). Based on three high tide
141 estimates, Bell (2008) found depth errors to be mostly within a 1 m range in the spatial
142 domain, however, estimates in the deep channel (> 20 m) were larger as waves only weakly
143 felt the bottom. More recently, 3D-FFT based DIAs have been applied to complex nearshore
144 situations, for example by Hessner et al. (2014), who built on work done by Seemann et al.

145 (1997) and Senet et al. (2001) by solving for d in addition to U for an analysis of two days of
146 radar data from a coastal site in New Zealand with strong tidal currents. Their near-surface
147 current estimates reasonably agreed with model data, yet simultaneous depth estimates lacked
148 validation. Similarly, Hessner et al. (2015) investigated a site at the southeast coast of the UK.
149 Here, accumulated depth estimates were compared to ground truth measurements and agreed
150 qualitatively but error metrics were not quantified. Ludeno et al. (2015) used an algorithm
151 proposed by Serafino et al. (2010) to jointly estimate d and U from 45 min of radar data from
152 a ferry near the harbour of Salerno (IT) and used a spatial partitioning technique to accelerate
153 computations. The local depth was between 10 and 20 m, which Ludeno et al. (2015)
154 estimated to have a bias of approximately 1 m. Rutten et al. (2017) were one of the first to
155 explore the possibility of estimating volume budgets from estimates of d in the nearshore
156 region over a long time period of one year, taking a first step from research to a potential use
157 of radar based DIAs in coastal management. A large depth bias of 2.3 m for depths smaller
158 than 6 m, however, caused volume estimates to be 3.9 million m³ short of what was expected.
159 While near-surface current estimates were not presented, they noted that poor d estimates
160 concurred with poor U estimates.

161 So far, 3D-FFT based depth inversion from XBand-radar data has focussed on the
162 development and (often conceptual) testing of DIAs (Bell, 2008; Hessner et al., 2014; Ludeno
163 et al., 2015). The accuracy of depth estimates is generally in a 1-2 m range and depends on
164 the location, radar, and the algorithm used. Moreover, presented error statistics are mostly
165 based on short, experimental data sets. The accuracy is generally lower in deeper areas where
166 waves are hardly affected by the depth (Bell, 2008) and in very shallow water where waves
167 become non-linear (e.g., Trizna, 2001; Holland, 2001). Even though the validation of near-
168 surface currents themselves is often lacking, it has been reported that including their effect on
169 waves is important: while it improves depth estimates (Bell, 2008), a poor current estimate

170 can also be an indicator for a poor, joint depth estimate (Rutten et al., 2017). The effect of
171 higher significant wave heights, H_s , has been shown to increase depth errors in shallower
172 waters (Trizna, 2001), while a minimum $H_s > 1$ m is needed for sufficient sea-clutter (Bell,
173 2008).

174 3D-FFT based DIAs have mostly been applied in an experimental setting and the question
175 arises whether they are ready to be used for practical coastal management purposes, such as
176 the quantification of volumetric changes caused by nourishments. To that end, they need to
177 run operationally on long-term radar data and hence be able to handle variations in
178 environmental conditions and data quality. In this paper, we present a 3D-FFT-based DIA
179 named XMFIt (**X**-Band **M**atlab **F**itting), which manages such variations by selecting the best
180 values from a set of $[d, U]$ -solutions, for every location in the radar domain at any point in
181 time. The generation of a set of solutions is done by a set of different energy thresholds to
182 separate spectral wave data from the noise floor. This is different from other currently used
183 DIAs, which may (i) optimize a $[d, U]$ -solution by iterating on a first, high energy threshold
184 guess with a lower energy threshold guess including aliases and higher order effects (Hessner
185 et al., 2014; Senet et al., 2001) or (ii) by maximizing a normalized scalar product between the
186 image amplitude spectrum and a characteristic function, which omits the use of thresholds
187 (Ludeno et al., 2015; Serafino et al., 2010). Similar to those algorithms, the present method
188 also includes the Doppler-shift (equation 1) to allow for the effect of near-surface currents on
189 the depth estimates. XMFIt uses different spectral filters, an anti-aliasing step and a least-
190 squares fitting procedure.

191 We validate the DIA using two different sites in the Netherlands: The Sand Engine, and the
192 ebb-tidal delta of the Ameland Inlet to the Wadden Sea. Detailed ground truth data from 2014
193 and 2018 are respectively used for validation. With 7.5 km, the XBand-radar range at the
194 Ameland Inlet is double the range previously reported for depth inversion studies and enables

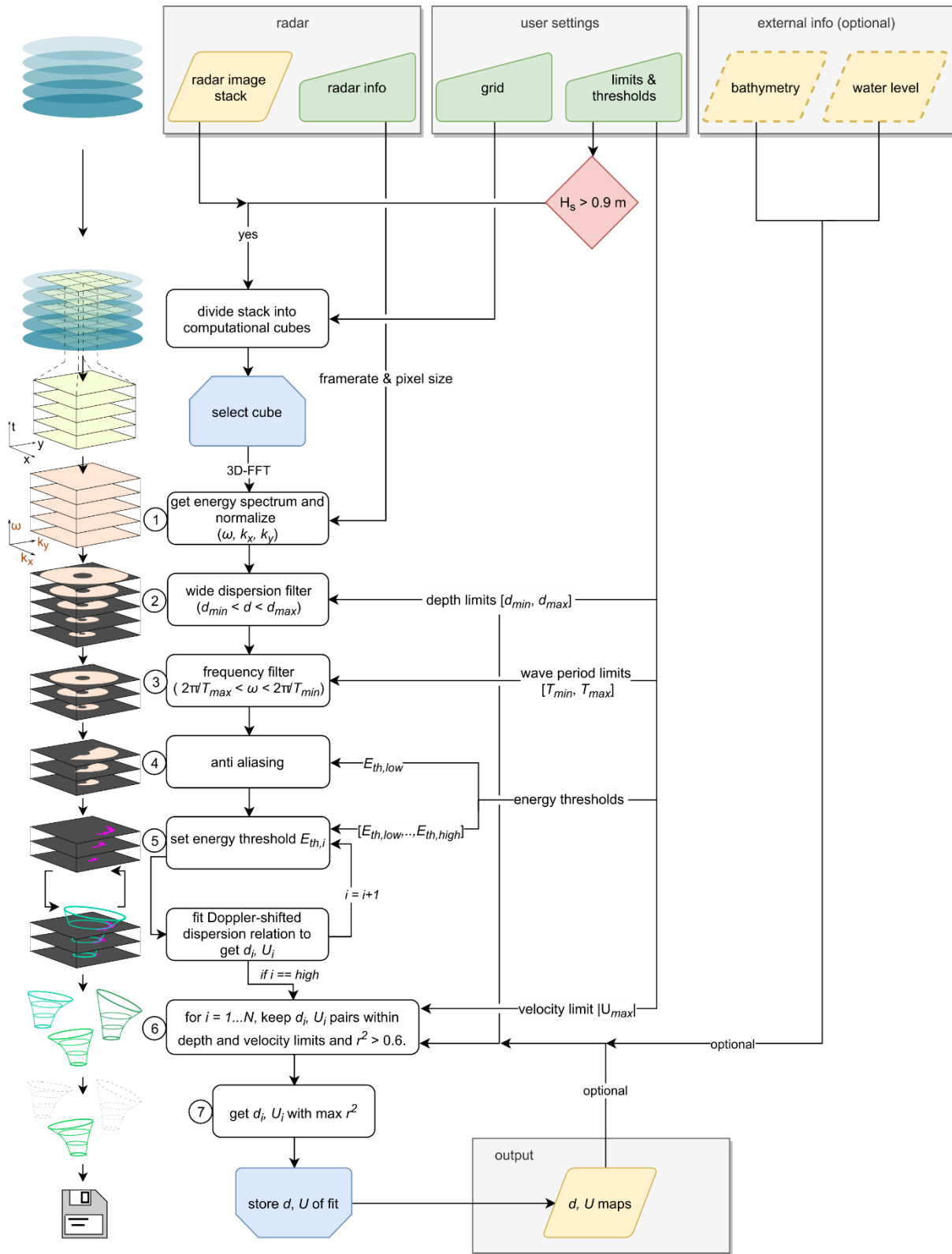
195 us to capture the extensive size of the Inlet. By that, we track a 5 million m³ ebb-tidal delta
196 nourishment at 7 km distance from the radar, creating a one-year time evolution of its volume.

197 Section 2 introduces the XMFit algorithm and its features. In section 3, the field sites and
198 data collection are described. Results on validation and monitoring the placement of the
199 nourishment are presented in section 4. In the Discussion section 5, we elaborate on errors
200 and methods to mitigate them and then conclude our findings in section 6. Radar specifics
201 and details on computational settings are documented in the Appendices.

202

203 **2 Depth-inversion Method**

204 The depth-inversion algorithm XMFit is based on an original idea by Young et al. (1985),
205 where radar image sequences of a wave field are first split into smaller cubes, then processed
206 via 3D-FFT to retrieve spectral wave characteristics, after which the Doppler-shifted
207 dispersion relation can be used to obtain estimates of depth and near-surface currents
208 (equation 1). In order to process an image sequence, the algorithm requires information about
209 the radar, user settings and optionally a bathymetry and a water level (Figure 1, top row). The
210 radar information includes the coordinates of the radar, its radius and the framerate of the
211 image sequence and pixel size. User settings include a grid definition, which consists of the
212 location and size of the computational cubes, and limiters that are used to constrain the
213 analysis.



214

215 Figure 1. XMFit workflow for depth and near-surface current inversion from an image
 216 sequence. Consecutive processing steps in the flowchart are visualized along their left. The
 217 flowchart includes: data (brown), user input (green), decision (red), process loop start (blue;

218 trimmed top corners) and process loop end (blue; trimmed bottom corners), and process
219 (white). Arrows and their annotations signify flow of information. The algorithm requires
220 input on radar specifics, user settings and optionally a bathymetry and water level (grey
221 squares top row). The output contains maps of depth estimates and near-surface current fields
222 (grey square bottom row). Symbols represent: $[k_x, k_y]$ = wavenumber components, ω = wave
223 frequency, $[d_{min}, d_{max}]$ = depth limits, $[T_{min}, T_{max}]$ = wave period limits, $|U_{max}|$ = velocity
224 magnitude limit, $[E_{th,low}, .. E_{th,i}, .. E_{th,high}]$ = array of spectral energy thresholds, $[d_i, U_i]$ = depth
225 and near-surface current estimates corresponding to $E_{th,i}$, and $[d, U]$ = optimal depth and near-
226 surface current pair.

227

228 Before an image sequence is analysed, a high-pass threshold on the significant wave heights
229 of $H_s = 0.9$ m is made, similar to (Bell, 2008) as a proxy for sufficient sea-clutter (Figure 1,
230 red diamond). Note that the wave height information has to be provided as an external input
231 to the DIA.

232

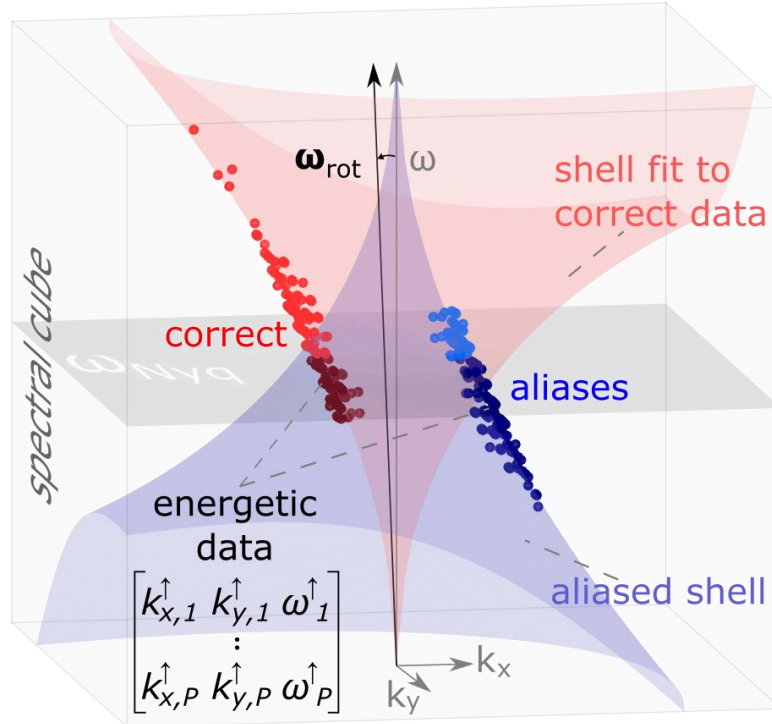
233 The processing of an image sequence commences by dividing it into a number of
234 computational cubes ($c = 1..N$) according to the user defined grid. Cubes are processed
235 consecutively, each providing an estimate for a depth, d_c , and near-surface current vector, U_c ,
236 at its location. The inversion of $[d_c, U_c]$ consists of seven steps (Figure 1, labels ①..⑦).
237 Since the procedure is identical for all cubes, we drop the subscript c from here onwards and
238 use $[d, U]$ for notational simplicity. The first step is to taper the computational cube with a
239 3D-Hanning window and to generate a k_x, k_y, ω -energy spectrum via 3D-FFT. If the time-
240 sequence is long enough, the spectrum may also be smoothed through spectral averaging in
241 time, by dividing the cube into smaller time-bins. Using min-max normalization, the spectral
242 energy is then converted to the range $[0,1]$ to prepare it for a fitting procedure later in the

243 process (Figure 1, ①). At this stage, the spectrum carries redundant information in non-
244 relevant spectral components, such as noise and aliases, which can be discarded to save
245 computer memory. A wide-dispersion filter removes spectral energy beyond realistic depths
246 (Figure 1, ②), by means of limiting dispersion shells corresponding to a minimum depth d_{min} ,
247 and a maximum depth d_{max} . These limiting dispersion shells do not include a Doppler-shift, as
248 experience shows that it does not provide additional result accuracy but does increase
249 computation time. A frequency filter removes spectral energy beyond realistic wave periods
250 (Figure 1, ③), by means of a minimum wave period T_{min} and a maximum wave period T_{max} .
251 The limits for realistic water depths and wave periods are supplied by the user and are
252 typically set around $[d_{min}, d_{max}] = [0.5, 25]$ (m) and $[T_{min}, T_{max}] = [4, 15]$ (s) respectively;
253 indicating the ranges where we expect waves to be mostly in intermediate or shallow water to
254 get reliable depth estimates. Note that for depths larger than approximately 15 m, shorter
255 period waves ($T < 6$ s) are mainly useful in determining near-surface currents.

256

257 If the frame rate of the image sequence is low due to a slow turning radar antenna, as is the
258 case in this study with $1/2.85$ s⁻¹, the filtered spectrum may show aliasing since the Nyquist
259 frequency is close to the governing wave periods. An anti-aliasing step removes these
260 unwanted by-products, (Figure 2; Figure 1, ④) and permits the use of data up to two times
261 the Nyquist frequency (Seemann et al., 1997).

262



263

264

265 Figure 2. Anti-aliasing on a spectral cube with dimensions k_x, k_y, ω . Energetic spectral data
 266 with energies above a threshold $E_{th,low}$ are given by a set of $p = 1 \dots P$ points with coordinates
 267 $k_{x,p}^{\uparrow}, k_{y,p}^{\uparrow}, \omega_p^{\uparrow}$. This set contains correct data points (red dots) and aliases (blue dots), below
 268 and above the Nyquist frequency (grey plane). Aliases are detected and removed via a
 269 singular value decomposition. The ω -axis rotates (ω_{rot}) towards the correct spectral data by
 270 which aliases can be separated and a non-linear fit can be done on the correct spectral data
 271 (red dispersion shell) according to equation 1. The blue shell indicates the orientation of
 272 aliases in the spectrum.

273

274 To separate the aliases from correct wave data a singular value decomposition (svd) (equation
 275 2) is performed on the energetic parts of the spectrum. Energetic parts are defined by all
 276 spectral data with energies above a user defined threshold $E_{th,low}$, which is the lower bound of
 277 the set $0 < \{E_{th,low} \dots E_{th,high}\} < 1$ used in the fitting procedure that follows this anti-aliasing
 278 step.

$$\mathbf{A} = \mathbf{U} \mathbf{\Sigma} \mathbf{V}^T,$$

where

$$\mathbf{A} = [\mathbf{k}_x^\uparrow \quad \mathbf{k}_y^\uparrow \quad \boldsymbol{\omega}^\uparrow] = \begin{bmatrix} k_{x,1}^\uparrow & k_{y,1}^\uparrow & \omega_1^\uparrow \\ k_{x,2}^\uparrow & k_{y,2}^\uparrow & \omega_2^\uparrow \\ \vdots & \vdots & \vdots \\ k_{x,P}^\uparrow & k_{y,P}^\uparrow & \omega_P^\uparrow \end{bmatrix}$$

2)

279 The matrix \mathbf{A} lists the $p = 1 \dots P$ energetic points in the spectrum by their spectral coordinates
 280 $k_{x,p}^\uparrow, k_{y,p}^\uparrow, \omega_p^\uparrow$ in the columns $[\mathbf{k}_x^\uparrow, \mathbf{k}_y^\uparrow, \boldsymbol{\omega}^\uparrow]$, where the upward arrow signifies energy higher
 281 than $E_{th,low}$. The amount of points, P , depends on the value of $E_{th,low}$ and the spectral wave
 282 signal. The svd factorizes the matrix \mathbf{A} into two unitary matrices \mathbf{U} , \mathbf{V} and a diagonal matrix
 283 $\mathbf{\Sigma}$. The superscript T denotes the transpose. In practice, \mathbf{V} represents a rotation of the k_x, k_y, ω -
 284 coordinate system: $\mathbf{V} = [\mathbf{k}_{x,rot}, \mathbf{k}_{y,rot}, \boldsymbol{\omega}_{rot}]$, which best follows the spectral data \mathbf{A} . Due to the
 285 position of the aliases in the spectrum, the ω -axis rotates ($\boldsymbol{\omega}_{rot}$) towards the correct spectral
 286 data and away from the aliases, which allows for a clear separation: Correct data have higher
 287 values on $\boldsymbol{\omega}_{rot}$ (found via $\mathbf{A}\boldsymbol{\omega}_{rot}$) compared to the original ω -axis and for aliases this is the
 288 opposite, which means that they are identified and can be removed.

289

290 After pre-processing the spectrum several spectral fits are done. Using a Levenberg-
 291 Marquardt minimisation, the Doppler-shifted linear dispersion relationship (equation 1) is
 292 fitted to all spectral data above a certain energy threshold E_{th} to yield an estimate for $[d, \mathbf{U}]$.
 293 Since the spectrum has been normalized this threshold lies between $0 < E_{th} < 1$. However, the
 294 optimal value of E_{th} is not known beforehand. The solution is to iterate an optimal value by
 295 making several fits for an array of energy thresholds $\{E_{th,low}, \dots, E_{th,high}\}$, which produces a set
 296 of depth and near-surface current pairs $\{[d_{low}, \mathbf{U}_{low}], \dots, [d_{high}, \mathbf{U}_{high}]\}$ (Figure 1, ⑤). By
 297 default, $\{E_{th,low}, \dots, E_{th,high}\}$ covers the range $\{0.4, \dots, 0.6\}$ in 10 increments, which is a

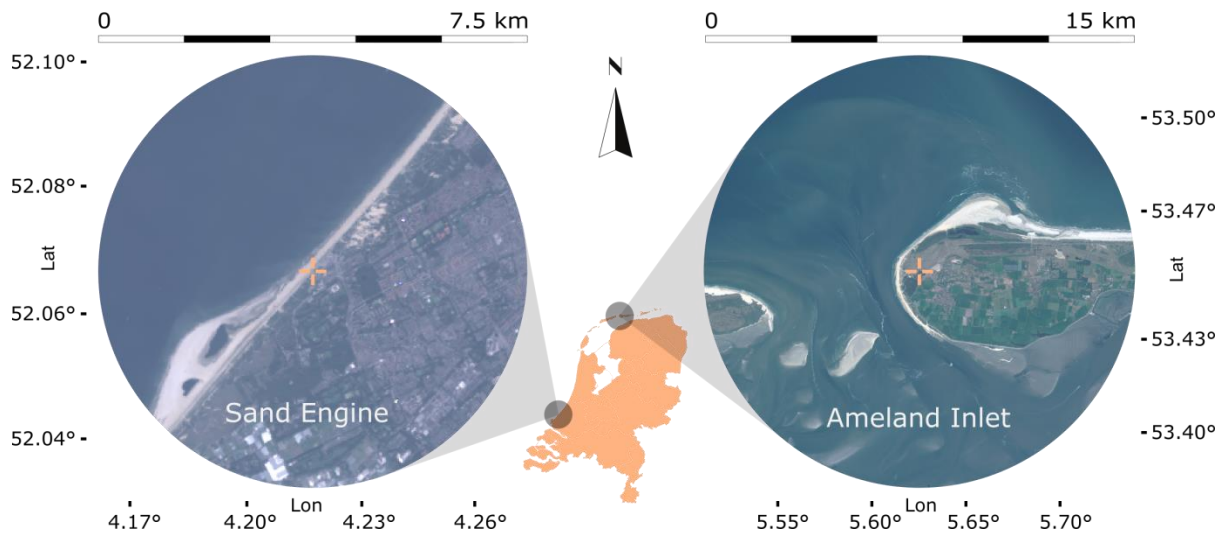
298 generic setting, but can be adjusted by the user. By using a set of E_{th} , instead of single
299 threshold, we omit the need to tailor the algorithm to each image sequence separately, which
300 makes the algorithm robust to use on long time-series of data.

301

302 The goal is now to find the optimal pair of $[d_i, \mathbf{U}_i]$ among the list of candidates $\{[d_{low},$
303 $\mathbf{U}_{low}], \dots, [d_{high}, \mathbf{U}_{high}]\}$. Pairs are retained using three criteria: (1) d_i falls within the pre-set
304 depth range $[d_{min}, d_{max}]$, (2) $|\mathbf{U}_i|$ is smaller than a user-defined maximum velocity magnitude
305 $|\mathbf{U}_{max}|$, and (3) the coefficient of determination $r^2 > 0.6$, (Figure 1, ⑥). Note that the depth
306 constraint $[d_{min}, d_{max}]$ has been used in an earlier step to reduce the spectrum with a wide
307 dispersion filter (Figure 1, ②). However, a poor candidate fit on those data may still suggest
308 a solution beyond those limits, therefore criterion (1) is needed here. To improve estimates of
309 an operational system, knowledge about previous depth estimates can be used to (A) tighten
310 criterion (1) or (B) in a Kalman filter. In case of option (A), an average is taken over a certain
311 number of M previous depth estimates, $d_{avg,M}$, and a margin Δd is chosen to tighten criterion
312 (1) by redefining $d_{min} = d_{avg,M} - 1/2\Delta d$ and $d_{max} = d_{avg,M} + 1/2\Delta d$. Option (B) is a postprocessing
313 step and does not affect the depth inversion procedure. In this study we used option (A) for
314 the site of Ameland (section 4) and experimented with option (B) for the Sand Engine
315 (section 5).

316 The r^2 of criterion (3) is used as the optimization criterion as it indicates how well the non-
317 linear fit represents the spectral data. This value is unity for a perfect match. Hence, the
318 optimal $[d, \mathbf{U}]$ amongst the remaining candidates is finally found by the fit with maximum r^2 ,
319 (Figure 1, ⑦) and can be stored as the representative estimate for the computational cube.
320 After a computational cube has been processed, the sequence of steps repeats for the next
321 computational cube in the grid (Figure 1: steps ①..⑦), eventually producing full maps of
322 depths and near-surface currents (Figure 1, output).

324 **3 Radar in-situ data collection**



325

326 Figure 3. Radar locations (centre crosses) and ranges (see top scales) at the two field sites of
327 Sand Engine (left) and the Ameland inlet (right). A map of the Netherlands (middle) indicates
328 the location of the two sites.

329 **3.1 Sand Engine**

330 The first field site is the Sand Engine, a sandy mega-nourishment of approximately 21 Mm³
331 constructed on the southwestern Dutch coast in 2011 (Figure 3, left). It was designed to
332 combat erosion by diffusing along the coastline over an extended period of 10-20 years,
333 while minimizing ecological stress and creating space for recreation (Stive et al., 2013). To
334 gain insight into the development and impact of the unprecedented scale of the nourishment
335 an extensive monitoring campaign was launched in 2012 (de Schipper et al., 2016). A radar
336 station was installed 3 km north of the nourishment area, covering approximately 40 km².
337 The available radar data covered a short timeframe of 18 h during 20-21 October 2014 and
338 were used to create a snapshot of the nourishment for that moment. Specific details on the
339 radar properties are summarized in table A.1.

340

341 The significant wave height (H_s) ranged from 1.0 m to 1.7 m and the peak period (T_p) from
342 6.0 s to 7.0 s, which are average wave conditions for the site (de Schipper et al., 2016). In
343 total, 184 image sequences were available, each consisting of 128 images in intervals of 2.85
344 s, translating to 6 min of wave motion at a resolution of 3.75 m. Ground truth data were based
345 on a detailed bathymetrical survey from 6 September 2014 which was merged with Jarkus
346 transect data from 2014 to get greater coverage offshore. A local tide gauge was used to
347 compensate for water level fluctuations in the depth estimates. For consistency, we only use
348 the term depth throughout this paper, but note that it excludes the influence of water level
349 modulation and is referenced to NAP (Dutch ordnance datum, about Mean Sea Level) for
350 both sites.

351 **3.2 Ameland tidal inlet**

352 The second field site is the Ameland Inlet, one of the tidal inlets of the Dutch Wadden Sea
353 (Figure 3,right). The inlet is characterized by a wave-dominated ebb-tidal delta and deep tide-
354 dominated inlet channels formed by strong tidal currents with maximum velocities around 1.5
355 m/s. The semi-diurnal tide has a mean range of approximately 2 m. Over the study period
356 Dec 2017 – Dec 2018, H_s ranged from 0.1 m to 6.2 m and T_p from 1.8 s to 17.0 s. Wave
357 conditions were on average $H_s = 1.3$ m and $T_p = 5.6$ s and exceeded $H_s > 3.0$ m and $T_p > 9.0$ s
358 during 5% of the time.

359 The inlet is being extensively monitored within the framework of the Coastal Genesis 2.0
360 (*Dutch*: Kustgenese 2.0) research program, which was commissioned by the Dutch Ministry
361 of Infrastructure and Environment in 2017 (Van Prooijen et al., 2019). As part of the
362 monitoring program, XMFit software runs operationally on X-Band radar data collected at
363 the Ameland lighthouse. The navigational radar monitors the tidal inlet and has a spatial
364 coverage of approximately 180 km² (Figure 3,right). Specific details on the radar properties
365 can be found in table A.1. The goal of employing the radar is to track the evolution of a pilot

366 nourishment of 5 million m³ at the outer rim of an ebb-shield. Commencing 20 March 2018,
367 the gradual placement of the nourishment ended in February 2019.

368 Radar image sequences at Ameland consist of 256 images spaced at 2.85 s. Image sequences
369 cover a time window of 12 min and are produced at 20 min intervals, leaving 8 min of
370 downtime in between. The pixel size is 7.5 m. Note that the range resolution is 7.5 m, but that
371 the beam widens with distance from the radar. Depending on the alignment of the radar beam
372 and wave crests, we estimate the resolution to be between 7.5 m and 57 m at 7 km distance
373 from the radar (see also table A.1). Due to presently limited storage space (in this case 16
374 TB), raw image sequences (each 3 GB) are overwritten after 2 months and hence not
375 available for reanalysis. The image sequences are processed locally in the light house such
376 that the much smaller sized result files (each 0.1-0.5 MB) can be transferred via a 4G internet
377 connection. Note that the storage buffer allows for the analysis of up to 72 image sequences a
378 day; the increasing lag can be caught up during times when $H_s < 0.9$ m.

379 Poor depth estimates were suppressed by tightening criterion (1) (section 2) using an averaging
380 window of $M = 5$ and a depth margin of $\Delta d = 4$ m. Initial bathymetry data was needed to start
381 the process. Tidal depth modulation was accounted for by passing information from a local
382 wave buoy at Terschelling (Figure 1: grey square, top right). As initial bathymetry data a
383 combination of surveys from February and September 2017 was used. Their initial influence
384 on the estimates quickly phased out due to the choice of a rather large depth margin Δd . To
385 additionally ensure that presented depth estimates were independent from the initial
386 bathymetry the first 1000 estimates were ignored in this study. The choices for the averaging
387 window and the allowable depth margin were made arbitrarily and other values may be
388 chosen, yet the current combination of values underlies the results presented in this study.

389

390 Between Dec 2017- Dec 2018, the operational system returned approximately 7500 estimates
391 of morphology. Within this period the Ameland Inlet was surveyed twice using a single beam
392 mounted on a vessel. The first survey was done in the beginning stage of nourishment works
393 31 May – 5 June 2018 (Survey #1) and the second survey about half way, from 12 – 14
394 October 2018 (Survey #2). The surveys were done during calm periods that fell below the
395 threshold of $H_s = 0.9$ m used by the operational system to produce depth estimates. For
396 validation, therefore the average was taken over daily median estimates with similar spatial
397 coverage shortly before and after each survey. Specifically for the nourishment location,
398 additional multibeam surveys were available, which were used in this study to compute
399 volumetric changes over the placement period of the nourishment.

400

401 The computational grids and user settings underlying the analyses of both the Sand Engine
402 and the Ameland Inlet can be found in Appendix B.

403

404 4 Results

405 4.1 Sand Engine

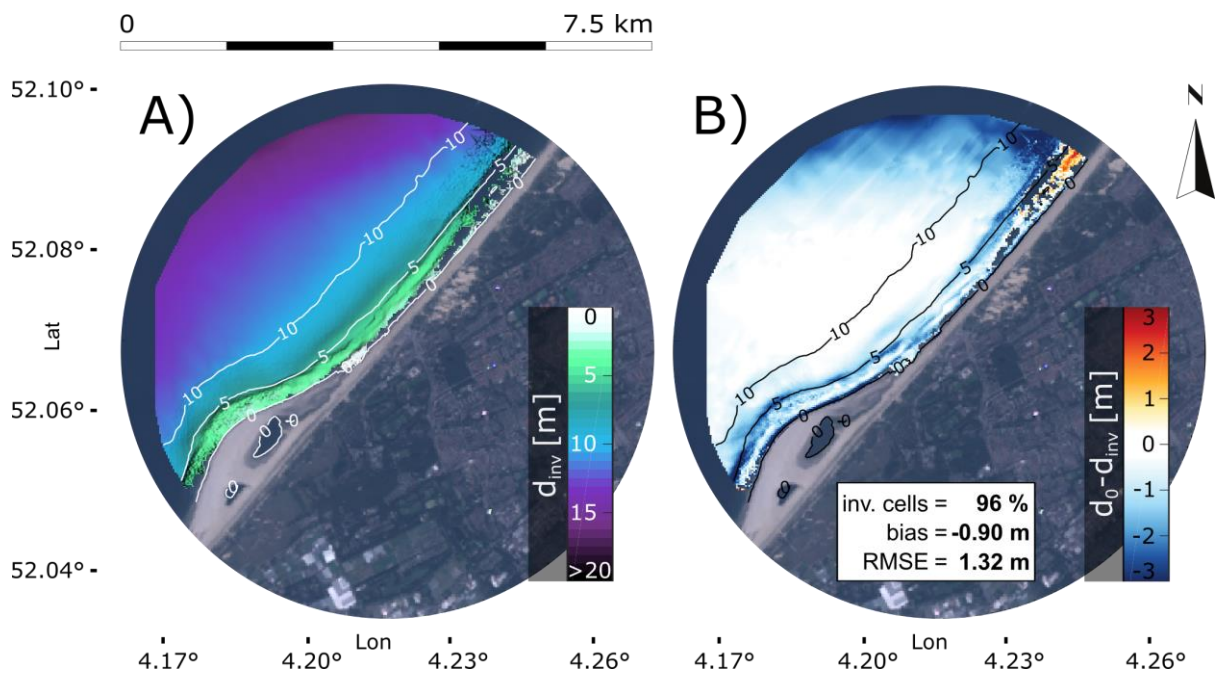
406 The application of XMFit to radar images from the Sand Engine produced spatially smooth
407 depth estimates (Figure 4a). Comparison of the median depth inversions with depth
408 measurements revealed an overall bias of -0.9 m, revealing a tendency for depth
409 overestimation by the DIA. The average standard deviation around a depth estimate was 0.85
410 m and likely stemmed from tidally induced changes in flow direction relative to the direction
411 of wave incidence, see also Discussion section 5.1. The spatial root mean square error
412 (RMSE) was 1.32 m and was mostly caused by inaccuracies close to shore and at the
413 northern boundary of the radar domain. Near the shoreline, especially around the 5 m depth
414 contour (Figure 4b), waves start to break over the nearshore bars and the used linear wave
415 theory is not representative, which causes errors to be locally larger. This is similar to a
416 previous observation by Bell, (2001) for Egmond aan Zee, a site about 60 km to the north of
417 the Sand Engine. Close to the boundary of the radar domain, the radar image quality degrades.
418 Furthermore, at the north-eastern end of the domain the radar beam aligns with wave crests,
419 and depth estimates were poor or not returned. It is interesting to observe that estimates at
420 large depths $d = 10\text{-}15$ m were generally close to ground truth, although peak wave periods
421 were relatively short $T_p = 6\text{-}7$ s, meaning that an error in wavenumber leads to a large error in
422 depth. There are two reasons why such errors are limited in the current approach: First,
423 wavenumber errors are minimized through spectral averaging with 5 temporal bins (see
424 Appendix B). Secondly, many spectral coordinates are used for the non-linear fit (Figure 1,
425 ⑤). For the Sand Engine at these large depths on average about 75 coordinates spread over
426 several angles and 11 frequencies. An important property of 3D-FFTs in combination with
427 anti-aliasing is that frequencies up to two times the Nyquist frequency can be used for the fit
428 (Seemann et al., 1997; Senet et al., 2001). This supplies extra spectral coordinates for the fit

429 (red points above Nyquist frequency in Figure 2), which especially for $T_p = 5-6$ s can offer
 430 some extra certainty on the depth estimate in this case.

431

432 Note that it is possible to improve the results by making changes to the spectral treatment of
 433 the radar data or by using a Kalman filter in post-processing, which we address in the

434 Discussion section 5.



435

436 Figure 4. Radar-derived results for the Sand Engine. (a) Inverted depths d_{inv} (m) (colorbar). (b)

437 Comparison of d_{inv} against in-situ measured depths d_0 (m), where red/blue colors indicate
 438 under-/overestimation of depth respectively. In both panels, contour lines of measured depths

439 are superimposed for reference. Results represent the median over 184 image sequences

440 spanning 18 h in total. Values are included for the percentage of grid cells returning a result

441 (inv. cells), the overall bias (bias) and the root mean squared error (RMSE).

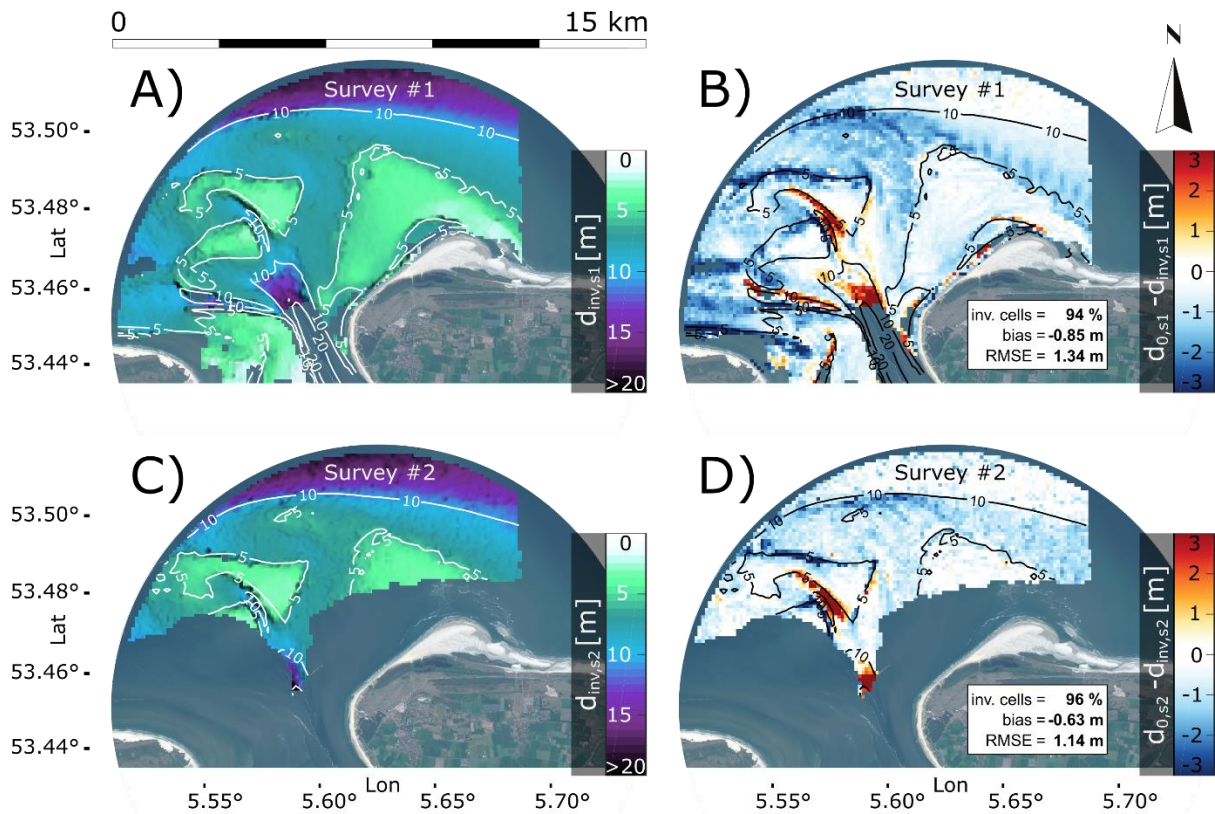
442 4.2 Ameland Inlet

443 Depth results for the Ameland Inlet distinctly captured the characteristic morphological

444 features of the outer delta (Figure 5a,c). The horseshoe-shaped ebb-shield in the west, the

445 central ebb channel, and the large swash platform fronting Ameland were detected by the

446 algorithm. The estimated depths at instances of Survey #1 and Survey #2 compared to ground
447 truth with spatially averaged biases of respectively 0.85 m and 0.63 m, and RMSEs of
448 respectively 1.34 m and 1.14 m (Figure 5b,d), which were largely determined by inaccuracies
449 between the 5-10 m contour lines. We hypothesize these imprecisions to be partly linked to
450 complex local hydrodynamics, which are not accounted for by equation 1, in combination
451 with some radar image related effects. For example, we expect some error due to tide driven
452 shear flows in the channel between the ebb-shield and the swash platform and intense wave
453 breaking and strong wave driven currents along the northern edges of these two features. In
454 the region close to the island of Terschelling, in the western part of the domain (Figure 5b),
455 we ascribe some error to the unfavourable angle of the radar beam with respect to the
456 incoming wave crests. Yet another source of error was present, as the ebb-shield and the
457 western branch of the ebb channel appeared slightly shifted to the south compared to single
458 beam data. This shift stood out in the comparison with ground truth data (Figure 5b,d)
459 through sharp negative biases around feature-edges facing north and corresponding positive
460 biases around feature-edges facing south. Revisiting the raw radar images, revealed that this
461 shift was partly rooted in a localized distortion of the raw radar image data, which was
462 probably caused by a slight misalignment of the radars Northing, but the full origin is
463 unknown and could therefore not be assessed in detail. In contrast, the system performed well
464 for shallow parts such as the large swash platform near Ameland and deep parts to the north
465 of the outer delta. Here, depth estimates were consistently accurate (Figure 5b,d: white areas).



466

467 Figure 5. XMFIt results from the operational Ameland system as compared to a survey from

468 31- May to 5- June 2018 (Survey #1) and a survey from 12-14 October 2018 (Survey #2).

469 Panels (a,c): average depth estimates over two days encompassing each survey, as indicated

470 by (a) $d_{inv,S1}$ for Survey #1 and (c) $d_{inv,S2}$ for Survey #2. Single beam observations are outlined

471 by white depth contours. Panels (b,d): difference of inverted depths d_{inv} with the

472 corresponding single beam measurements d_0 (now accentuated by black contours instead of

473 white contours) as indicated by (b) $d_{0,S1} - d_{inv,S1}$ for Survey #1 and (d) $d_{0,S2} - d_{inv,S2}$ for Survey

474 #2. Similar to the Sand Engine a mostly negative bias (depth overestimation; blue) is

475 observed, being a little higher for Survey #1 (bias = -0.85 m) than Survey #2 (bias = -0.63 m).

476

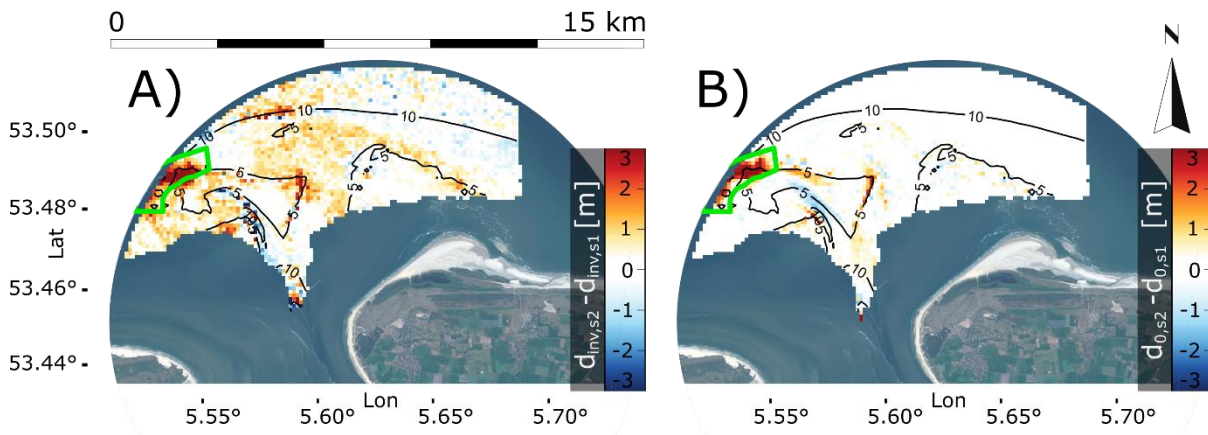
477 The difference between the two time instances of Survey #1 and Survey #2 brought out the

478 signature of the nourishment at the outer rim of the ebb-shield, in the single beam

479 measurements (Figure 6b) as well as radar-inverted results (Figure 6a). These results were in

480 line with the location of the nourishment site as provided by the dredging contractor. A

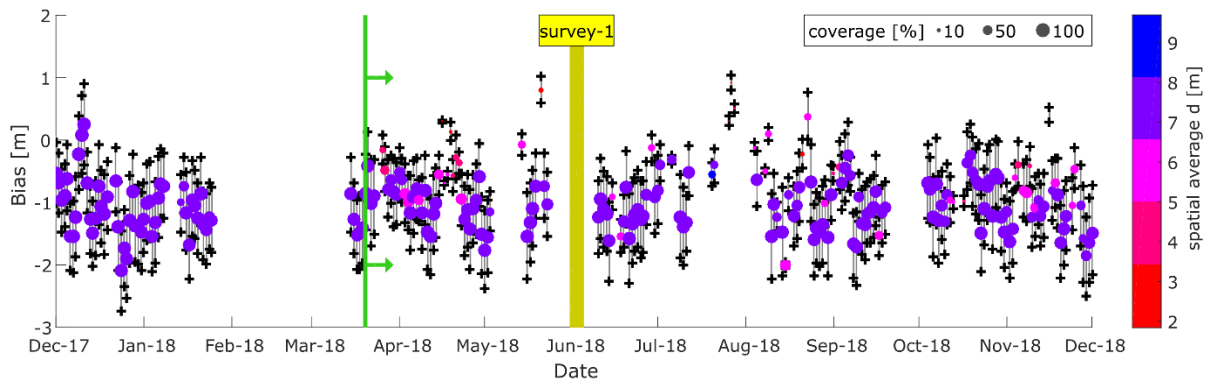
481 succession of sedimentation-erosion patterns across north-eastern direction over the ebb-
 482 shield furthermore suggested a slight, clockwise turning of the ebb-shield over this four-
 483 month period. Although less pronounced than in the single beam measurements (Figure 6b),
 484 these patterns were also found in the radar-derived results (Figure 6a).
 485



486
 487 Figure 6. Difference between June (Survey #1) and October (Survey #2) as derived for radar
 488 and single beam measurements. (a) radar: inverted depths $d_{inv,S1}$ of Survey #1 are subtracted
 489 from $d_{inv,S2}$ of Survey #2. (b) single beam: accordingly, measurements $d_{0,S1}$ of Survey #1 are
 490 subtracted from $d_{0,S2}$ of Survey #2. The pilot nourishment fronting the ebb shield is clearly
 491 visible in both cases and its position is in line with expectation (green polygon). Note that the
 492 surveys do not cover the entire radar domain. For visual clarity, differences between radar
 493 results (a) are truncated to the same area as the surveys (b).
 494

495 Since the nourishment was clearly visible in the time snapshots, the analysis was refined
 496 towards a more detailed time evolution to see whether we were able to monitor volume
 497 changes in the nourishment area during placement. For this, we used all the results produced
 498 between Dec 2017- Dec 2018. Before analysing nourishment volumes, the noise of the radar-
 499 derived depth estimates throughout the radar domain was assessed, as this noise could impact
 500 volume calculations. A timeseries of the spatially averaged depth bias was computed by the

501 difference between radar-derived estimates and single beam data from Survey #1 (Figure 7).
502 It was assumed that the influence of actual morphological change on the bias was negligible
503 compared to the variability in radar depth estimations (cf. Figure 6b and Figure 5b). Although
504 tidal water level changes were accounted for, the timeseries of depth biases fluctuated
505 roughly between -2 m and 0 m. The average standard deviation around a daily depth estimate
506 was 0.71 m. This noise was inherent to the operational system and was likely a product of a
507 combination of factors, such as differences in radar image quality due to external factors
508 (wind, rain, fog), but was also a consequence of applying idealized theory (equation 1) to a
509 complex and variable outer delta environment: we found weak linear dependencies of the
510 depth bias on the water level and the wind speed. For low water levels, NAP -1.5 m, the
511 depth bias was on average -0.74 m and decreased linearly to -1.06 m for high water levels of
512 NAP +1.5 m. Yet, with a standard deviation of 0.84 m the uncertainty in these depth bias
513 values was high and showed that it would be difficult to predict the depth bias from a given
514 water level. A similar linear relation was found between depth bias and wind magnitude: for
515 wind speeds of 3 m/s the depth bias was on average ~ -0.5 m, while for wind speeds of 15
516 m/s this bias was ~ -1.2 m. Yet again, the standard deviation was high at 0.81 m, showing
517 that a prediction of the depth bias based on wind speed would be uncertain. Depth estimates
518 also correlated with simultaneous near-surface current estimates, whose directions and
519 magnitudes are indicators for local depth underestimation or overestimation, as we discuss in
520 detail in section 5.1. Since the current fields constantly change in space and time, they likely
521 contribute to the observed fluctuations in the overall depth bias. No correlations of the depth
522 bias with wind direction, wave height or wave period were found.



523

524 Figure 7. Mean spatial bias over the full radar domain of XMFit estimates with ground truth
 525 data surveyed between 31 May to 5 June 2018 (Survey #1, yellow). The start of nourishment
 526 works is indicated by a vertical green line. Representative bed elevations are obtained by
 527 subtracting local water level measurements from the XMFit depth estimates. Dots represent
 528 the daily median result and whiskers the corresponding 25th and 75th percentiles. Colors
 529 indicate the average depth over the parts of the radar image that contain results and show that
 530 the bias appears lower for moments when only small (small marker size), shallow (magenta,
 531 red) areas could be inverted. When coverage is high (large marker size) the bias also accounts
 532 for sensitive deeper parts (purple, blue). Note that the lack of data during February is due to a
 533 temporary system shutdown.

534 On the time scale of days, the observed noise would severely impact the calculation of
 535 nourishment volumes, therefore a straightforward solution was to ensemble average over a
 536 time window: we based volume calculations on median depth estimates in the nourishment
 537 area over a sliding time-window of one month. Besides denoising, volume estimates were
 538 then continuous in time, bridging over gap periods where the radar system had not been able
 539 to produce depth estimates for the nourishment area (Figure 8, gaps between grey bars). A
 540 window size of one-month was chosen as most data gaps could be overcome, except for a
 541 large gap in February 2018, while noise was largely suppressed. Volume changes were
 542 calculated by multiplying the average depth changes by the nourishment area (see Figure 6,

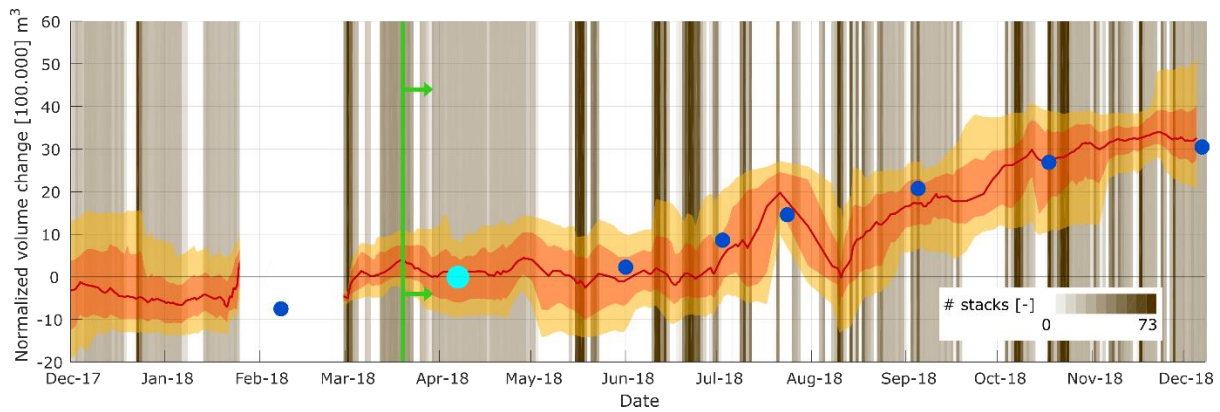
543 green polygon). For the comparison, volumes were computed based on inverted depths as
544 well as the depths from the multibeam surveys of the nourishment.

545

546 To focus the comparison between radar-estimates and multibeam measurements on volume
547 changes, we referenced both the radar estimates and the measurements to the second
548 multibeam measurement. The reason for this is a bias of 2 million m³ between the radar
549 estimates and the measurements in the nourishment area at the time of the second multibeam
550 survey (Figure 5). We assumed this bias to be constant in time, as fluctuations caused by
551 environmental conditions and data quality should average out using a one-month averaging
552 window over a long period of time. This meant that volume changes could be studied.

553

554 Computed volume changes in the nourishment area were relatively stable until they started to
555 increase at the beginning of March 2018 (Figure 8). Considering the start of nourishment
556 works (20. March 2018), this increase appeared two weeks premature. This could be
557 explained by the one-month time window to suppress noise, while having no pre-nourishment
558 data in February to counter balance March data. A RMSE of 276.000 m³ was calculated
559 based on the 7 instances where radar-derived volumes could be related to the multibeam
560 surveys. It represented an error of 7% on the total placement volume of 3.8 million m³. It is
561 interesting to note that the location was at more than 7 km distance from the radar station,
562 near maximum range.



563

564 Figure 8. The time-evolution of the sediment volume changes in the nourishment area (Figure
 565 6, green polygon) for the period Dec 2017 – Dec 2018 according to radar (red line) and
 566 multibeam surveys (blue dots). Volume changes are normalized to the 2nd multibeam survey
 567 (cyan dot). Per day, the number of available XMFIt results that covered the nourishment area
 568 - and could hence be used for volume calculations - is indicated by a vertical grey band (see
 569 colorbar). The monthly median radar estimate (red line) is presented with corresponding 25 –
 570 75 percentile range (shaded red) and 10th – 90th percentile range (shaded yellow). The start of
 571 nourishment execution, 20 Mar. 2018, is indicated by the vertical green line.

572 **5 Discussion**

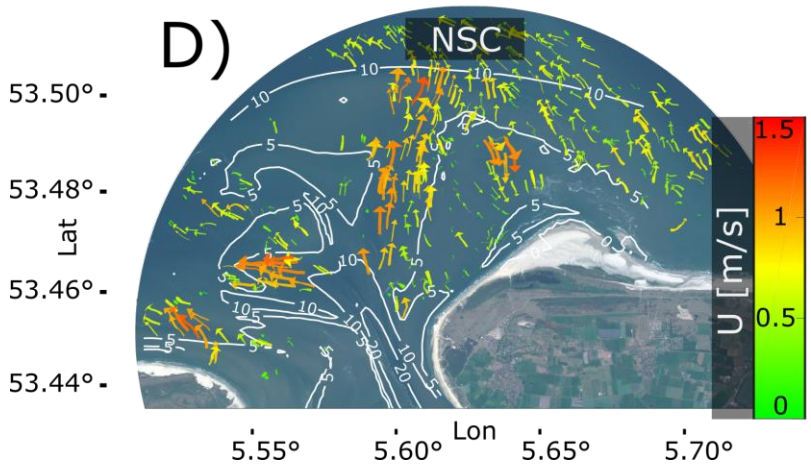
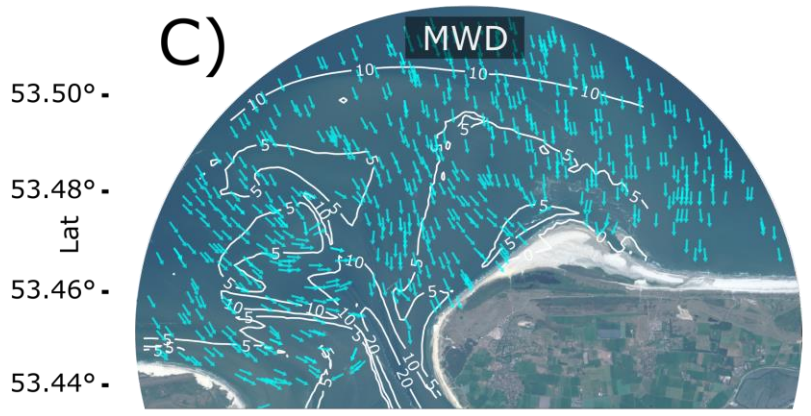
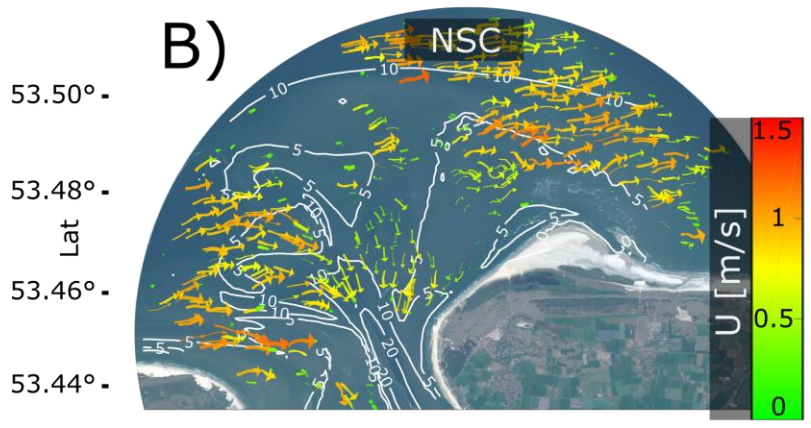
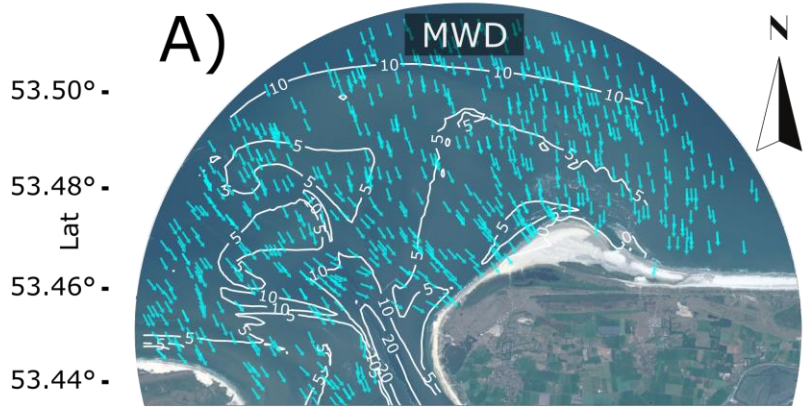
573 The depth inversion showed skill for both the Sand Engine as well as the complex Ameland
 574 Inlet. Yet, the depth was often overestimated in regions (i) that were close to the boundary of
 575 the radar domain (ii) where the radar beam aligned with wave crests (iii) where we expected
 576 complex hydrodynamics due to wave breaking, strong currents or shear flows. These errors
 577 are related to the backscatter, but also to the limitations of using a simplified physical model
 578 (i.e., equation 1, idealized wave-current interaction) for depth inversion. The quality of d
 579 estimates by their covariance with U estimates provides insight into the role of the Doppler-
 580 shift. This is done from a statistical point of view, based on the extensive dataset from the
 581 Ameland Inlet (section 5.1). The d estimates can also be improved. By changing the
 582 computation procedure (section 5.2) and/or by post-processing the results (section 5.3), errors

583 in (i) - (iii) are reduced. Experiments to reduce depth errors were conducted for the Sand
584 Engine, since the image sequences could be recomputed at this site. Note that Ameland depth
585 estimates were collected during a time where the DIA did not yet include a measure for error
586 variance, which means that we could not test the Kalman filter on those data.

587 **5.1 The role of near-surface current estimates in depth inversion**

588 Near-surface currents are estimated per computational cube via the Doppler-shift ($+k \cdot U$,
589 equation 1), being the dot product of a wavenumber vector with a near-surface current vector.
590 Only current components in/against the wave direction alter the wave frequency and thereby
591 affect the depth estimate d . To investigate the effect of U on d , near-surface current directions
592 were translated to near-surface current angles ($NSCA$) with respect to wave direction, which
593 was here taken to be the energy-weighted mean wave direction (MWD) over the spectrum.

594 First a preliminary check was done whether patterns of U and MWD were realistic and
595 thereby suited for further analysis (Figure 9). This appeared to be the case: The MWD
596 captured the effect of wave refraction, being stronger during low tide conditions (Figure 9c)
597 than during high tide conditions (Figure 9a). It also revealed more intricate patterns as for
598 example waves which followed ebb-channels to meet at the bifurcation just below the
599 horseshoe-shaped ebb-shield (Figure 9c). Estimated U -vectors also appeared realistic,
600 reflecting the characteristic tidal flows expected for the area: The tidal wave travels along the
601 barrier islands (Figure 9b,d: vector fields in north-northeast of domain) pushing water into the
602 inlets at upcoming tide (Figure 9b: east-south-eastward flow through ebb-channels) and
603 causing outward flow at falling tide (Figure 9d: westward flow through western ebb-channel
604 and northward flow through central ebb-channel). Details such as flow through the small
605 flood channels near Terschelling at rising tide were also captured.



MWD

607 Figure 9. Examples of mean wave directions (MWD) and near-surface currents (NSC) at the
608 Ameland Inlet, as estimated by XMFIt. Turquoise arrows indicate MWD-patterns. NSC
609 arrows are scaled and colored according to magnitude (colorbar). Panels (a,b): An example
610 from 25 Oct 2018 at 05:50, rising tide with a water level (WL) = NAP +1.1 m. Panels (c,d):
611 An example from the preceding falling tide at 01:30, with WL = NAP -0.9 m.

612 For the Doppler-shift analysis, we retrieved the required *NSCAs* by expressing near-surface
613 currents relative to the collocated *MWDs*. The accuracy of depth estimates was measured by
614 the local depth bias $d_{0,SI} - d_{inv}$, which was computed for each cube in the domain and for all
615 available time instances. In this way a comprehensive dataset was constructed, comprising
616 more than 20 million pairs of depth biases and coincident near-surface current vectors.
617 Analogous to Figure 7, we used Survey #1 as reference to calculate depth biases.

618 The analysis revealed that near-surface current estimates in direction of wave propagation
619 ($NSCA \rightarrow 0^\circ$) generally cooccurred with underestimation of depth, while near-surface current
620 estimates against the direction of wave propagation ($NSCA \rightarrow \pm 180^\circ$) coincided with an
621 overestimation of depth (Figure 10a: sinusoidal shape). These under- and overestimations
622 increased with increasing near-surface current magnitudes (Figure 10a: bright colors at peak
623 $NSCA = 0^\circ$, and trough $NSCA = \pm 180^\circ$). However, weak near-surface current estimates in
624 direction of wave propagation did not guarantee a good depth estimate (Figure 10a: dark
625 colors between $NSCA -60^\circ$ to $+63^\circ$). Still, the observations generally show that the Doppler-
626 shift overcompensates for the presence of currents, as without the Doppler-shift we would
627 expect current-induced depth errors to behave the opposite way (Honegger et al., 2020; eq.
628 10).

629 In shallow water, $d_{0,SI} = 0.5-5.0$ m, depth overestimations and depth underestimations nearly
630 balanced each other over the range of *NSCAs* from -180° to 180° (Figure 10b: median depth

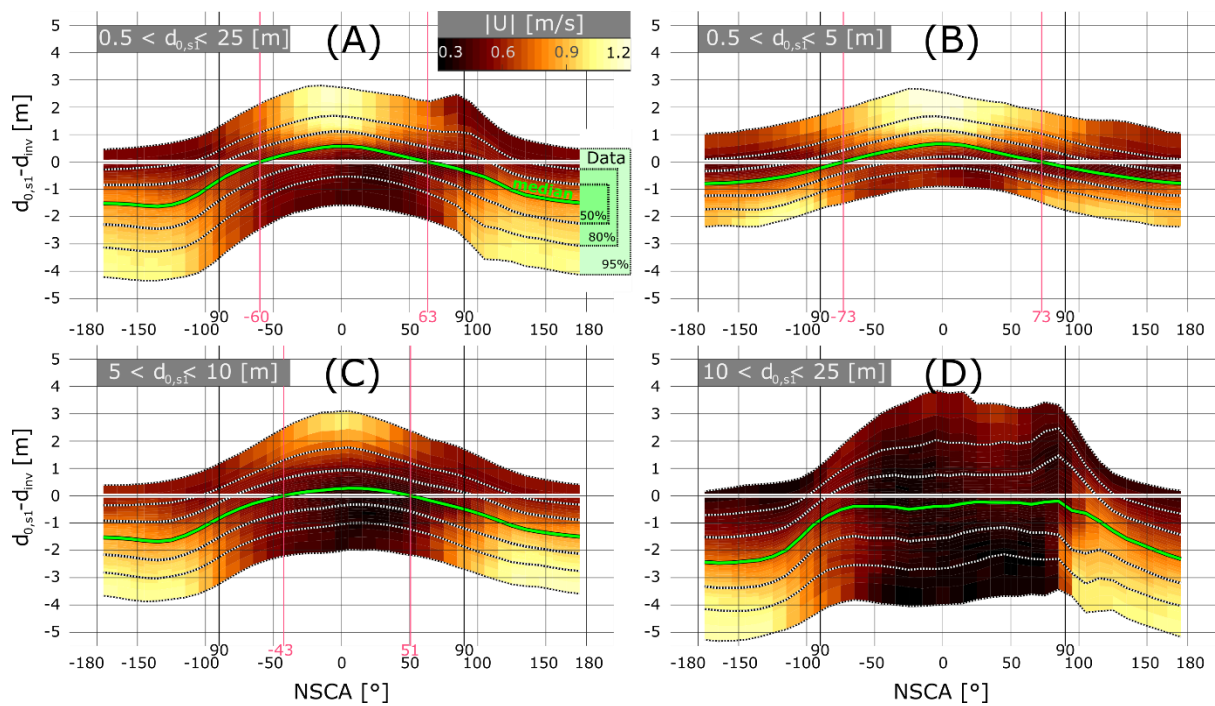
631 bias per *NSCA*, green curve, undulates around zero. Transition from general depth
632 underestimation to overestimation at $NSCA = \pm 73^\circ$, vertical magenta lines). This changed
633 with increasing depth, $d_{0,SI} = 5.0-10.0$ m, as depth overestimations started to dominate depth
634 underestimations for most *NSCA*s (Figure 10c: green curve only positive for *NSCA* between -
635 43° to $+52^\circ$), with chronic overestimation for $d_{0,SI} = 10.0-25.0$ m (Figure 10d: green curve
636 stays below zero). However, in direction of wave propagation these overestimations were on
637 average small with values close to zero (Figure 10d: green curve within $NSCA < \pm 90^\circ$).

638 Besides the tendency towards depth overestimations, also the sensitivity in the depth
639 estimates increased with increasing depth (cf. Figure 10b-d: bandwidth, given by 2.5th -97.5th
640 percentile range, increases from b) ~ 3 m to c) ~ 4 m to d) ~ 6 m) especially for situations
641 where near-surface current estimates pointed in direction of wave propagation (cf. Figure
642 10b-d: bandwidth larger for $NSCA < \pm 90^\circ$). It was interesting to observe that for shallow
643 depths estimated maximum near-surface current magnitudes were larger in direction of wave
644 propagation than against it (Figure 10b: brightest colors for $NSCA \rightarrow 0^\circ$, depth
645 underestimation). For large depths, maximum near-surface current magnitudes were
646 estimated against direction of wave propagation (Figure 10c,d: brightest colors for $NSCA \rightarrow$
647 180° , depth overestimation), while near-surface current estimates in direction of wave
648 propagation appeared to be underestimated (Figure 10c,d: dark colors for $NSCA < \pm 90^\circ$).

649 In summary, observed biases in both depth and near-surface current estimates suggest that the
650 non-linear fit of equation 1 to the spectral data is sensitive to the local depth and the wave
651 direction: (1) Generally, depths are underestimated for near-surface currents following the
652 direction of wave propagation and depths are overestimated for opposing near-surface
653 currents. (2) Strong near-surface current estimates correlate with strong depth biases, but a
654 weak near-surface current estimate in direction of wave propagation does not guarantee a
655 small depth bias. (3) For increasing depth, the depth estimate is more uncertain, tends

656 towards overestimation, and especially so for opposing near-surface currents. (4) This is
 657 correlated with near-surface currents against direction of wave propagation having larger
 658 magnitudes than in direction of wave propagation.

659 The observations suggest that depth estimates may benefit from stricter constraints on
 660 maximum surface current magnitudes (e.g. $|U_{max}| < 0.5$ m instead of $|U_{max}| < 1.5$ m). This
 661 entails that it be difficult to find an optimal solution among the list of $[d_i, U_i]$ -candidates
 662 which satisfies the stricter criterion (Figure 1, ⑥). A way to solve this problem could be to
 663 penalize the non-linear fit for large $|U|$.



664
 665 Figure 10. Observed depth bias (vertical axis) as a function of the near-surface current angle
 666 (NSCA) with respect to mean wave direction (horizontal axis). At $NSCA = \pm 0^\circ$, near-surface
 667 currents point in direction of wave propagation, whereas for $NSCA = \pm 180^\circ$ they oppose each
 668 other. The depth bias is used as proxy for the depth error. Corresponding near-surface current
 669 magnitudes ($|U|$) are shown in bronze colors (colorbar). Panels present data within different
 670 ranges of depth: a) $0.5 < d_{0,sl} < 25.0$ m (all data); b) $0.5 < d_{0,sl} < 5.0$ m; c) $5.0 < d_{0,sl} < 10.0$ m;

671 d) $10.0 < d_{0,sl} < 25.0$ m. Depth biases are calculated as the difference between measured
672 depths from Survey #1 and water level corrected inverted depths, $d_{0,sl} - d_{inv}$. Per *NCSA*, the
673 95% range of observed depth biases is presented (bandwidth) along with their median value
674 (green line); the 95%, 80% and 50% range contours are indicated with dotted black lines and
675 labelled as shown by the green boxes in panel (a). $NCSA = \pm 90^\circ$ are emphasized by additional
676 vertical grid lines, to indicate where near-surface currents have no effect on waves according
677 to equation 1. The angles that are optimal for depth inversion are given by the zero crossings
678 of the median depth bias and are emphasized by vertical magenta grid lines. The dataset
679 includes the results of all analysed cubes over the entire period from Dec 2017 – Dec 2018,
680 amounting to > 20 million observations.

681 **5.2 Choice of spectrum (amplitude vs. energy)**

682 Depth estimates can also be improved in other ways. Depth inversion results are a product of
683 relating wave characteristics to wave theory. A different representation of the wave
684 characteristics may lead to different results, which is investigated by using amplitude spectra
685 instead of energy spectra. The difference is simply that spectra are not squared after
686 performing the 3D-FFT. It does not alter the wavenumber-frequency relationships, but their
687 weights and hence changes the sets of spectral data that are passed to the non-linear fitter
688 during the thresholding procedure (Figure 1, ⑤).

689 The results of this experiment suggest that more favorable sets of spectral data are established
690 if amplitude spectra are used, as the overall depth bias (median over all analyzed image
691 sequences) improved by 0.13 m, from -0.90 m to -0.77 m (cf. Figure 11a,b). The
692 improvements especially occurred around the bars where waves break (Figure 11a,b, right
693 column: red line vs. green line between $d_0 = 4-8$ m). This was also emphasized by an
694 improvement of the bias by 0.22 m for the nearshore area, above the 10 m depth contour.
695 Similarly, also the RMSE improved by 0.20 m from 1.32 m to 1.12 m with improvements

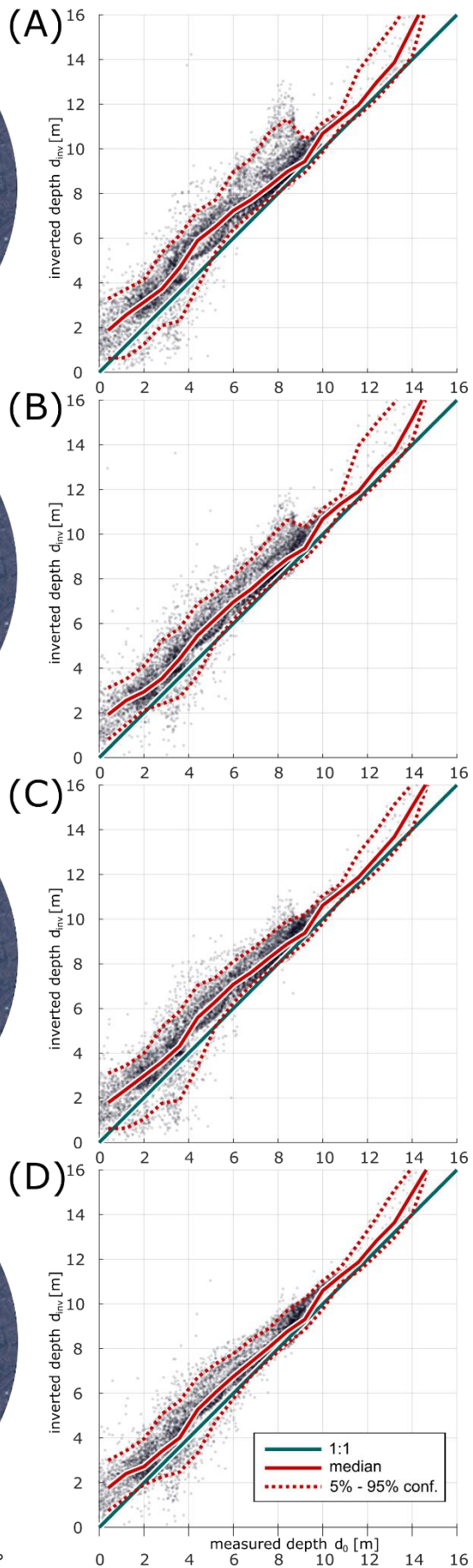
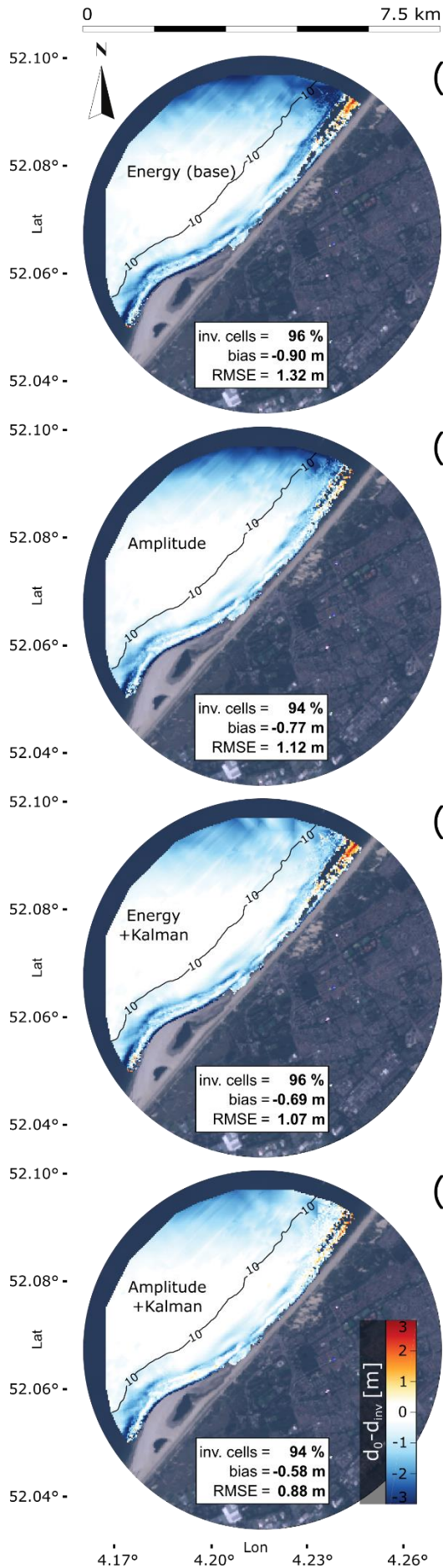
696 being largest in shallow regions and the bar area. This effect can be explained by the
697 disproportionate spectral weight of breaking waves in the image spectrum who by their
698 asymmetry do not agree with the linear dispersion assumption underlying the analysis. Using
699 an amplitude spectrum keeps the spectral weights closer together and thereby reduces the
700 impact of breakers. Improvements were also noticed for the more difficult area to the north-
701 east of the Sand Engine (Figure 11a,b,left column: whitening of north east area), which we
702 ascribe to a relatively weaker impact of bad wave representations; in this case due to radar
703 beam - wave crest alignment and lesser image quality.

704 **5.3 Kalman filtering**

705 An alternative way to improve the XMFit results is through post-processing with a Kalman
706 filter. The Kalman filter is used in time on the derived morphological changes, assuming
707 slowly varying morphology in comparison to the radar sampling interval, analogous to
708 Holman et al. (2013). The Kalman filter is an instrument for quality control and improvement:
709 It weighs the current depth estimate d_t at time t against a previous estimate \bar{d}_{t-1} at $t-1$ using the
710 Kalman gain, K , by $\bar{d}_t = \bar{d}_{t-1} + K(d_t - \bar{d}_{t-1})$, where overbars denote Kalman adjusted estimates.
711 The Kalman gain requires an indication for the confidence we have in the current d_t estimate
712 (R in eq. 5 of Holman et al. (2013)). In line with Holman et al. (2013), we use the error
713 variance σ^2 of the non-linear fit for this purpose. This error variance of d_t is compared against
714 the variance σ^2 of \bar{d}_{t-1} (P in eq. 5-7 of Holman et al. (2013)), which depends on previous
715 estimates of σ^2 , but also on process variance (Q in eq. 6 of Holman et al. (2013)). The process
716 variance, Q , accounts for morphological change that may occur over the period of
717 observations, but since Sand Engine data only cover a period of 18 h, we neglect it (i.e., $Q =$
718 0). For further details on the application of a Kalman filter to bathymetry estimates from a
719 DIA, we refer to Holman et al. (2013). This experiment presents the results after the last,
720 184th Kalman filter iteration.

721 The Kalman filter reduced the depth bias by 0.21 m, from -0.90 m to -0.69 m, and the RMSE
722 by 0.25 m, from 1.32 m to 1.07 m (cf. Figure 11a,c). In this case, the improvements were
723 quite evenly distributed across all depths, including deeper areas (Figure 11a,c,left column:
724 whitening of northern area; Figure 11a,c,right column: narrowing of d_{inv} -confidence interval
725 for $d_0 > 10$ m). The combined effect of a Kalman filter and an analysis based on amplitude
726 spectra was a reduction of the overall depth bias to -0.58 m and RMSE to 0.88 m (Figure
727 11d). The broad improvements clearly showed when compared to the base case (cf. Figure
728 11a,d): Depth estimates of the difficult regions in the north and north-east improved (Figure
729 11a,d,left column), but also the breaker region (Figure 11a,d,right column), which is known
730 to experience larger errors (Bell, 2008). Hence, on the short term, the application of a Kalman
731 filter without process variance is superior to using the median estimate. Though we
732 recommend the data to cover at least one tidal cycle as to dampen out temporary tide induced
733 inaccuracies.

734 Although we could not test the Kalman filter on the Ameland data, due to lacking information
735 on σ^2 , it is also not straightforward to apply. While the Kalman filter has proved itself
736 valuable for the Sand Engine and also other uniform coastlines such as Duck (Holman et al.,
737 2013), more complex coastal systems – like an ebb-tidal delta – may pose a problem when
738 viewed over long periods of time, as morphological change needs to be described by process
739 variance as a function of time and location, $Q(t,x,y)$. Tidal deltas are subject to various drivers
740 and mechanisms that move sediment (Elias et al., 2019; Lenstra et al., 2019). Their influence
741 and interactions continuously change in both space and time, which makes it difficult to
742 formulate and quantify $Q(t,x,y)$. A spatiotemporally uniform implementation could be the
743 choice of an upper bound $Q = \max(\text{morphological change})$, however, remains subject for
744 further study.



746 Figure 11. Methods to improve the XMFit results for the example case of the Sand Engine,
747 shown by comparisons of inverted depths d_{inv} (m) against in-situ measured depths d_o (m). The
748 left column presents difference maps where red/blue colors indicate under-/overestimation of
749 depth respectively. The right column presents direct comparisons of d_{inv} against d_o , including
750 the 1:1 reference (green), the median over all d_{inv} at a certain d_o (red), and the 5%-95%
751 confidence interval (dashed red). Panels (a,b): Median depth estimates over all 184 image
752 sequences from 20-21 Oct. 2014, for (a) the base case using the energy spectrum and (b)
753 using the amplitude spectrum. Panels (c,d): The final, 184th estimate of the Kalman filter after
754 application to results produced using (c) energy spectra and (d) amplitude spectra.

755 By reducing both bias and RMSE, the change of spectrum (section 5.2) and the Kalman filter
756 (section 5.3) have demonstrated that results can be improved. Stricter constraints on near-
757 surface current magnitudes may also increase the accuracy of depth estimates (section 5.1).
758 Future work might provide insights that could lead to additional improvement of the results
759 since some bias and RMSE remains. Early thoughts on common sources of error are (i) more
760 radar image pre-processing to enhance radar image quality with increasing distance from the
761 sensor, for example using FFT-accelerated video reconstruction techniques (Chan et al., 2011)
762 (ii) the application of multiple radars to cover unfavourable wave-angles and (iii) including
763 breaker intensity as a proxy for depth-induced dissipation to improve estimates in breaker
764 zones (van Dongeren et al., 2008).

765

766 **6 Conclusions**

767 A depth inversion algorithm (DIA), XMFIt (**X**-Band **M**ATLAB **F**itting), is a radar-based
768 technique to monitor coastal evolution on large space (10s of kilometers) and time (months)
769 scales. We mapped and analyzed two nourishments in the Netherlands using this technique:
770 (1) an 18-hour snapshot of the beach mega nourishment, the Sand Engine, and (2) a one-year
771 time-series of a 5 million m³ pilot nourishment in the ebb-tidal delta of the Wadden Sea
772 island Ameland. Derived morphologies in both cases largely agreed with ground truth data.
773 Depth biases were around -0.9 m at Sand Engine and fluctuated between approximately -2 –
774 0 m at the Ameland ebb-tidal delta. By averaging and debiasing the radar-derived
775 morphologies, it was possible to accurately quantify the growth of the ebb tidal delta
776 nourishment at Ameland during its placement in 2018 with a volumetric margin error of 7%.
777 Depth errors in the Ameland delta correlated with near-surface current magnitude and
778 direction relative to the direction of wave propagation. The depth errors were generally
779 smaller for small surface current magnitudes and respectively showed under- and
780 overestimation for near-surface currents, in and against the direction of wave propagation.
781 For the Sand Engine, experiments with the spectral treatment and the conceptual employment
782 of a Kalman filter in post-processing improved the depth bias to 0.6 m. Further improving the
783 results and the algorithm remains a scientific and operational challenge.

784 This research presents the successful operation of a DIA on data from a navigational X-Band
785 radar to monitor a mega nourishment in a complex tidal inlet system, allowing coastal
786 managers to assess volume changes over time.

787

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801

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918

919

920 **Appendices**

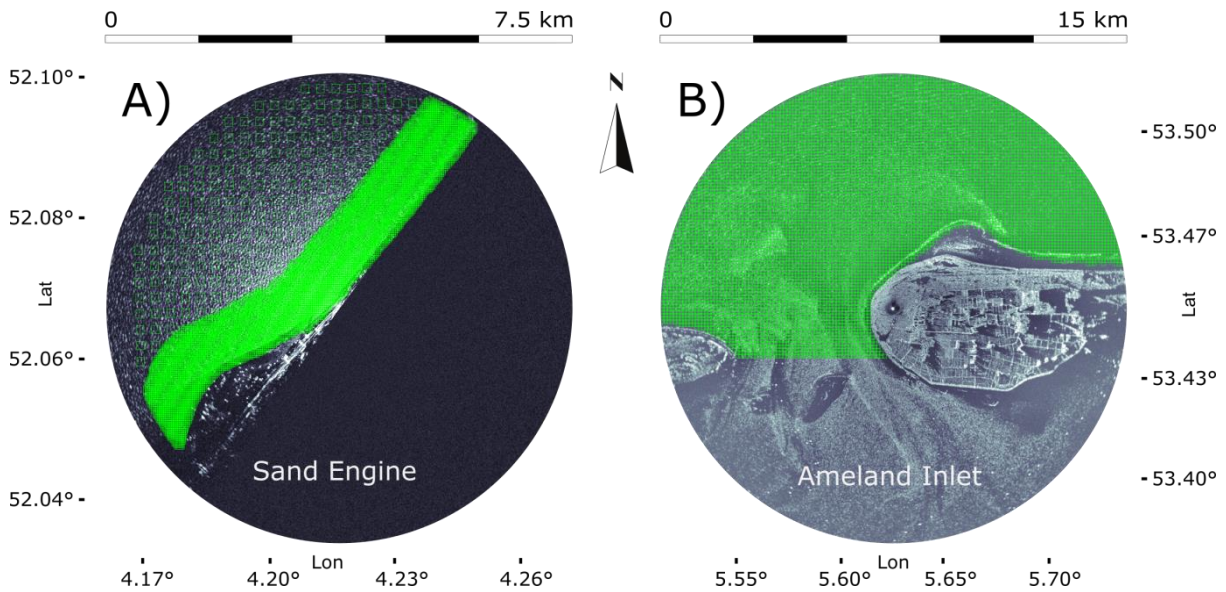
921 **A**

922 Table A.1. Radar properties at the Sand Engine and Ameland

Properties	Sand Motor	Ameland Inlet
Antenna Height [m, NAP]	15	60
System Type	Terma Scanter 2000	Terma Scanter 2001
Antenna Width [ft]	14	21
Range [km]	3.75	7.5
Pulse Length [ns]	50	60
Horizontal Beam Width [deg]	0.5	0.43
Vertical Beam Width [deg]	23	23
PRF [kHz]	4	2.2
Rotation Speed [rpm]	25	21
Output Power [kW]	25	25
Polarization	VV	VV

923

924 **B**



925

926 Figure B.1. Computational grids (green) used for (a) the Sand Engine (b) and the Ameland

927 Inlet. The grids are overlaid on typical radar images of both sites.

928 **Sand Engine**

929 For computational efficiency of XMFIt, a variable grid spacing of 25 m near the shoreline

930 and 250 m further offshore was used, resulting in 9380 grid points. The computational cubes

931 were time-averaged by subdividing them into 32 image bins with 8 images overlap. The
932 spatial extents were 64px (240 m) within 300 m from the shoreline and 128px (480 m) further
933 offshore. The reduced cube size in the nearshore region was chosen in order to capture more
934 morphological detail.

935

936 For consistency, XMFit settings were chosen to be similar to the application at Ameland. The
937 spectral frequency filter was set to include shorter wave periods, $[T_{min}, T_{max}] = [3.5, 15]$ (s)
938 (Figure 1, ②). Depth limits were set to $[d_{min}, d_{max}] = [0.5, 25]$ (m) (Figure 1, ③), and the
939 near-surface current velocity limit was set to $|U_{max}| = 1.25$ (m/s) (Figure 1, ⑥).

940 **Ameland Inlet**

941 In case of the Ameland Inlet, a constant grid spacing of 100 m was used amounting to 8328
942 grid points in total. Computational cubes were time-averaged using 32 image bins without
943 overlap and had a spatial extent of 128px (960 m).

944

945 The inversion process was constrained by the wave period limits $[T_{min}, T_{max}] = [5, 15]$ (s)
946 (Figure 1, ②), depth limits $[d_{min}, d_{max}] = [0.2, 25]$ (m) (Figure 1, ③), and $|U_{max}| < 1.5$ (m/s)
947 (Figure 1, ⑥).

948