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4D Objects-By-Change: Spatiotemporal Segmentation of Geomorphic Surface Change from LiDAR Time Series

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Abstract

Time series of topographic data are becoming increasingly widespread for monitoring geomorphic activity. Dense 3D time series are now obtained by near-continuous terrestrial laser scanning (TLS) installations, which acquire data at high frequency (e.g. hourly) and over long periods. Such datasets contain valuable information on topographic evolution over varying spatial and temporal scales. Current analyses however are mostly conducted based on pairwise surface or object-based change, which typically require the selection of thresholds and intervals to identify the processes involved and fail to account for the full history of change. Detected change may therefore be difficult to attribute to one or more underlying geomorphic processes causing the surface alteration. We present an automatic method for 4D change analysis that includes the temporal domain by using the history of surface change to extract the period and spatial extent of changes. A 3D space-time array of surface change values is derived from an hourly TLS time series acquired at a sandy beach over five months (2,967 point clouds). Change point detection is performed in the time series at individual locations and used to identify change processes, such as the appearance and disappearance of an accumulation form. These provide the seed to spatially segment '4D objects-by-change' using a metric of time series similarity in a region growing approach. Results are compared to pairwise surface change for three selected cases of anthropogenic and natural processes on the beach. The obtained information reflects the evolution of a change process and its spatial extent over the change period, thereby improving

37 upon the results of pairwise analysis. The method allows the detection and spatiotemporal
38 delineation of even subtle changes induced by sand transport on the surface. 4D objects-by-
39 change can therefore provide new insights on spatiotemporal characteristics of geomorphic
40 activity, particularly in settings of continuous surfaces with dynamic morphologies.

41 **Keywords:** Terrestrial laser scanning, high-frequency observation, spatiotemporal analysis,
42 beach monitoring, temporal domain

43

44 **1. Introduction**

45 Earth surface morphology is continually shaped by dynamic processes. Induced surface changes
46 within a natural landscape occur at varying locations and at different spatial scales, frequencies,
47 and movement rates. Monitoring of geomorphic activity therefore requires the observation of a
48 multitude of individual, often superimposed processes. Alterations to surface morphology are
49 often quantified based on the distance between surface locations recorded at successive points
50 in time, referred to as epochs in geospatial analysis (Eitel et al., 2016; Lindenbergh & Pietrzyk,
51 2015). At present, such change analyses are mostly conducted as pairwise comparisons,
52 referring to the quantification of change between two epochs. Pairwise analysis involves the
53 drawback that change information is obtained as an aggregated representation of individual
54 underlying processes. When observed as local surface changes at single points in space and
55 between only two snapshots of the topography, it is not possible to infer which process led to the
56 current state of the surface and how it evolved through time. At the same time, the underlying
57 change is not necessarily distinguishable into deposition, erosion, and transport without ambiguity
58 (Fig. 1). Relating quantified local surface change to the processes that shaped the surface is
59 therefore a widespread challenge in the analysis of geomorphic activity (Fey et al., 2019; Mayr et
60 al., 2018).

61 Analysing time series of geospatial data has the potential to increase insight into the mechanisms
62 of geomorphic activity (Eltner et al., 2017; O’Dea et al., 2019). This study focuses on the
63 morphodynamics of a sandy beach, where sediment transport is driven by an interplay of agents,
64 including wind and wave forcing, as well as anthropogenic modifications. The resulting multi-
65 process characteristics of periodic, gradual and continual change processes occurring at different
66 time scales apply to a range of natural topographies, including rock slopes (Kromer et al., 2015a),
67 glaciers (Rossini et al., 2018), rock glaciers (Zahs et al., 2019) or permafrost coasts (Obu et al.,
68 2017). The observation of individual change processes and analysis of their contribution to the
69 geomorphic system requires data acquired at spatial and temporal resolutions that account for
70 the range of scales at which the induced changes occur (Rumson et al., 2019).

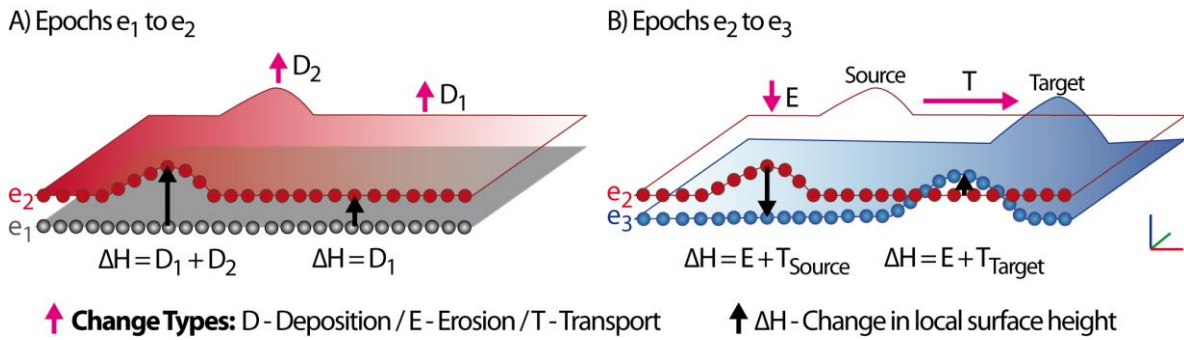


Figure 1: Pairwise observation of change types 'deposition', 'erosion', and 'transport' co-occurring in a geomorphic system. The processes that underlie single values of local surface height change are ambiguous. A) Observed change can result from superimposed surface alterations (e.g. D_1 and D_2). The spatial extent of accumulation from D_2 on the continuous surface is not distinct. B) Local surface height decrease at the source of transported material and increase at the target location cannot be attributed unambiguously to the respective change types erosion E and transport T .

71 As the research on and the variety of applications of geospatial monitoring grow, more series of
 72 multitemporal data are being acquired at repetition rates that are annual, monthly, or even shorter
 73 (Eitel et al., 2016) with a range of topographic survey techniques. High-frequency (sub-hourly to
 74 weekly repetition intervals) time series of high spatial resolution (sub-centimetre to metre) and
 75 long acquisition periods (months to years) are becoming increasingly available through near-
 76 continuous terrestrial laser scanning (TLS; e.g. Kromer et al., 2017; O'Dea et al., 2019; Vos et al.,
 77 2017; Williams et al., 2018).

78 While datasets are being captured at increasing temporal resolution, methods for analysing
 79 surface change from geospatial time series mostly follow the described approach of pairwise
 80 analysis of local surface changes. This approach is well-established in analysing conventional
 81 multitemporal LiDAR data of several epochs (typically < 100 ; e.g., Corbí et al., 2018; Fey et al.,
 82 2019; Mayr et al., 2018; Zahs et al., 2019). Pairwise analyses are also suitable in settings where
 83 surface change is progressing in a more or less uniform direction, i.e. deposition or erosion is the
 84 dominant change type, and the effect on surface morphology is irreversible. This applies, for
 85 example, in the case of continuous erosion on a slope or rockfall on a cliff (e.g. Kromer et al.,
 86 2017; Williams et al., 2018). In such settings, the possible change processes are mostly known a
 87 priori and pairwise surface change can be attributed to the respective (expected) process.

88 An alternative approach to surface change quantification is object-based geomorphic change
 89 analysis (Anders et al., 2013; Liu et al., 2010). These methods quantify the surface or volume
 90 change and displacement of individual geomorphic features or objects within a scene. Such
 91 features are extracted from each epoch of the multitemporal data and are typically based on
 92 morphometric properties, such as breaks in curvature at edges or planar surfaces on objects. The
 93 approach is used, for example, to monitor the change of characteristic units or structures on
 94 beaches (Corbí et al., 2018; Fabbri et al., 2017; Le Mauff et al., 2018) or the displacement of
 95 breaklines as geomorphic features, representing scarps or ridges (Mayr et al., 2018; Pfeiffer et

96 al., 2018). The required identification and classification of objects typically implies the definition of
97 morphometric properties for target objects from the outset. This becomes particularly challenging
98 when monitoring over long periods, where features can occur in many variations of their spatial
99 properties. It also requires that objects can be spatially delineated within each epoch, which is
100 only possible if they have a distinct morphology. In the flat and gently sloping surface morphology
101 of a sandy beach, for example, the exact spatial extent of an accumulation form is difficult to
102 determine even to a human observer both on site and in high-resolution topographic data.

103 Binary surface change information (change/no change) between successive epochs has been
104 considered for the spatial delineation of objects in the segmentation of morphometric features
105 (Mayr et al., 2017). Change objects are defined as spatially connected areas of pairwise change,
106 which has been introduced into coastal monitoring (Liu et al., 2010). If such object-based
107 assessment considers change between only two epochs, the spatial boundary of individual
108 change types may remain concealed by coinciding surface alterations caused by multiple
109 processes. For example, localised accumulations within an area of large-scale accretion will be
110 aggregated into a single change object of combined extent. The spatial and temporal properties
111 of the processes involved, however, often differ over time. Accretion is a slow, continual process
112 while local accumulation may occur more rapidly and, from this, become distinct in the evolution
113 of surface change at the location. This additional information that can be gained from the
114 temporal domain, and in particular the history of change of each point on the surface is difficult to
115 integrate into the interpretation of change for a given location at a single, specific point in time.
116 The identification of objects therefore requires the entire history of change of a given point on the
117 surface.

118 Our research develops a novel approach to 4D (3D + time) change analysis that fully
119 incorporates the temporal domain, with the aim of improving the identification of change
120 processes in time series of geospatial data. We make use of the full available history of surface
121 change for the purpose of spatiotemporal object segmentation, in doing so advancing the concept
122 of pairwise change objects to '4D objects-by-change'. Spatial neighbourhoods that experience
123 similar surface change within certain periods are delineated based on their similarity in the
124 temporal domain. This removes the requirement of object detection and re-identification in single
125 or pairwise snapshots and removes the need of having a strict definition of object in terms of
126 temporal processes or morphometric properties, such as size and shape. Integrating time series
127 into surface change analysis allows the inclusion of a variety of spatial and temporal scales
128 (extent, magnitude and duration) in the identification of geomorphic change. A metric of time
129 series similarity integrates flexibility of spatial extent in object extraction. Otherwise, spatial
130 delineation of change may mainly depend on the definition of threshold values even if object
131 boundaries are difficult to determine conceptually.

132 Our method provides a novel view on time series-based surface change analysis, which allows
133 automatic and generic extraction of the 4D geoinformation present in time series of 3D
134 topographic data. 4D objects-by-change generate more detailed histories of identified surface
135 change as compared to pairwise surface change analysis. This will provide a basis for relating
136 individually identified change types to specific geographic processes, and to assess their
137 contribution to the dynamic shaping of a landscape.

138 2. Study Site and Data

139 We present our method using a time series of 3D point clouds acquired at the sandy beach of
140 Kijkduin (52°04'14" N, 4°13'10" E; Fig. 2), the Netherlands. A Riegl VZ-2000 TLS (Riegl LMS,
141 2017) was mounted in a stable reference frame overlooking the beach during the winter of 2016-
142 2017 (Vos et al., 2017). The scene was scanned every hour with a vertical and horizontal point
143 spacing of 9 mm at 10 m measurement range. The target area of the beach ranges between
144 100-600 m from the sensor resulting in point densities of 2-20 points/m².

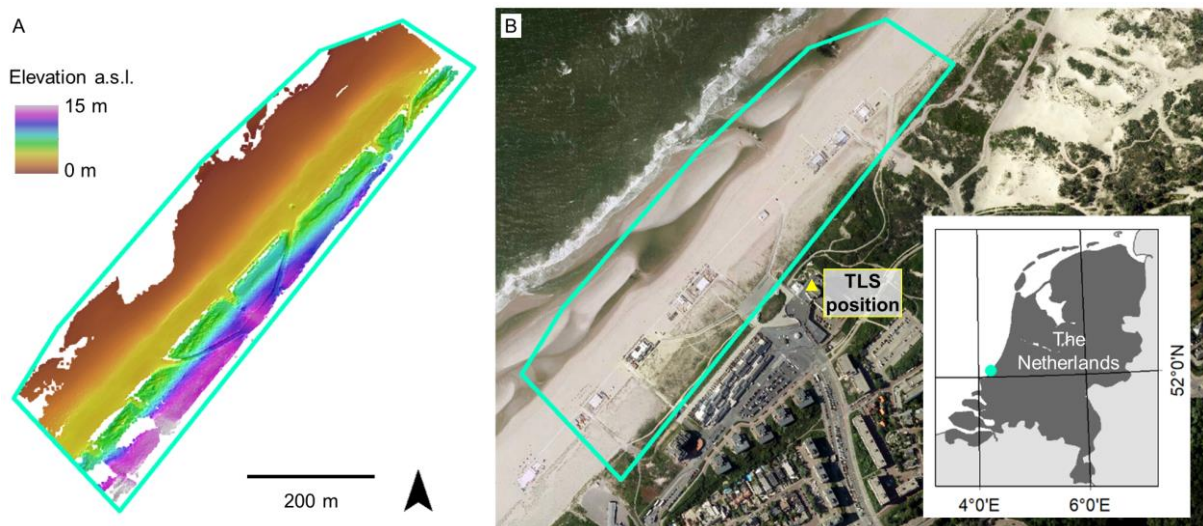


Figure 2: (A) Terrain elevation of the study site (based on TLS data) with extent designated in (B) aerial imagery of the beach at Kijkduin with map of the study site location in the Netherlands. Data: Aerial imagery © pdok.nl 2017, World Borders © thematicmapping.org 2017.

145 The period examined starts on 2017-01-15 at 13:00 (Central European Time; UTC+1), following a
146 storm event in the days before, and ends on 2017-05-26 at 8:00, which is the end date of the
147 fixed TLS acquisition at this site. Several epochs are missing due to rainfall that prevented any
148 data from being acquired at the measurement range of the target area. In total, the time series
149 comprises 2,967 point clouds. Gaps in local areas of an epoch may exist due to missing data in
150 the respective point cloud caused by occlusion of the ground surface (e.g. temporary objects
151 such as machinery and people) or the presence of water on the surface (e.g. at high tides) during
152 scan acquisitions.

153 Pre-processing of the TLS data consists of fine alignment of each point cloud to a global
154 reference point cloud of the first day (2017-01-15, 15:00). This fine alignment is conducted with
155 an Iterative Closest Point method (Besl and McKay, 1992). The alignment accuracy is assessed
156 based on point-to-plane distances for planar surfaces distributed in the stable region of the point
157 cloud scene, which are distinct from the surfaces used for fine alignment. The method of fine
158 alignment and the determination of alignment accuracy are described in detail in Anders et al.
159 (2019). The pre-processed TLS time series has a mean alignment accuracy of 4 mm with a
160 standard deviation of 2 mm. The minimum detectable change is further limited due to a range-
161 dependent refraction effect in the LiDAR measurements that varies over time with atmospheric
162 conditions (cf. Friedli et al., 2019). At the measurement range of the beach area, the minimum
163 detectable change is estimated to reach up to 0.05 m (cf. Anders et al., 2019). The temporally
164 dense measurements of the dataset can be leveraged to reduce uncertainty from the quantified
165 change. We make use of this in a temporal averaging step (Section 3.1). Each point cloud is
166 filtered to remove off-terrain points based on the relative height of points over the local minimum
167 in a neighbourhood of 1.0 m raster cells. The filtering threshold is set to a maximum relative
168 height of 0.2 m to account for surface roughness and the slightly sloping terrain morphology. We
169 use the software OPALS (Pfeifer et al., 2014) for the pre-processing steps of fine alignment and
170 terrain filtering. This time series of pre-processed point clouds is used for all subsequent analyses
171 in this paper.

172 **3. Methods**

173 For the extraction of 4D objects-by-change, we develop a method of spatial segmentation with
174 respect to the history of surface change. The method identifies change processes as temporal
175 features within the time series of surface change. The features include both raising of the surface
176 followed by lowering and lowering of the surface followed by raising. The locations are used in a
177 regular grid structure, derived from point cloud distances per epoch. Local neighbourhoods are
178 then spatially grown into 4D objects-by-change based on the similarity of time series segments
179 (Fig. 3). The methodological steps are presented in detail in the following sub-sections (Sections
180 3.1 to 3.3). We evaluate the results of our approach in comparison to the current standard
181 procedure of pairwise, binary threshold-based analysis (Section 3.4), which provides single
182 images of surface change between two epochs instead of the full history of surface change
183 contained in our approach.

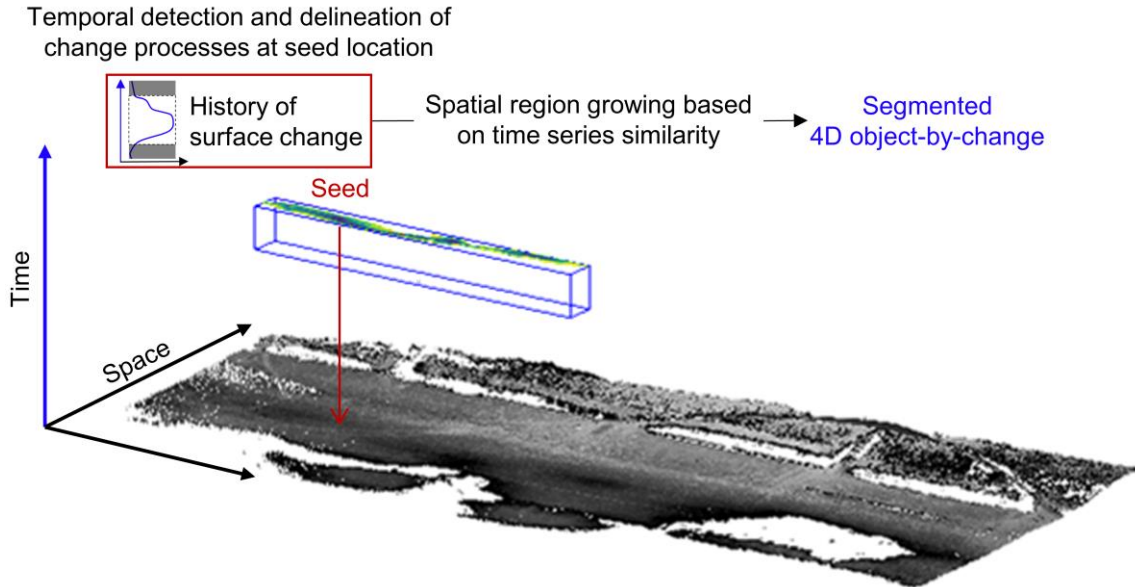


Figure 3: Approach for the extraction of 4D objects-by-change. A change process is detected and delineated in the time series of surface change at one location. The temporal change feature is used as seed for spatial region growing. The homogeneity criterion for region growing is the similarity of time series in the period of the temporal change feature. The segmented 4D object-by-change has a temporal and spatial extent in the space-time array.

184 3.1 Deriving a Space-Time Array of Surface Change

185 For the developed approach, the time series of 3D point clouds is processed into a time series of
 186 surface change in a regular grid structure. Re-sampling into this 3D space-time array of surface
 187 change values facilitates data access along the temporal domain.

188 We quantify surface change on the beach as the vertical distance of the surface between each
 189 epoch and a reference point cloud on the first day of the analysed period (2017-01-15, 13:00).
 190 The epoch at this time of day was selected due to the low tide, enabling measurements over a
 191 large extent of the beach area. Point cloud distances are derived using the Multiscale Model to
 192 Model Cloud Comparison (M3C2) algorithm (Lague et al., 2013). We use a regular grid with 0.5 m
 193 horizontal spacing to define the 2D locations at which distances between the two point clouds are
 194 calculated. This spacing is chosen regarding the lowest point spacing in the target scene
 195 (Section 2). The projection radius (Lague et al., 2013), representing the neighbourhood within
 196 which the position of each point cloud is averaged during distance calculation, was set to 1.0 m.
 197 The distance calculation at the regular grid locations uses all original TLS points within the
 198 projection radius.

199 Using the obtained space-time array of surface change, we perform averaging of the surface
 200 change values for every 2D point location on the beach along the temporal domain, i.e. based on
 201 the values at previous and successive points in time. This enables the identification of values that
 202 notably deviate from their temporal neighbours and are less likely to represent actual change

203 rather than measurement errors in the point cloud. Each surface change value in the time series
 204 of a location is averaged by setting it to the median of its temporal neighbourhood in a window of
 205 defined size. The approach benefits from sampling redundancy in the temporal domain
 206 particularly if the acquisition frequency exceeds the rate of observed surface change.
 207 Accordingly, the averaging window needs to be sufficiently small to avoid smoothing out the
 208 temporal trend of the actual surface change (Kromer et al., 2015b). We use a temporal averaging
 209 window of one week (168 h) on the beach data in this study. This offers a compromise between
 210 removing temporal measurement effects from variable atmospheric conditions (Anders et al.,
 211 2019) and preserving morphologic change, providing an interdependent combination of
 212 exceeding the minimum detectable change (in terms of magnitude) and the temporal scale (in
 213 terms of duration).

214 3.2 Identification of Temporal Change Features

215 Our approach to 4D change analysis begins by identifying the occurrence of a change-inducing
 216 process in the time series of change values (Fig. 4). We first determine the points in time at which
 217 the height change values in the time series change with respect to the mean. These change
 218 points are used to delineate change features in the temporal domain based on the shape of the
 219 time series.

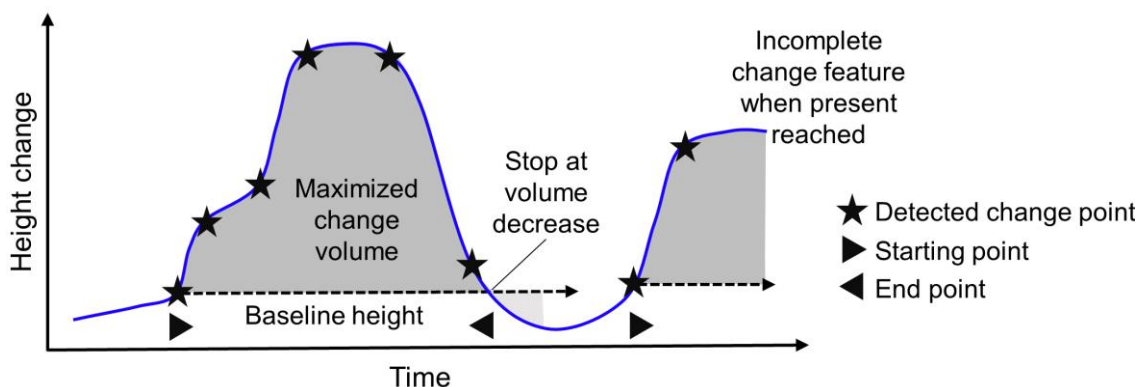


Figure 4: Schematic representation of temporal change feature delineation using the earliest change point that is not within a previous change feature as a starting point. The end point is increased as long as the volume of surface change (area under the curve) increases with respect to the starting point's change value as baseline.

220 Change point detection can be performed by comparing the distribution of values between two
 221 successive periods, i.e. segments of the time series. The instants at which this relationship
 222 changes are to be detected as change points (Kawahara & Sugiyama, 2012; Truong et al., 2019).
 223 Segments are derived based on changes in the median of the change values, i.e. the central
 224 point of the value distribution within a segment, with least absolute deviation as measure of
 225 homogeneity (Bai, 1995; Truong et al., 2019). The change point detection method uses a sliding
 226 temporal window to compute the discrepancy between two adjacent windows that move along the
 227 signal. This sliding temporal window is subsequently referred to as change point detection

228 window. Peaks in the discrepancy curve determine the position of change points (Truong et al.,
229 2019). As the number of change points to be detected is unknown in our application, a constraint
230 needs to be introduced for dividing the time series into increasingly small segments. We use a
231 complexity penalty in the time series segmentation which acts in relation to the amplitude (i.e.
232 magnitude) of changes to detect. The higher the penalization, the stricter the change point
233 detection. Conversely, the lower the penalization value, the more change points are detected
234 down to discrepancies that derive from noise in the signal (Maidstone et al., 2017; Truong et al.,
235 2019).

236 We use a change point detection window of 24 h, considering that change values are smoothed
237 in an averaging window of one week (Section 3.1). This ensures that the smallest temporal scale
238 of change occurrences that are contained in the time series dataset are detected. We set the
239 penalty for change point detection to 1.0, such that the number of detected change points does
240 not strongly alter with an increase or decrease of the penalty. The step size of the change point
241 detection window is 1 h, so change points can potentially be detected at each epoch of the time
242 series. We constrain the change point detection by setting a minimum distance of 12 h between
243 change points so that there is no overlap between temporal windows of detected change points.
244 The change point detection is performed using the implementation in the Python library *ruptures*
245 (Truong et al., 2018).

246 Change processes are identified within the time series of surface elevation change by using a
247 normalised volume maximization approach to identify their start and end times (Piltz et al., 2016).
248 From a detected change point as starting point, the change feature is grown along the temporal
249 axis by increasing the time of the end point for as long as the area under the curve of surface
250 change values is increasing. The increase or decrease of the change volume is determined
251 relative to the value of the starting point as baseline. In the process, the cumulative surface
252 change of the change feature is maximized. As soon as adding another epoch of surface change
253 has the effect of decreasing this cumulative value, the process is stopped (Fig. 4). This step is
254 applied to all change points detected in the time series, starting from the earliest. Successive
255 change points are only used as new starting points if they do not lie within a previously detected
256 change feature. By this, over-sensitively detected change points are automatically discarded. To
257 be able to delineate both positive and negative change features, we include a check if the surface
258 change in epochs following the starting point is negative (relative to the starting point). For
259 negative features, the time series is inverted so the same procedure of delineation can be
260 applied. All time series are shifted to contain only positive values for this step. Once a change
261 feature is delineated in the temporal domain of a location, the next step is to segment the 4D
262 object-by-change spatially based on neighbouring locations of similar temporal change features.

263 **3.3 Spatial Segmentation of 4D Objects-By-Change**

264 We assume that geomorphic change at a given location causes similar surface alterations within
 265 a local neighbourhood. We use this to group spatially contiguous locations with a similar history of
 266 surface change in the period of a temporal change feature. In a region growing approach, an area
 267 is segmented based on the similarity of neighbouring time series as homogeneity criterion
 268 (Fig. 5), to form a 4D object-by-change.

269 For the period of features derived in Section 3.2, we derive the similarity of the time series for
 270 each point in the grid using Dynamic Time Warping (DTW, Berndt & Clifford, 1994). This method
 271 finds the alignment between two time series by stretching and shrinking a reference time series
 272 along the temporal domain. The sum of minimized distances between point pairs in the time
 273 series yields the DTW distance as a similarity measure (Berndt & Clifford, 1994; Salvador &
 274 Chan, 2007). We subtract the median value from each input time series segment for this
 275 calculation to assess the time series similarity independent from the previous history of surface
 276 change. As surface change is quantified using a fixed epoch as reference, this history may differ
 277 between neighbouring locations but they still belong to the same 4D object-by-change. We
 278 compute the DTW distance using the implementation of the Fast DTW algorithm (Salvador &
 279 Chan 2007) in the Python library *fastdtw* (Tanida, 2019).

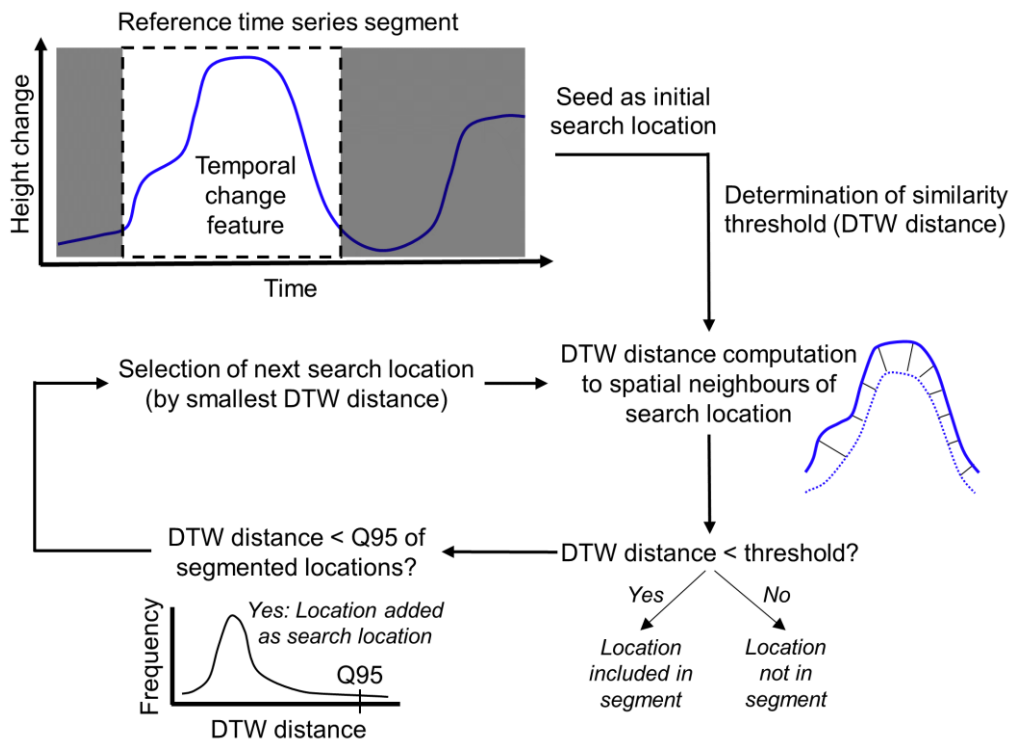


Figure 5: Spatial segmentation of a 4D object-by-change starting from the location of the detected temporal change feature as seed and computing the Dynamic Time Warping (DTW) distance as similarity criterion for adding locations to the segment and using them as additional search locations for region growing.

280 The spatial region growing starts at a seed location by computing the DTW distance to all eight
281 connected spatial neighbours of the 2D time series locations. If the distance of a compared
282 location exceeds a defined similarity threshold, it is discarded. Otherwise, the similar locations are
283 added to the current segment. We use a stricter, but adaptive criterion of using a segmented
284 location as a new search location based on the distribution of distance values in the current
285 segment. A location for searching further spatial neighbours as candidates is added if the DTW
286 distance of the segmented location is smaller than the 95th percentile of all distance values
287 segmented so far (Rabbani et al., 2006). The percentile threshold of adding candidates as
288 additional search locations initiates when the segment reaches a minimum segment size of 10,
289 corresponding to an area of ~2.5 m² for the dataset in this study. Before this segment size is
290 reached, all segmented locations are used as neighbour search locations. After checking all
291 neighbours of a current search location, the candidate with the lowest DTW distance is used. The
292 growing of a segment is stopped when no more search locations are available.

293 For the segmentation threshold, there is no single DTW distance that can be used as general
294 similarity value, as the order of DTW distance values between two time series that are regarded
295 as similar relate to the overall change energy, i.e. the total surface height changes within the
296 process, as well as magnitude and duration of the respective change process. We therefore
297 selected a threshold by assessing the distribution of DTW values within the 10 × 10 m
298 neighbourhood of initial seeds. According to the results of this assessment, we set the threshold
299 to the mean of DTW distance values.

300 **3.4 Test Cases and Comparison to Pairwise Surface Change Analysis**

301 To evaluate the time series-based change analysis compared to results from simple pairwise
302 analysis, we pick representative cases of change processes with different spatial and temporal
303 properties to examine the improvement in information obtained from the 4D approach. The
304 following cases are selected from the acquisition period at the Kijkduin beach scene:

- 305 1) An accumulation of sand that was later removed by heavy machinery. The change has a
306 high magnitude (> 1.5 m surface height increase) and is limited to a small spatial extent
307 (~4 × 4 m). Both accumulation and removal of the sand occur quickly relative to the time
308 interval of monitoring.
- 309 2) A sand bar that forms and later disappears near the shoreline. The sand bar has a high
310 magnitude of change (> 0.8 m) but does not have distinct spatial borders (Section 1) as it
311 translates and deforms over time.
- 312 3) A mass of sand transported towards the upper beach area on destruction of the sand bar.
313 The resulting temporary surface height increase (> 0.15 m) is well above the minimum
314 detectable change but only subtly visible in the topography, which makes it difficult to
315 spatially delineate.

316 For comparison to a pairwise analysis, we use individual 2D slices from the 3D space-time array,
317 which represent pairwise surface height change of an epoch to the reference epoch. These
318 change rasters are derived from the epochs in the beginning and end of a segmented 4D object-
319 by-change, and at the highest magnitude of surface change within the period of the change
320 process.

321 4. Results

322 In this section, we present the results of the change feature delineation and spatial segmentation
323 based on time series similarity. We then present the extracted 4D object-by-change of selected
324 cases as compared to pairwise surface change.

325 4.1 Identification of Temporal Change Features

326 The examples of change described in Section 3.4 were detected from the time series of surface
327 change (Fig. 6). Additional change features were detected in the time series of cases 1 and 3. In
328 case 3, the second change feature is not completed with an end point, as the time series ends
329 before completion.

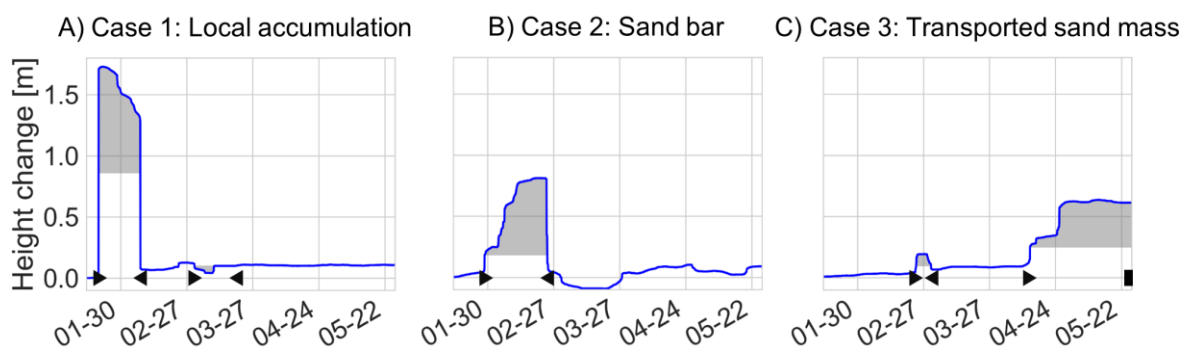


Figure 6: Result of temporal change feature delineation for the selected cases of (A) an accumulation of sand shifted by heavy machinery works, (B) a sand bar forming and disappearing near the shoreline, and (C) a mass of sand being transported that is manifested in local surface height increase and decrease at the selected location. Starting and end point of change features are marked by triangles. Dates are provided as month-day.

330 The method for change point detection accurately delineates the periods of change in the
331 selected cases. These cases show that the spatial scale and temporal pattern of surface change
332 does not influence the delineation of the targeted features. The placement of starting and end
333 points in the change features may not provide the optimal positions to determine the onset and
334 end of a change process for all types. For example, the starting point of accumulation in a change
335 feature may be set at a point after surface height increase of the process has already started
336 (Fig. 6, case 1). This does not influence the extraction of 4D object-by-change, but can become
337 relevant to subsequent analyses, for example to quantify the contribution of individual change
338 processes to the volume budget in the geomorphic system.

339 For the dataset at hand, we perform retrospective change point detection, that is, all data has
 340 been collected and the full time series is processed. As we use a window-based approach that
 341 can continuously advance into the future independently from past occurrences, the method can
 342 be applied in an operational, online setting to detect change processes as soon as possible after
 343 or even while they occur.

344 4.2 Spatial Segmentation of 4D Object-By-Change

345 We show the result for the three selected cases as time series plots of all segmented locations
 346 within the period of the change feature, and the spatial extent on the beach area (Fig. 7). We
 347 additionally show the distribution of DTW distance values, which altogether provides a visual
 348 summary of the information contained in a 4D object-by-change.

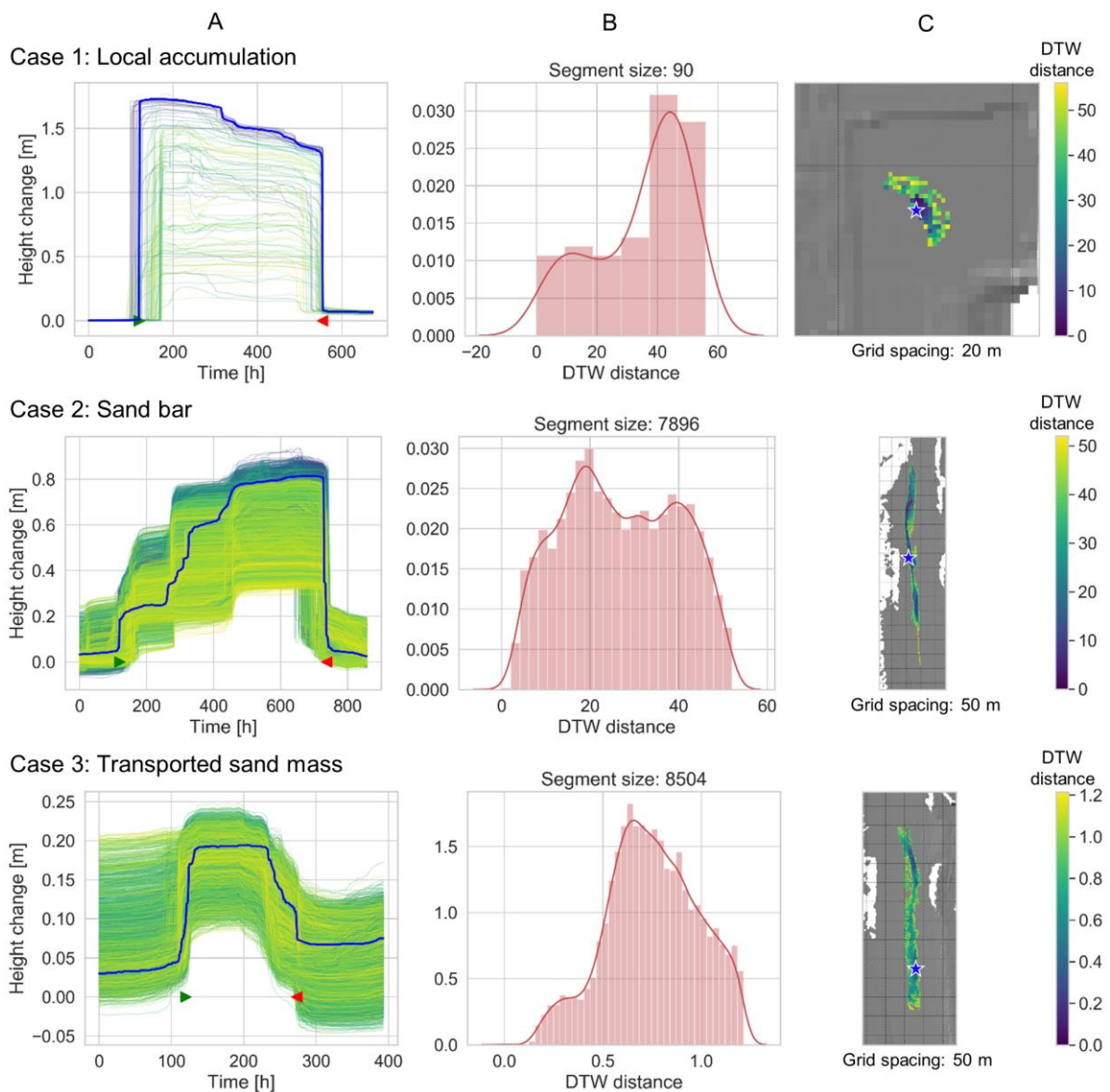


Figure 7: 4D object-by-change for three example cases resulting from region growing segmentation based on Dynamic Time Warping (DTW) distance as time series similarity in the period of a temporal change feature at a

seed location. (A) Time series of all 2D locations included in the segment coloured by DTW distance, with the reference time series (in blue) as seed location marked with star in (C) overview map. (B) Distribution of DTW distances in the segment with Gaussian kernel density estimate.

349 The time series plots (Fig. 7, subfigures A) show the constellation of (i) the temporal course of
350 surface change values and (ii) the spatial scale of surface change values within the segment. The
351 skewness in the distribution of DTW distance values (Fig. 7, subfigures B) expresses the
352 characteristics of continuous change of the sandy surface. Starting from a central seed location of
353 high magnitude in a local elevation maximum, the similarity will gradually decrease mainly with
354 increasing spatial distance. Limiting the region growing into space by the percentile threshold of
355 adding new search locations (Section 3.3) provides a suitable means of constraining the
356 segmentation.

357 The decisive factor in the spatial delineation of 4D objects-by-change is the parametrization of the
358 segmentation, i.e. the selection of a suitable DTW distance threshold for adding locations to the
359 segment. The segmentation threshold influences the strictness in the spatial delineation of
360 change processes. A larger threshold increases the spatial extent of a segmented change object,
361 which is expressed in the distribution of DTW distance values, i.e. similarities in the history of
362 surface change over time. However, no definition of spatial object boundaries for individual
363 change processes is required. A variation of similarities within the area of a 4D object-by-change
364 represents the degree of vagueness in its spatial extent.

365 The spatial extents resulting for the selected cases show that the determination of the DTW
366 distance threshold is independent of the spatial scale of a change process. Both a small area
367 (case 1) and larger areas (cases 2 and 3) with different ranges of DTW distance values are
368 spatially delineated (Fig. 7, subfigures C). Automatic parametrization is important for the
369 application of the approach in operational geomorphic monitoring, where multiple process types
370 can be detected. The transferability of the parameter determination method to other types of
371 change processes and use cases requires investigation.

372 The spatial segmentation of the different change processes for the selected cases is compared to
373 pairwise surface change in the following section and shows how the 4D objects-by-change in our
374 use case represent the change forms.

375 **4.3 Evaluation of 4D Objects-By-Change in Relation to Pairwise Change Detection**

376 In this section we compare the results obtained from the pairwise analysis to the 4D objects-by-
377 change. Animated visualizations are provided to illustrate the temporal evolution of surface
378 change reflected in the time series segments of respective 4D objects-by-change (Supplements I-
379 III).

380 The sand accumulation shifted by heavy machinery (case 1) is a case of surface change that is
381 easily identifiable in the pairwise change detection as a spatially contiguous area of surface

382 change increase. Our approach is able to extract the change process at least as well in its spatial
383 extent (Fig. 8).

384 In comparison to the pairwise surface change analysis, the 4D objects-by-change provides
385 additional information on the detected change process, such as its temporal evolution. It
386 becomes apparent that the accumulation occurred rapidly and only little material was removed or
387 shifted subsequently (Fig. 8A). From the simultaneous appearance and disappearance in the
388 time series at all locations within the 4D object-by-change, we can deduce that it is a local
389 accumulation form and no movement of the sand body occurred.

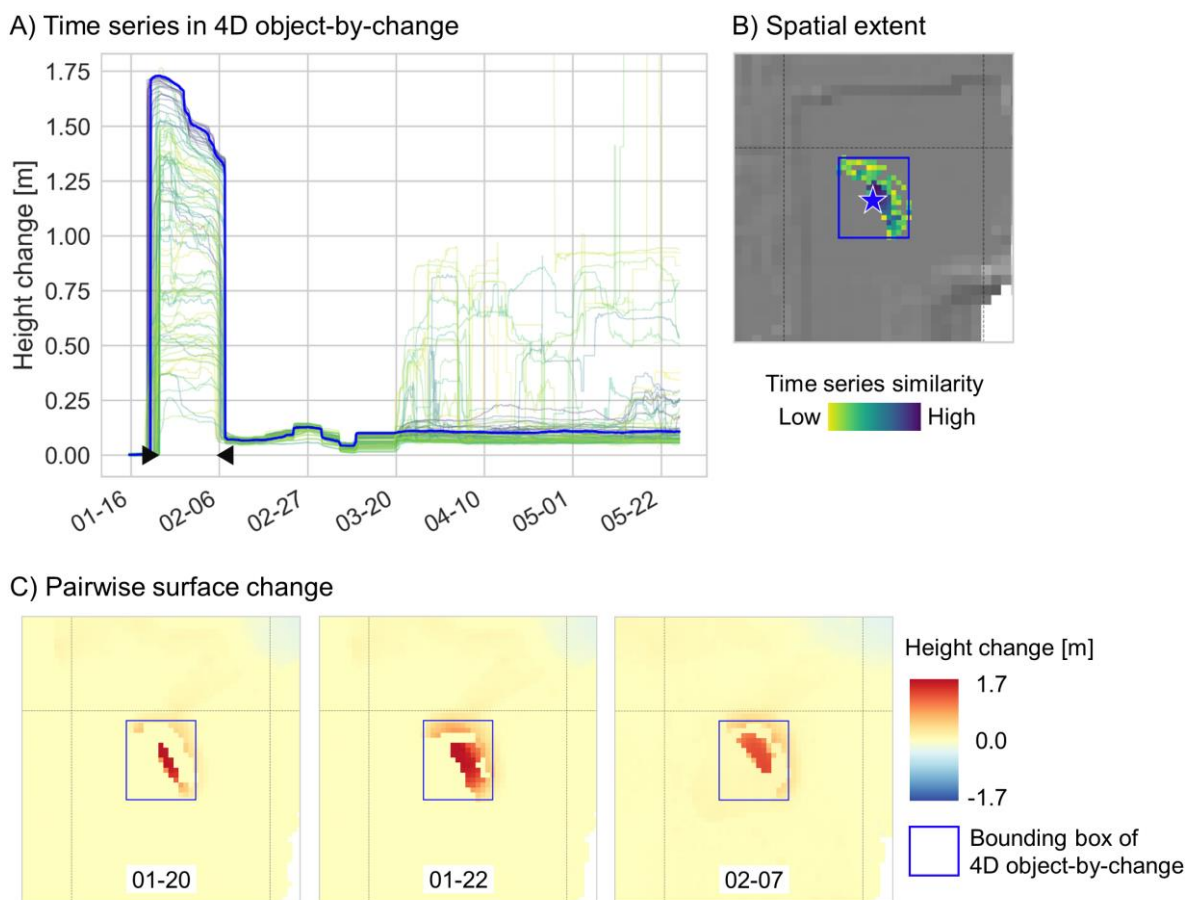


Figure 8: 4D object-by-change extracted for an accumulation of sand built up and removed by heavy machinery (case 1). (A) Time series of all 2D locations included in the segment coloured by the similarity metric (Dynamic Time Warping distance). (B) Spatial extent and location of the reference time series (see location, marked by star). (C) Rasters of pairwise surface height change at the start, maximum magnitude, and end of the temporal change feature compared to the first epoch of the time series. Start and end are marked by the triangles in the time series plot (A). Axes grid has a spacing of 20 m.

390 The sand bar (case 2) is a natural accumulation that is visible in the topography but is not easily
391 detected in the surface change data, as its spatial extent is difficult to define quantitatively. The
392 segmented 4D object-by-change presents the spatial extent of the form with increasing

393 vagueness towards the borders, while the elongated core area shows high inner-segment
 394 similarity regarding the time series of surface change during existence of the sand bar (Fig. 9B).

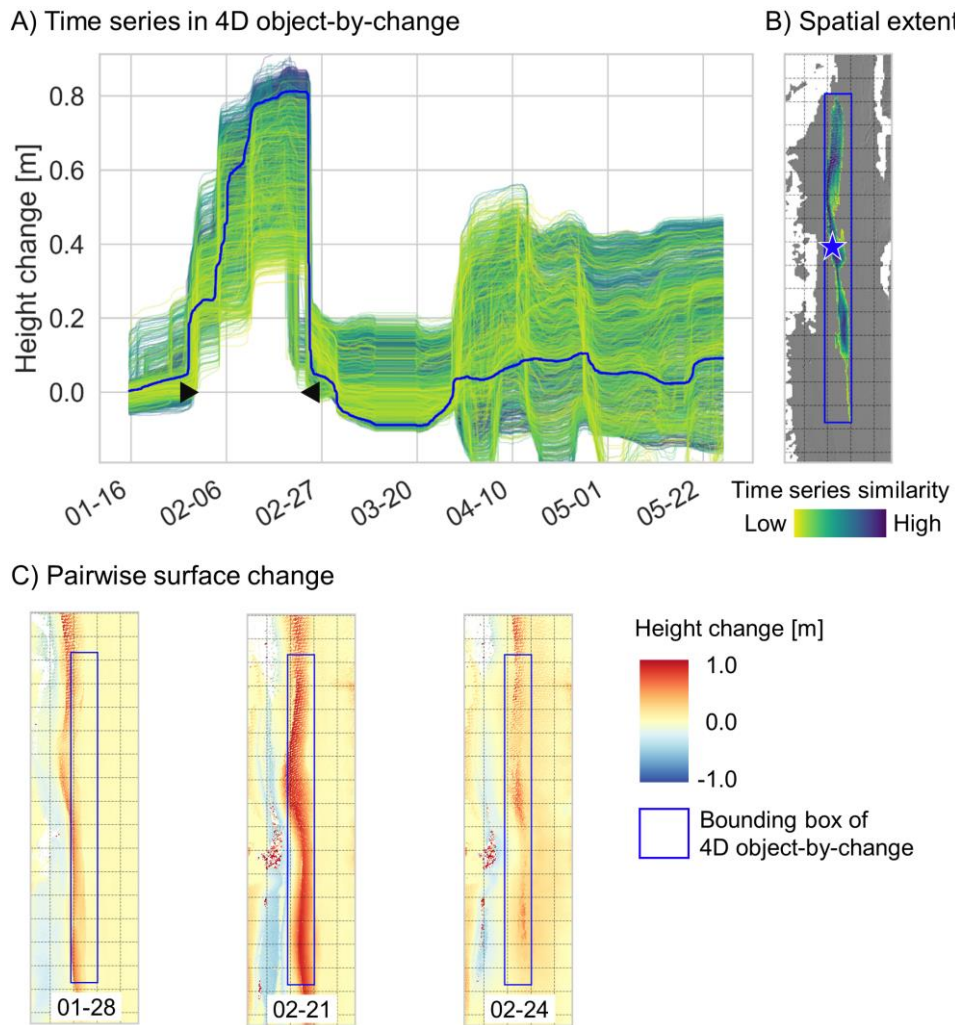


Figure 9: 4D object-by-change extracted for a sand bar (case 2). (A) Time series of all 2D locations included in the segment coloured by the similarity metric (Dynamic Time Warping distance). (B) Spatial extent and location of the reference time series (seed location, marked by star). (C) Rasters of pairwise surface height change at the start, maximum magnitude, and end of the temporal change feature compared to the first epoch of the time series. Start and end are marked by the triangles in the time series plot (A). Axes grid has a spacing of 50 m.

395 The pairwise raster of the sand bar shows a state where the change object becomes
 396 distinguishable as a high-magnitude accumulation object (Fig. 9C, 2017-02-21). However, the
 397 visible pattern in the course of time series segments indicates that the sand bar deformed.
 398 Further, the sand bar moved over the time of its existence. This becomes visible in the animation
 399 of pairwise surface change, where the sand body is shifted in the bounding box of the 4D object-
 400 by-change (Supplement II). The 4D change analysis therefore provides a more comprehensive
 401 assessment on the spatial extent of the sand bar than individual epochs of positive surface height
 402 change.

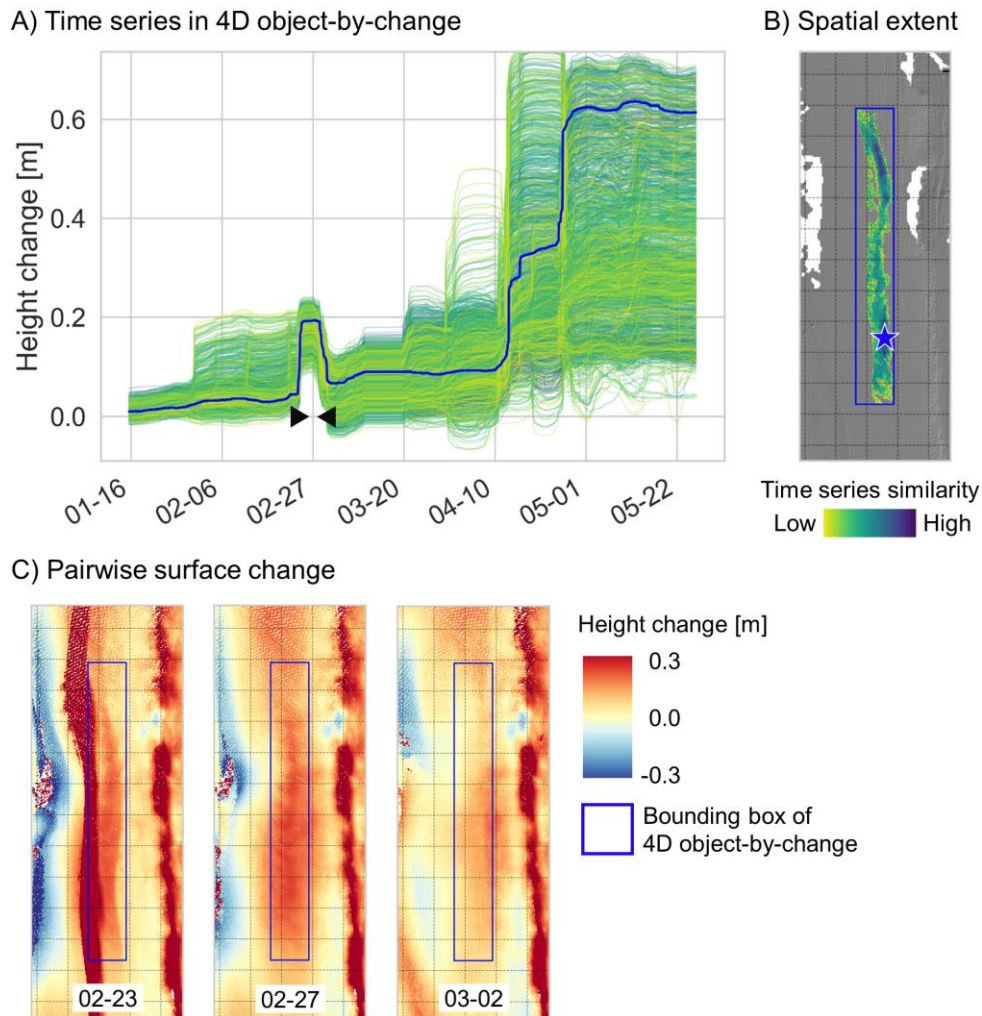


Figure 10: 4D object-by-change extracted for a form expressed through sand transport (case 3). (A) Time series of all 2D locations included in the segment coloured by the similarity metric (Dynamic Time Warping distance). (B) Spatial extent and location of the reference time series (seed location, marked by star). (C) Rasters of pairwise surface height change at the start, maximum magnitude, and stop of the temporal change feature compared to the first epoch of the time series. Start and stop are marked by the triangles in the time series plot (A). Axes grid has a spacing of 50 m.

403 This aspect is advanced with the third case of sand material transported on destruction of a sand
 404 bar. This is only subtly manifested in the areal surface change, although it is well-delineable in
 405 the time series at individual locations (Fig. 10A). The relevance of considering the temporal
 406 domain for identifying this change process becomes particularly evident here. The change does
 407 not appear as distinctly delineable in the pairwise surface change and would likely not be
 408 identified from such analysis. Particularly in contrast to the surrounding higher magnitude
 409 changes, the surface change is hardly identifiable in individual rasters as spatially contiguous,
 410 delimited area of an individual change process (Fig. 10C). With this, time series-based change
 411 analysis improves the detection of change processes. To illustrate the representation of the

412 change process in the combined spatial and temporal domain, we refer to the animation provided
413 in Supplement III.

414 **5. Discussion**

415 At present, standard approaches to geospatial change analysis are based on pairwise
416 comparison between epochs. In multi-process geomorphic settings, this will often lead to
417 quantified surface change being ambiguous to the underlying geomorphic change. Observed
418 change can then not be linked to individual change processes.

419 **5.1 Improvement over Pairwise Surface Change and Implications for Geomorphic** 420 **Analyses**

421 Existing methods of pairwise surface and object-based change analysis mostly require epochs to
422 be selected for change quantification and thresholds to be set to detect and delineate observed
423 objects and changes, which is typically based on their morphometric parameters. This
424 requirement is difficult to meet on continuous surfaces, as given by the morphology of sandy
425 beaches. Beach morphology and changes therein have conventionally been examined using
426 surface elevation profiles (Smith & Zarillo, 1990), with multitemporal LiDAR being used to
427 supplement these data in recent years (e.g. Miles et al., 2019; Stockdon et al., 2009; van
428 Houwelingen et al., 2006). Accumulation forms, such as sand bars, can be localised in profiles
429 based on their crests, and troughs in between, and their migration can be detected from the
430 displacement of crests in repeatedly sampled profiles (Cohn et al., 2018; Levoy et al., 2013; Miles
431 et al., 2019, Reichmüth & Anthony, 2008). This approach is convenient as the shaping and
432 migration of forms is mainly wave-driven in a cross-shore direction. Sampling of parallel cross-
433 shore profiles accounts for long-shore variability in beach morphology (Grunnet & Hoekstra,
434 2008; Masselink & Anthony, 2001). However, it has become evident that more comprehensive
435 consideration of 3D morphology is required, for example, to understand the evolution of bar
436 systems from their individual width and volume (Miles et al., 2019). LiDAR data provide high-
437 resolution 3D morphology of surfaces, yet describing morphologic forms from these data requires
438 an approach for spatial delineation. When analysing the evolution of change forms, our method
439 enables delineation directly in the spatial domain by making use of the surface change history,
440 removing the need to localise morphometric parameters as is done in terrain profiles. Obtained
441 4D objects-by-change provide a basis for analysing the spatial properties of extracted forms.

442 In addition to improved spatial delineation, we obtain information regarding the evolution of the
443 surface for all change types delineated in a 4D object-by-change in drawing upon the temporal
444 domain. The temporal evolution of surface change can be used to interpret detected change
445 processes. Considering the representative cases of morphologic change on the beach shown in
446 this paper, cases 2 and 3 in particular require change evolution as information to deduce the

447 types of geomorphic activity involved. The transport of a sand mass given in case 3 does not
448 become evident in either the spatial or temporal domain. If considered as image of pairwise
449 surface change, the process would likely be interpreted as overall accretion on the surface within
450 the spatial domain. Considering the time series of surface change at a single location, the change
451 process may represent local accumulation and disappearance of material, formed naturally or by
452 anthropogenic modification as in case 1. These aspects highlight the enhanced level of
453 information given by a 4D object-by-change. The method uses this information in combining the
454 spatial and temporal domains for spatiotemporal delineation, while current methods consider
455 smaller subsets of data (pairwise) or information (only spatial or temporal domains). The further
456 interpretation of identified and extracted change processes holds potential for improved
457 comprehensiveness in the analysis and interpretation of geomorphic activity, for example by
458 linking the transported sand mass as consequence to the destruction of a sand bar. Identifying
459 and understanding relations between change processes is an important task in geomorphology,
460 which is supported by our method. A prominent example is the detection of pre-failure
461 deformation leading up to a rockfall event (Kromer et al., 2017; Royán et al., 2014). By spatially
462 segmenting the area affected by pre-failure deformation using our method, the spatiotemporal
463 properties of the resulting 4D object-by-change can provide information on the mechanisms of
464 failure evolution. The detection of precursors to geomorphic change events and their
465 spatiotemporal delineation represents an opportunity to apply our method, which can be
466 integrated to increase the understanding of geomorphic process dependencies and the
467 realization of early warning systems in hazard management (cf. Abellán et al., 2016).

468 The ability to detect and delineate increasingly subtle change forms is a useful addition to the
469 interpretation of change. We show this in our use case with the example of a mass of sediment
470 being transported on destruction of a sand bar (case 3). Time series-based surface change
471 analysis enables the capture of transient forms, which are important features of temporary
472 sediment mobility particularly in the context of aeolian sand transport (Nield et al., 2011). Such
473 short-term mobility and resulting displacement of sand mass was identified from linear trends in
474 surface height change by de Vries et al. (2017) using short-term sub-hourly TLS time series
475 acquired in a beach plot. Applying the extraction of 4D objects-by-change to the time series data
476 could provide additional information on the behaviour of mobilised sand in this setting. Similar to
477 case 3 in this paper, migrating features would be delineated as individual objects and can be
478 separated from locations that are subject to local erosion or accumulation only. By delineating
479 change forms spatiotemporally, our approach enables to decouple them from other potentially
480 overlapping changes, such as longer-term overall accretion on the beach co-occurring with the
481 transient change form of case 3.

482 **5.2 Methodological Considerations for 4D Objects-By-Change**

483 We present the detection and delineation of surface change acting bidirectionally on a location,
484 such as the formation and disappearing of an accumulation form (cases 1 and 2) or the transient
485 form of a transported sand mass that appears in local surface change only temporarily (case 3).
486 The methodological aspect to be highlighted here is that the temporal delineation of bidirectional
487 change is independent from the temporal scale, i.e. definitions of timing and duration of a change
488 process. Given a topographic time series, bidirectional change can therefore be captured and
489 considered in the analysis of volume change in a geomorphic system. The effect of such changes
490 being lost to the observation was highlighted in Anders et al. (2019), where observed volume
491 change on a sandy beach was reduced by a factor of five if temporary accumulation forms, such
492 as the existence of a sandbar over few weeks, are not included in the analyses. The application
493 of our method is not necessarily exclusive to surface change values, as it may also be used
494 directly upon time series of gridded elevation data (e.g. Digital Elevation Models) and then does
495 not require a decision on the reference epoch. The strength of our approach and previously
496 outlined improvements over current approaches of surface change analysis apply particularly in
497 geomorphic settings where material is deformed and transported over predominantly continuous
498 surface morphology.

499 While focusing on the detection of bidirectional change which characterises complex geomorphic
500 settings, the temporal change delineation in our presented method can be extended to include
501 further geomorphic change types. Generically, this regards the identification of unidirectional
502 changes such as erosion being permanent after a discrete event or on conclusion of a continual
503 change process. This will require application-dependent definitions of when a change is
504 considered permanent to conclude a change process, such as continuous surface height
505 increase through accretion on the beach. Discrete events on the beach can be erosion induced
506 by heavy storms, which often interrupt continual processes (O’Dea et al., 2019). While time
507 series-based surface change analysis thereby provides an approach for comprehensive
508 observation of geomorphic activity in multi-process systems, it might be less useful to replace
509 current approaches in settings where morphologic change occurs predominantly unidirectionally
510 and event-driven. For example, in rockfall monitoring on a coastal cliff – in contrast to rockfall
511 events embedded in the multi-process setting of an active landslide – discrete events are
512 distinctly identifiable in the three-dimensional surface morphology and their volume can be
513 quantified from pairwise comparison of the pre- and post-event state of the surface (Williams et
514 al., 2018). For general applicability to the analysis of geomorphic activity, we expect our method
515 to be useful as soon as the temporal sampling of the topographic data exceeds the movement
516 rate of change, i.e. the transition from the initial to the altered surface morphology is represented
517 in several epochs of the time series. To what temporal resolution the time series can be reduced
518 for different change types and use cases will require investigation.

519 In addition to the spatial and temporal properties of a surface change process, the spatial-
520 temporal grouping of time series segments provides a new information layer given in the similarity
521 metric of DTW distance. Grouping change processes extracted from large geospatial time series
522 builds the basis for identifying patterns, such as periodicity in the timing of occurrence or spatial-
523 temporal sequences of change types. For example, sand bar evolution can be investigated on the
524 level of single objects, but also regarding patterns of migration within the system for different
525 object types (cf. Section 5.1). For this, the inner-segment distribution of similarities provides an
526 attribute for semantic classification of process types for a number of objects, even generically
527 where not all occurrences are known. This renders the approach advantageous also for change
528 analysis where the delineation of areas or objects underlying morphologic change is distinct and
529 defined. Where spatial boundaries are not definite, the distribution of DTW distances in the area
530 of an identified change process reflects extensional uncertainty, for example in case of
531 decreasing similarity towards the spatial boundary of an object. This vagueness in the spatial
532 extent of objects has been subject to research particularly for the case of sandy beaches
533 (Molenaar & Cheng, 2000; Stein et al., 2004). When handling geomorphic objects or change
534 forms as vague spatial objects (Dilo et al., 2007), DTW distances could be used as quantification
535 of vagueness provided in a 4D object-by-change.

536 **6. Conclusion**

537 We have presented a technique to extract 4D objects-by-change using time series-based change
538 analysis of natural surfaces within settings of spatially and temporally variable change. The
539 approach improves the level of information that can be gained from time series of topographic
540 data compared to standard pairwise analysis. It enables the detection of processes of change
541 over a range of timescales and without requiring a selection of epochs to use for surface change
542 quantification. Change forms are spatially delineated, which is independent of thresholds that are
543 typically required for extracting objects from epochs of surface change. The extracted 4D objects-
544 by-change provide information on the characteristics of change processes with detailed histories
545 of identified surface change that are present in geospatial time series. Several fields of
546 application are discussed where the method can improve change analysis and provide new
547 insights on spatiotemporal properties of geomorphic activity. This methodological advancement is
548 particularly relevant in light of the growing availability of time series data both through continued
549 survey repetitions and increasing numbers of near-continuous TLS acquisitions at increased
550 temporal resolution.

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