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14 **Geometry and topology of estuary and braided river**
15 **channel networks automatically extracted from**
16 **topographic data**

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27 **Key Points:**

- 28 • A new volume-based method enables extraction of multi-thread channel net-
29 works from bathymetry across bed level jumps
- 30 • Both network topology and geomorphic information can be extracted at a range
31 of spatial scales
- 32 • Estuaries typically form a single dominant channel at the largest spatial scale,
33 while braided rivers show no scaling break

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Abstract

Automatic and objective extraction of channel networks from topography in systems with multiple interconnected channels, like braided rivers and estuaries, remains a major challenge in hydrology and geomorphology. Representing channelized systems as networks provides a mathematical framework for analyzing transport and geomorphology. In this paper, we introduce a mathematically rigorous methodology and software for extracting channel network topology and geometry from digital elevation models (DEMs) and analyze such channel networks in estuaries and braided rivers. Channels are represented as network links, while channel confluences and bifurcations are represented as network nodes. We analyze and compare DEMs from the field and those generated by numerical modeling. We introduce a metric called the sand function that characterizes the volume of deposited material separating channels to quantify the spatial scale attributed to each link. Scale asymmetry is observed in the majority of links downstream of bifurcations, indicating geometric asymmetry and bifurcation stability. The length of links relative to system size scales with sand function scale to the power of 0.24-0.35, while the number of nodes decreases against system scale and does not exhibit power-law behavior. Link depth distributions indicate that the estuaries studied tend to organize around a deep main channel that exists at the largest scale while braided rivers have channel depths that are more evenly distributed across scales. The methods and results presented establish a benchmark for quantifying the topology and geometry of multi-channel networks from DEMs with an automatic and objective tool.

Plain Language Summary

Channels are features of the Earth's surface that carry water, sediment, nutrients, and organisms across the continents towards the coasts. Scientists have long recognized that knowing the shapes, sizes and connections of channels in rivers, estuaries and deltas is vital for predicting future change. A useful way to represent channels is with a network. However, automatically identifying channel networks from surface elevation has been a major challenge because channels display a wide range of different shapes, sizes, and patterns, and often have many intersections with other channels. We have developed a method for identifying channel networks from height maps. We first find the "lowest path" in a channel network, meaning the channel that is at generally lower elevations than all other channels. We subsequently find the next lowest paths, where the measure for channel separation is the volume of sand that needs to be displaced to join neighboring channels. This method allows us to identify the channel network. We show previously unknown similarities and differences between the channel networks of estuaries and wide rivers with sand bars. Our work helps researchers more fully understand and predict how channel networks develop and evolve.

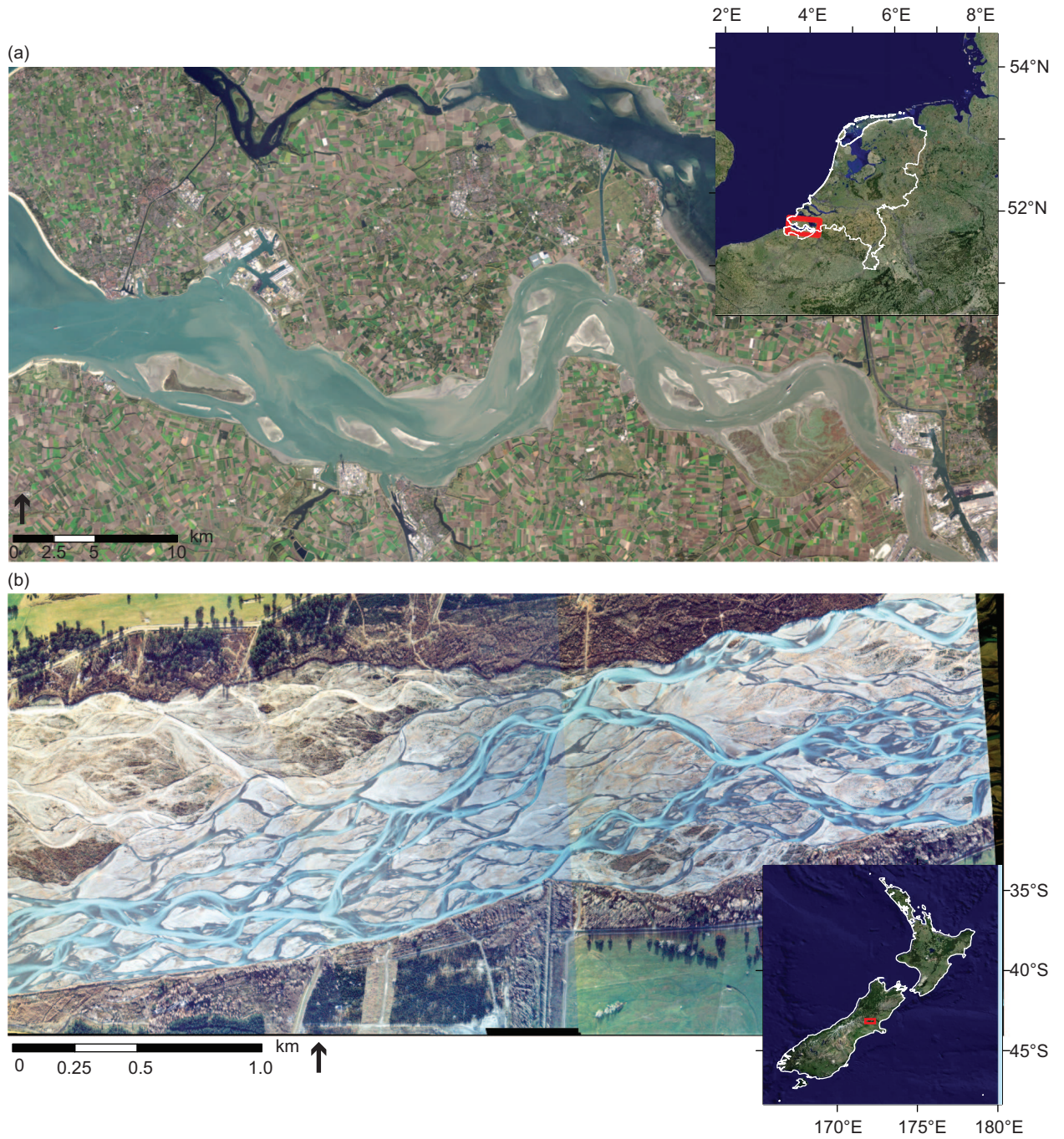
1 Introduction

Channels are ubiquitous features of Earth's surface that are important pathways for the transport of water, solids, and solutes across landscapes, provide a range of ecosystem services, and support economic activity. Channel patterns range significantly in complexity, from single-thread, meandering rivers cutting across continents and the sea floor, to multi-thread channel systems that bifurcate and converge in braided rivers, estuaries, and deltas. These patterns exist over a range of spatial scales. Understanding and quantifying channel network patterns and geometry are vital precursors to predicting many important environmental processes including geomorphological change, water and sediment transport, and ecosystem dynamics. However, automated recognition of channels and their connections from bathymetry is not straightforward because most channel systems have large spatial and temporal variations in bed elevation, arrangement, and water depth.

85 Quantifying patterns, structure, and geometries of channels is necessary to un-
86 derstand and predict landscape dynamics. Networks, which are mathematical repre-
87 sentations of objects and the connections among those objects [Newman, 2003, 2010],
88 are useful representations of topology and geometry in channelized systems [e.g., Benda
89 *et al.*, 2004; Czuba and Foufoula-Georgiou, 2014; Dai and Labadie, 2001; Marra *et al.*,
90 2014; Maidment, 2016; Rodriguez-Iturbe and Rinaldo, 1997; Tejedor *et al.*, 2015a,b;
91 Smart and Moruzzi, 1972]. Generally-speaking, three types of channel networks exist
92 [Kleinhans, 2010; Limaye, 2017]: (1) systems where flow paths are generally conver-
93 gent, such as tributary stream networks with more frequent confluences than bifur-
94 cations; (2) systems with divergent characteristics like deltas and alluvial fans with
95 more frequent bifurcations than confluences, and (3) chain-like systems such as braided
96 rivers, anastomosing rivers and estuaries with similar frequencies of bifurcations and
97 confluences (Fig. 1). While methods relying on surface gradients are generally success-
98 ful at extracting channel networks from topography in convergent systems [Tarboton
99 *and Ames*, 2001; Passalacqua *et al.*, 2015], the extraction of chain-like, divergent and
100 bifurcating channel networks from topographic data remains an open challenge. While
101 progress has been made [e.g., Limaye, 2017; van Dijk *et al.*, 2019], there is a need for
102 an objective, algorithmic method for the extraction and analysis of multi-thread chan-
103 nel network topology and geometry from topographic data. Consequently, we do not
104 know and cannot quantify in what aspects the channel networks of braided rivers,
105 deltas and multi-channel estuaries differ beyond the obvious. This paper aims to fill
106 that gap. Results from earlier versions of this framework have been presented in *van*
107 *Dijk et al.* [2019].

113 Channel networks are often identified from either digital elevation models (DEMs)
114 [Fagherazzi *et al.*, 1999; Montgomery and Dietrich, 1989; Passalacqua *et al.*, 2015; Tar-
115 *boton et al.*, 1991; Tarboton, 1997] or imagery [Dillabaugh *et al.*, 2002; Edmonds *et al.*,
116 2011; Isikdogan *et al.*, 2015, 2017; Marra *et al.*, 2014; Passalacqua *et al.*, 2013; Pavel-
117 *sky and Smith*, 2008]. Classically, methods for extracting channel networks from DEMs
118 have relied on the concepts of steepest descent, flow direction assignment, and the
119 delineation of channels based on flow accumulation [e.g., Lacroix *et al.*, 2002; Pel-
120 *letier*, 204; Shelef and Hilley, 2013; Tarboton *et al.*, 1991; Tarboton, 1997; Tarboton
121 *and Ames*, 2001]. With the advent of high-resolution topography data from lidar
122 [Tarolli, 2014], more sophisticated channel network identification algorithms for high-
123 resolution data have emerged in recent years [Lashermes *et al.*, 2007; Passalacqua
124 *et al.*, 2010; Pelletier, 2013; Sangireddy *et al.*, 2016a]. Methods relying on surface
125 gradients and flow accumulation are generally effective in convergent systems like
126 tributary networks, but fail in multi-threaded channel networks that bifurcate and
127 recombine. Important reasons are that the condition of flow following the path of
128 steepest descent is violated, bed steps with negative slopes are present at bifurcations
129 and confluences, and channels may diverge over shallow bars, shoals and sills which
130 renders their recognition with local path-seeking algorithms impractical. These meth-
131 ods are also sensitive to noise and local highs. An alternative strategy for delineating
132 channel networks from DEMs is through the use of hydrodynamic modeling to track
133 inundation patterns. This strategy can robustly capture bifurcations and convergences
134 in a complicated system [e.g., Limaye, 2017], but currently does not yield a network
135 topology nor does it identify the channel thalweg, while it is computationally expensive
136 and sensitive to assumptions in boundary conditions and hydraulic resistance.

137 The identification of channels from imagery often requires the use of spectral
138 thresholding or classification schemes to distinguish between water and land features,
139 followed by mapping of channels from the resulting image in both the experimental
140 [e.g., Ashworth *et al.*, 2006; Wickert *et al.*, 2013] and natural settings [e.g., Edmonds
141 *et al.*, 2011; Marra *et al.*, 2014; Passalacqua *et al.*, 2013; Welber *et al.*, 2012]. In nu-
142 merical models generating multi-thread systems, thresholds are often used to distin-
143 guish channels from bars and floodplains [e.g., Schuurman and Kleinhans, 2015; Liang



108 **Figure 1.** Examples of multichannel networks with similar frequencies of bifurcations and
 109 confluences: (a) The Western Scheldt Estuary in the Netherlands (LANDSAT 8 image down-
 110 loaded from USGS Earth Explorer at <https://earthexplorer.usgs.gov/>) and (b) the Waimakariri
 111 River, a braided river north of Christchurch in New Zealand (imagery from *Hicks et al.* [2007]).
 112 Inset images are composite satellite images produced by MDA Information Systems.

144 *et al.*, 2016]. More sophisticated algorithms exist [Dillabaugh *et al.*, 2002; Isikdogan
 145 *et al.*, 2015, 2017; Pavelsky and Smith, 2008], but current methodologies are sensitive
 146 to local bed elevation increases and still struggle to maintain channel network connec-
 147 tivity at bifurcations and confluences [Isikdogan *et al.*, 2015].

148 Channel planform geometry is influenced by a plethora of environmental factors
 149 including water discharge [Leopold and Wolman, 1957; Van den Berg, 1995], sedi-
 150 ment composition and transport [Church, 2006; Orton and Reading, 1993; Braat *et al.*,
 151 2017], lithology [Townend, 2012; Nittrouer *et al.*, 2011], bank strength and vegetation
 152 [Millar, 2000; Tal and Paola, 2010; Tal *et al.*, 2004; Vandenbruwaene *et al.*, 2011],
 153 climate [Phillips and Jerolmack, 2016], receiving basin characteristics like tides and
 154 waves [Galloway, 1975; Jerolmack and Swenson, 2007; Rossi *et al.*, 2016; Geleynse
 155 *et al.*, 2011; Nienhuis *et al.*, 2018]. Braided rivers have high rates of morphological
 156 change, which is due to the abundance of non-cohesive sediment and high stream power
 157 [Kleinhans and van den Berg, 2011]. The primary requirements for the development
 158 of braided river patterns are thought to be the presence of a movable bed and a wide
 159 braid plain [Kleinhans, 2010; Kleinhans and van den Berg, 2011], although modeling
 160 work also suggests that bank erosion and boundary condition fluctuations are neces-
 161 sary for maintaining dynamic equilibrium [Schuurman *et al.*, 2013]. Estuarine channel
 162 network morphology is shaped by the competition between tidally- and fluviually-driven
 163 transport [van Veen, 1950; Robinson, 1960; Van der Wegen and Roelvink, 2012] and
 164 sediment composition [Baat *et al.*, 2017]. While subject to different boundary condi-
 165 tions, braided rivers and estuaries can share similar chainlike multichannel networks
 166 that bifurcate and recombine at similar frequencies (Fig. 1a,b). Thus, an investiga-
 167 tion into the similarities and differences in channel network structures of estuaries and
 168 braided rivers may yield insight into the processes affecting their morphologies.

169 This paper introduces a mathematically rigorous, practical, and noise-insensitive
 170 method for extracting multichannel networks from topographic data of rivers and
 171 estuaries in reality, models, and experiments in order to analyze the structure and
 172 geometry of the channel network. The channel extraction tool, called LowPath, utilizes
 173 an algorithm first introduced by Kleinhans *et al.* [2017] that relies on identifying sets
 174 of channels that have the lowest path (in terms of elevation) from the source to the
 175 sink of the system. This framework can produce a topologically-complete network
 176 with geometric attributes using only topographic information. Comparisons are made
 177 between estuaries with multiple channels and braided rivers from both nature and
 178 morphodynamic numerical models. The output from these analyses yields insight into
 179 the processes affecting the morphology of multi-channel systems.

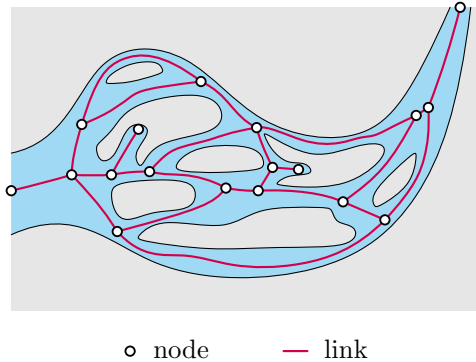
180 The remainder of this paper is organized as follows. Section 2 provides an
 181 overview of the network extraction method, LowPath, and details the location of or
 182 modeling setup of four case studies: the Western Scheldt estuary in the Netherlands,
 183 Waimakariri River in New Zealand, the braided river model of Schuurman *et al.* [2013],
 184 and the multi-channel, bar-built estuary model of Braat *et al.* [2017]. The results of
 185 the network extraction are presented in Section 3, followed by results of the topological
 186 and geometric analyses performed on the extracted channel networks (Section 4). The
 187 implications of the results are discussed in Section 5, along with an exploration of the
 188 role of scale in network delineation from topographic surfaces. Section 5 also contains
 189 notes for future avenues of research. The conclusions are stated in Section 6.

190 **2 Background and Methods**

191 **2.1 A primer on network terminology**

192 A network is a mathematical representation of a set of objects and the con-
 193 nections among those objects [Newman, 2003]. Networks are made up of two types of

194 elements, *links* and *nodes*, where *links* delineate how *nodes* are connected to each other.
 195 The mathematical representation of the interconnectedness in a network is called the
 196 network *topology*, which can be represented by an adjacency matrix where rows and
 197 columns represent nodes and the entries of the matrix represent the links between
 198 the nodes. In the case of a braided river or estuary, nodes represent bifurcations, or
 199 sometimes polyfurcations, confluences, inlets, and outlets, while links represent chan-
 200 nel centerlines or thalwegs (Fig. 2). A path is a sequence of links that connect the
 201 starting and ending nodes of the system.

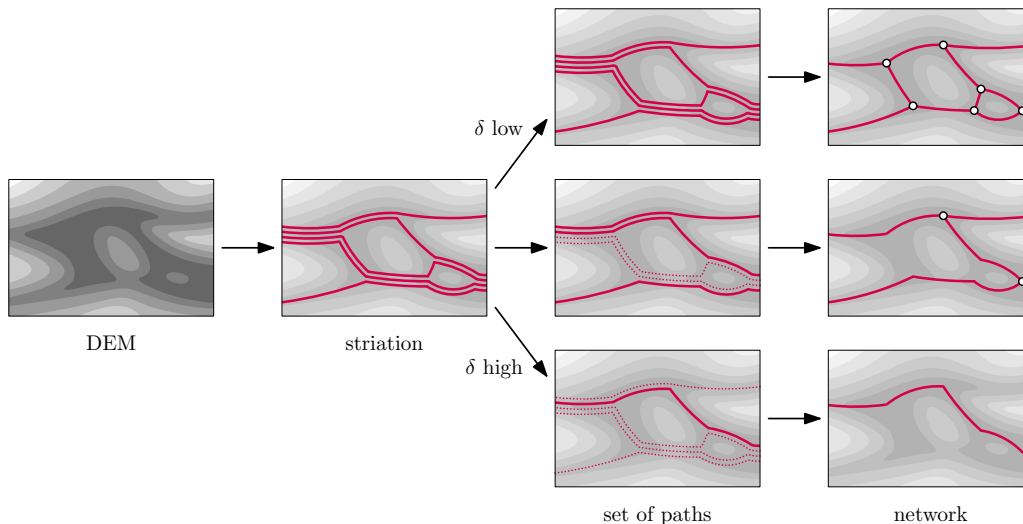


202 **Figure 2.** Example of a network for a multichannel system.

203 2.2 Theory

204 A common challenge in geomorphology and hydrology is delineating a channel
 205 network from a DEM. Objectively doing so in a dataset containing many bifurcations
 206 and confluences has proved elusive, due to complications such as longitudinal varia-
 207 tions in channel depth and slope, and violations of steepest descent principles, among
 208 others. Recently, however, a mathematically-rigorous framework was introduced by
 209 *Kleinhans et al.* [2017] for the extraction of multi-threaded channel networks from to-
 210 pographic surfaces. This method is an effective data reduction method for complete
 211 DEMs without elevation-thresholding or binarization, that is especially suitable for
 212 calculations of bed elevation and other properties on channels. Additionally, its ap-
 213 plication is not limited to multichannel systems, as a single channel network can also
 214 be objectively identified. Whilst not pursued here, the delineation of channels also
 215 implies that the method can be used to identify bars at a range of scales. Here we
 216 qualitatively describe the theory behind the operation of the LowPath algorithm at a
 217 level required to understand the results presented below. A detailed description of the
 218 mathematical principles underlying the method, as well as mathematical proofs, can
 219 be found in the work of *Kleinhans et al.* [2017].

220 The algorithm takes as input a DEM of the bed level of a braided river or es-
 221 tuary. Because it uses only the elevation of the bed level, the generated network is
 222 independent of the water level. However, the algorithm could in principle be applied to
 223 other maps, including depth or velocity fields. To construct the network, the algorithm
 224 computes so-called *lowest paths* through the DEM. A lowest path between two points
 225 is a path that does not traverse any elevations higher than those necessary to connect
 226 the two points. To help in constructing lowest paths, the algorithm first computes a
 227 *descending Morse-Smale complex* (MSC) [*Edelsbrunner et al.*, 2001; *Kleinhans et al.*,
 228 2017; *Shivashankar et al.*, 2012]. The MSC of a DEM is a topological complex that
 229 describes the structural elements of the terrain. It contains the local minima, maxima
 230 and saddle points (points that are a local minimum in one direction while being a



244 **Figure 3.** A qualitative depiction of how LowPath determines the channel network. First,
 245 from the river bed DEM, the striation is computed (left). Consequently a set of sufficiently dif-
 246 ferent paths is found (center; here depicted for three values of δ), which form the final network
 247 (right).

231 local maximum in the other), and steepest-descent paths (called *MS-links*) from sad-
 232 dle points towards minima. *Kleinmans et al.* [2017] showed that lowest paths always
 233 traverse the MS-links of the MSC, which means that lowest paths can be computed
 234 efficiently.

235 Instead of just one single lowest path, the algorithm needs to compute a complete
 236 set of paths that together form the entire channel network. To achieve this, the
 237 algorithm sequentially finds lowest paths in parts of the DEM. More precisely, after
 238 the first lowest path π is found, the DEM is split around π into two parts. Then the
 239 lowest paths in those two parts of the river are found, the DEM is split around these
 240 paths, and so on. (In fact, the splitting procedure is somewhat more complicated, to
 241 avoid issues if π does not entirely lie on the boundary of its part of the DEM. We refer
 242 to *Kleinmans et al.* [2017] for more details.) All the paths found in this fashion
 243 form an ordered set of non-crossing paths, called a *striation* (see Fig. 3 left).

244 In general the striation contains a large number of paths. Since the resolution of a
 245 DEM typically is such that channels are several to many grid cells wide, it may contain
 246 several paths within the same channel, which would be undesirable in the network.
 247 To alleviate this, we need a way to determine for two striation paths whether they
 are ‘sufficiently different’ to form two separate channels. Then, the algorithm picks a
 subset of the striation paths, which are all sufficiently different, to obtain the network
 (see Fig. 3 center and right).

255 To decide if two paths are sufficiently different, we consider the volume of sedi-
 256 ment that separates them: the larger the volume, the more different the channels
 257 are. The sediment volume is a morphologically meaningful way to distinguish chan-
 258 nels, because volume is related to the morphological work required to cut bars and
 259 merge channels [e.g. *Kleinmans*, 2005]. The volume is measured using a so-called *sand*
 260 *function*, which is defined mathematically as the minimum volume above a descend-
 261 ing isotopy between the two paths. Informally speaking, this means measuring the
 262 volume of sediment that obstructs one path from sliding downhill towards the other

263 path. Then we define two paths to be sufficiently different, and allow them to be
 264 in the network together, if and only if the volume is larger than some threshold δ .
 265 Lowering δ means that channels with smaller bars in between are distinguished as
 266 sufficiently different channels. Higher δ values on the other hand require larger bars
 267 between channels for them to be distinguished as sufficiently different. Therefore, by
 268 generating several networks with different values of δ , channels across a range of scales
 269 are identified (Fig. 3).

270 In the resulting network, the existence of a path can be affected by the existence
 271 of another path in seaward (downstream) or landward (upstream) direction. This is
 272 the result of the threshold δ being reached by the summation of several bar deposits
 273 between paths. This means that the threshold volume could in principle be reached
 274 by the volume at one end of the system alone depending on the order of the sorted
 275 paths. Therefore, for example, two paths in the network may be close to one another
 276 in one section of the system, simply because they are separated by a large volume of
 277 sediment in another section.

278 2.3 Workflow

279 The general workflow, including pre- and post-processing steps, necessary to
 280 generate a network from a DEM is briefly described. The three main steps are the
 281 preparation of the DEM, application of the LowPath algorithm as described in the
 282 previous section, and the assignment of topographic and geometric information to
 283 links and nodes.

284 We used an extended version of the implementation used in the original paper
 285 by *Kleinhans et al.* [2017]. As input, this implementation requires only a topographic
 286 surface (image file or text file) to output the set of lowest paths and network nodes.
 287 Geometric properties of the DEM must be specified, including the horizontal resolu-
 288 tions of the grid cells in the x- and y-directions. Only rectangular grids are accepted,
 289 but the grid cells do not need to be square. The elevation range (i.e., the minimum
 290 and maximum elevations) of the DEM must be included for the image-based input to
 291 be able to properly calculate volumes, because this is the best available estimate of
 292 the reworkable sand body that is assumed in the sand function. To ensure that only
 293 the river bed itself is analyzed for network paths, and not for example the surrounding
 294 floodplain, as a preprocessing step the user is able to mask grid cells that they do not
 295 want included in the calculation. The user must also specify the δ value or range of
 296 values.

297 As described in the previous section, LowPath generates a network consisting
 298 of a set of sufficiently different paths. How many paths are included in the network
 299 is determined by the selection of δ . At the higher end of the δ spectrum (i.e., large
 300 volumes of sediment) only a single path is extracted. This is the overall lowest path
 301 that traverses the riverbed. As δ decreases, the number of paths extracted generally
 302 increases, because the volume between adjacent paths needed to identify channels as
 303 sufficiently different is decreasing. Eventually, as δ nears zero, the returned network
 304 contains all striation paths. In other words, varying the parameter δ allows us to
 305 obtain networks across a wide range of scales.

306 In this paper, we want to classify individual channels in the river based on their
 307 importance. Because the number of channels increases when δ decreases, a measure of
 308 the importance of a channel is the highest δ value at which that channel still appears
 309 in the network. To compute these δ values per channel, we first perform the network
 310 computation for a wide range of δ values, say, $\delta_1 > \delta_2 > \dots > \delta_k$. This results in
 311 k networks, called differential networks, which we then combine into a single composite
 312 network (Fig. 4). In every network computation, the striation is identical, because the
 313 computation of the striation is independent of the value of δ . However, the set of

paths selected for inclusion in the network differs. Generally, paths included in the network for δ_i will also be included for δ_{i-1} , which leads to significant path overlap when condensing the sets of paths into the composite network. This issue is rectified by a series of post-processing steps as follows:

1. Channels that are included for multiple δ scales are filtered such that only the largest δ scale at which the channel was detected remains (Fig. 4c). Thus the paths detected by the LowPath algorithm have been converted to network links with starting and ending nodes.
2. In some cases, paths at the same scale overlap at certain points in space, which may cause connectivity issues following step 1. To maintain connectivity, links may be split into smaller sections and nodes are added at their endpoints.
3. The channel network is then further segregated into smaller differential networks that detail the nodes and links found at each δ scale (Fig. 4d-g).

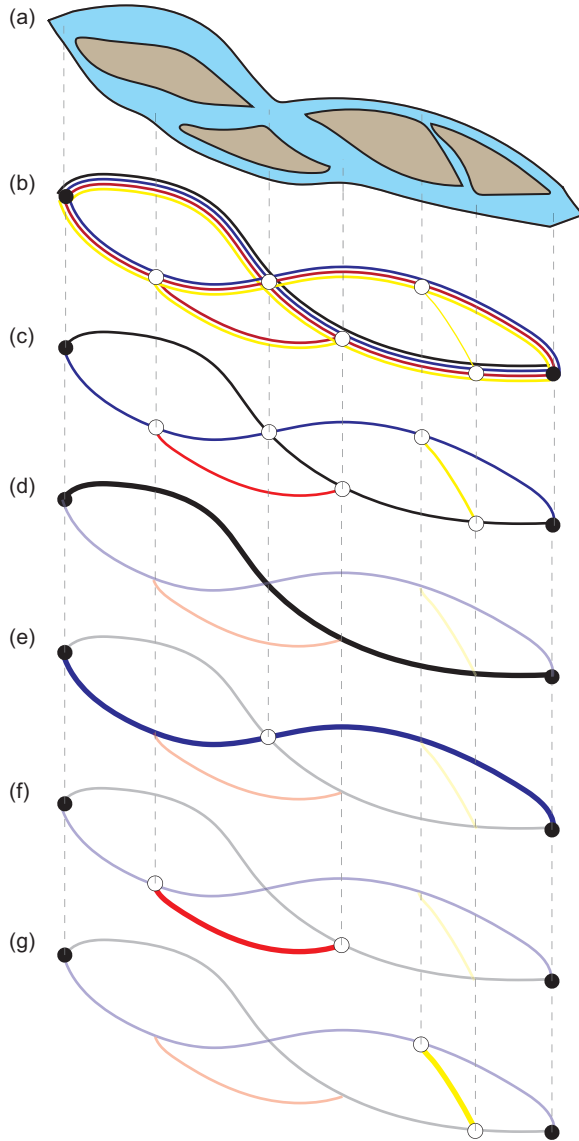
After these post-processing steps, data detailing the coordinates, scales, and the topology of links and nodes is available. An adjacency matrix A is generated for the composite network and the δ differential as a representation of the topology. Geometric information can also be assigned to the links and nodes, such as elevation, channel slope, channel length, or sinuosity.

2.4 Analysis

In this paper, we use LowPath and the previously-described processing methodology to extract channel network and geometric information from topographic data for both estuaries and braided rivers for analysis and comparison. Both the differential networks and the complete composite network for each dataset are analyzed. Four datasets are used: a set of DEMs resulting for the morphodynamic modeling of a braided river [Schuurman et al., 2013], a lidar DEM of the Waimakariri River in New Zealand [Hicks et al., 2007], a set of DEMs from a morphodynamic model of estuary development [Braat et al., 2017], and a DEM of the Western Scheldt estuary in The Netherlands [van Dijk et al., 2018, 2019]. In an earlier paper the original implementation of the algorithm was also demonstrated to work for experiments [Kleinhans et al., 2017].

A range of statistical metrics have classically been used to describe channel network topology and geometry after the channel network has been extracted. Previous research has largely focused on planform geometries of channels and bars for characterizing the geometry of multi-thread channels [e.g., Limaye, 2017; Leuven et al., 2016, 2017, 2018, and add others]. Braiding index or intensity is another commonly-utilized metric that quantifies the number of active channels across the width of the channel belt, which we forgo in this paper because it has been addressed and quantified in other studies [e.g., Howard et al., 1970; Germanoski and Schumm, 1993; Egozi and Ashmore, 2008; Crosato and Mosselman, 2009; Bertoldi et al., 2009; Kleinhans and van den Berg, 2011; Schuurman et al., 2013; Leuven et al., 2016, 2017; Braat et al., 2017; Leuven et al., 2018]. Redolfi et al. [2016] identified the utility of using reach-scale bed elevation distributions in braided rivers to inform morphological trajectories. However, there lacks information regarding bed-elevation distributions within the channel network itself, likely due to limitations in network extraction methodologies. This paper focuses on describing multi-thread channel networks as a function of channel bed elevation distributions across different morphologically-informed scales (i.e., the sand function scale δ).

For each dataset, we analyze the structure of the network at a range of sand function scales (δ), measure the distribution of elevations along each link in the network, measure the number of nodes and links at each scale, and calculate the distribution



332 **Figure 4.** Breakdown of the steps necessary to create a network from topographic data (a)
 333 using LowPath and post-processing tools. (b) Channel centerlines and locations of overlap or
 334 nodes (circles) are output from LowPath across a range of sand function scales (from smallest
 335 to largest scale: yellow, red, blue, black). Adjacent lines depict overlap of channels extracted at
 336 different scales. The smallest scale channels are detected everywhere that a larger scale channel is
 337 also detected, leading to relatively large/deep channels being detected at a large number of scales
 338 (depicted by adjacent links). (c) Overlapping channels are systematically removed such that each
 339 detected channel centerline belongs to a single sand function scale. (d-g) Finally, the network is
 340 segmented into smaller sub-networks that depict the network associated with a single sand func-
 341 tion scale. Doing so allows channel geometries to be assigned to the network independent of the
 342 influence from other scales.

396

Table 1. Summary of the sand function scales for each data set

Data Set	δ range (m^3)	grid resolution ($\text{m} \times \text{m}$)	est. avg. braid belt width (m)
Braided River	$3.98 \times 10^2 - 3.98 \times 10^9$	200×80	3280
Waimakariri	$1.09 \times 10^2 - 1.09 \times 10^7$	8×8	1050
Estuary Model	$1.20 \times 10^2 - 1.20 \times 10^8$	50×50	2590 (mouth) - 250 (upstream)
Western Scheldt	$1.20 \times 10^2 - 1.20 \times 10^9$	100×100	5660 (mouth) - 2500 (upstream)

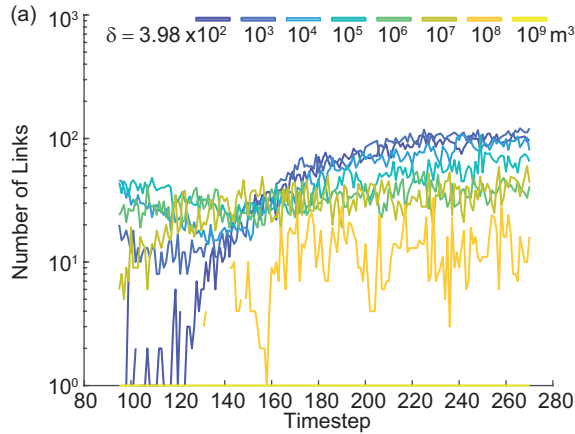
375 of link lengths for each scale. The elevation distributions are calculated by extracting
 376 the elevation in the DEM cell at each coordinate for every link in the network. Cells
 377 located at channel confluences and bifurcations are excluded, because these points may
 378 bias the results when partitioning the data among the various δ scales. For example,
 379 if a small, narrow, and shallow secondary chute channel meets the deep main chan-
 380 nel, the depth at their confluence may significantly skew the depth distribution of the
 381 smaller channel, since the main channel is significantly deeper. Therefore, elevations
 382 at these coordinates are excluded when calculating elevation distributions.

383 Each case study is run at δ scales ranging several orders of magnitude (Table 1).
 384 The range of scales is determined by the geometric characteristics of each individual
 385 system (e.g., elevation relief, planform extent, system slope, etc.). Since the four case
 386 studies chosen range considerably in size, the ranges of δ values are different for each
 387 system. However, δ values were selected to ensure that the largest δ scale produced a
 388 single main channel and a simple sensitivity analysis was performed to determine the
 389 minimum scale at which this channel is manifested. After the largest δ was determined,
 390 δ values were sequentially decreased by one order of magnitude until reaching a δ scale
 391 that was on the same order as the horizontal grid cell size. Values of δ below this value
 392 are physically unrealistic, because channels cannot be detected at finer resolution than
 393 one pixel. In the results section, δ is represented qualitatively (from high to low values)
 394 rather than quantitatively (actual δ values) for convenience when comparing data sets
 395 of significantly different size (see Table 1).

397 **3 Channel network extraction**

398 The network structure and geometries are presented for the four datasets dis-
 399 cussed in Section 2.4. The LowPath algorithm produces channel networks that follow
 400 the lowest paths through the topographic surface. Therefore, the extracted network
 401 links represent channel thalwegs (the deepest portion of the channel) for the full extent
 402 of each channel. For the modeling studies, a representative timestep was chosen for
 403 analysis based on the changes to the number of nodes and networks likes across δ scales
 404 through time (e.g., Fig. 5). For example, the braided river model of *Schuurman et al.*
 405 [2013] was determined to be at a dynamic equilibrium state at around timestep 180
 406 (Fig. 5), which is equivalent to about 12 months of morphological development under
 407 permanent bankfull flow conditions. The timestep was selected because it marked the
 408 beginning of a relatively stable period for the number of nodes and links extracted.
 409 The same procedure was performed for the estuary model.

413 Networks are decomposed into differential networks (Fig. 6) to isolate the effects
 414 of scale on network structure. We use topography from the braided river model of
 415 *Schuurman et al.* [2013] to illustrate these results in Fig. 6. At the highest sand func-
 416 tion scale (δ), there is one (and only one) lowest path that traverses the landscape
 417 from the upstream to downstream boundary (Fig. 6). The single link detected at

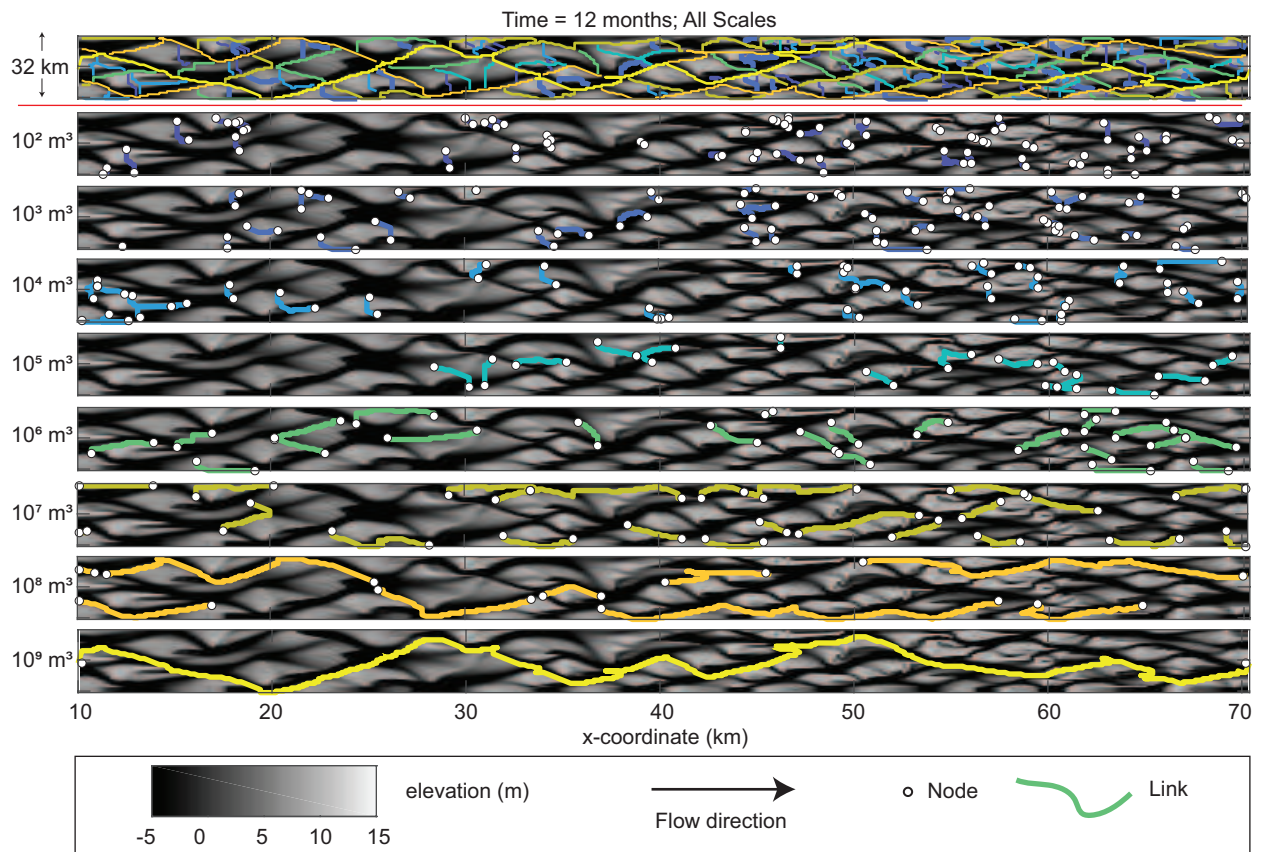


410 **Figure 5.** Network change over time for the braided river model of *Schuurman et al.* [2013].
 411 The channel network at timestep 180 was chosen for analysis in Fig. 6 because it represents the
 412 beginning of a relatively steady period of number of nodes and links at each δ scale.

418 the largest δ scale is representative of the “main” channel of the system. Decreases
 419 in δ tend to cause a greater number of channels to be detected, and those channels
 420 appear to become shorter in length relative to larger scales (Fig. 6). In the braided
 421 river model (Fig. 6), the link detected at the highest δ value (i.e., the main channel)
 422 follows an uninterrupted, sinuous path from the inlet to the outlet. The links with
 423 the second-highest δ value follows a largely similar pattern, but interruptions in the
 424 continuity of the links result generally from where these links connect with the highest
 425 δ scale link. Discontinuities among the links at scale δ are often due to intersections
 426 with links at scales greater than the δ of interest.

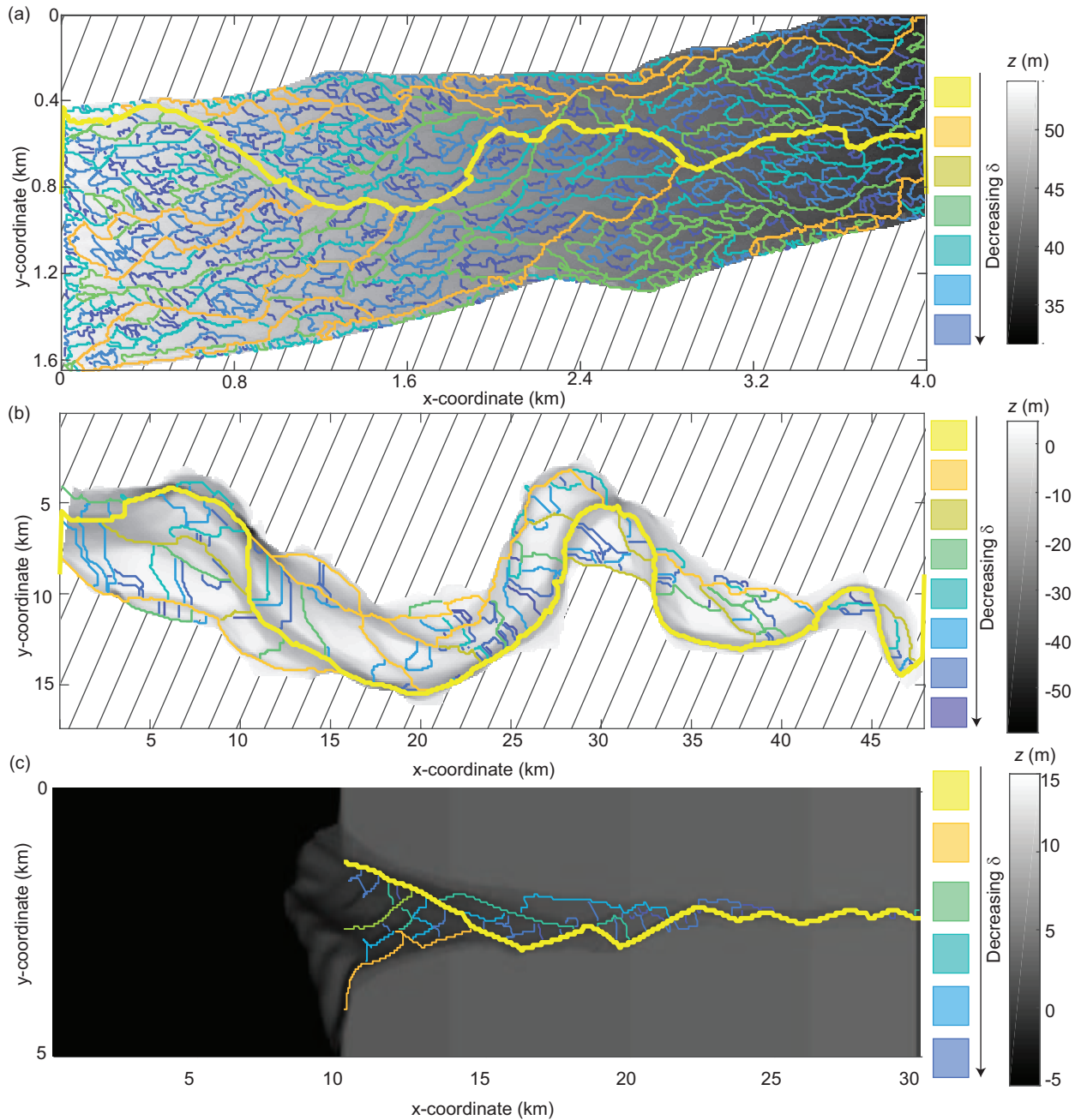
435 The spatial arrangement of channels in the two estuarine examples differs from
 436 the two braided river systems. Both the channel network of the braided river model
 437 (Fig. 6) and the channel network of the Waimakariri River (Fig. 7a) exhibit a high link
 438 density relative to their estuarine counterparts: the Western Scheldt (Fig. 7b) and the
 439 estuary model (Fig. 7c). The estuarine systems tend to have relatively large portions
 440 of the channel belt where no links were detected, which is indicative of relatively
 441 flat, un-channelized portions of the landscape. These regions vary in size and position
 442 within the landscape. By contrast, the links of the braided river systems are uniformly
 443 represented throughout the landscape and the un-channelized portions of the landscape
 444 have a relatively uniform size and spacing. There does not appear to be a clear spatial
 445 clustering associated with the δ value at which channels are detected in the braided
 446 river case studies (Figs. 6 and 7a), but there appear to be zones of high density of small
 447 δ scale channels with bar complexes in the estuarine example of the Western Scheldt
 448 (Fig. 7b). This behavior is difficult to identify within the estuary model (Fig. 7c)
 449 because relatively few channels are detected across scales, and the resolution of the
 450 numerical model is lower.

451 Channel bifurcations and confluences are identified during network extractions,
 452 and nodes are placed where links bifurcate or join. LowPath maintains the connectivity
 453 of these network elements, such that topological information is not lost. The geometric
 454 information of bifurcations and confluences is nested within both the elevations at
 455 which links and nodes are extracted, but is also manifested in the δ scales of bifurcating
 456 or joining links. Notably, most bifurcations involve branches that are identified at
 457 different δ values, indicating that the geometry of the two branch channels and the
 458 deposited material separating them differ. This indicates that many of the identified



427 **Figure 6.** Summary of a multi-scale network in the modeled braided river dataset. The top
 428 panel shows the channel network for a range of scales (network nodes are excluded for visualization
 429 clarity). The colors of the channels indicate the sand function scale. The following panels
 430 show the channel network partitioned by volumetric sand function scale. At lower sand function
 431 scales, channels are relatively short and are often oriented perpendicular to the flow direction.
 432 Channels become longer and more parallel to the mean flow direction with increasing scale. The
 433 elevation scale is truncated at the lower end for visualization and to match the representation in
 434 *Schuurman et al.* [2013].

459 bifurcations are not morphologically-symmetrical (Fig. 7). The tendency of bifurcating
 460 channels to be at different δ scales can be seen by decomposing the channel network
 461 into separate layers based on δ scale (e.g., Fig. 6).



462 **Figure 7.** Network extractions for (a) the Waimakariri River (New Zealand), (b) the West-
 463 ern Scheldt estuary (Netherlands), and (c) the results of an estuarine morphodynamics model
 464 [Braat *et al.*, 2017]. Note the scale exaggeration of the y-coordinate of (c) done for visualization
 465 purposes.. The hashed lines represent areas outside the domain.

466 Link length decreases with decreasing δ scale. The relatively-deep and -wide
 467 main channel traverses the extent of the system and is thus significantly longer than

468 those smaller, narrower channels that develop on top of bar surfaces (Fig. 6). In
 469 between these two extremes, there is a general behavior of increasing link length with
 470 increasing δ . This result is expected, since δ is representative of the relative spatial
 471 scale of the channel, and larger channels are less likely to be intersected by channels
 472 of equal or larger size, and therefore have a tendency to be detected as relatively-long
 473 and continuous links. This phenomenon holds for both the all of the cases studied.

474 4 Topology and geometry

475 This section presents analyses performed on the extracted networks from Section
 476 3 and identifies several topological and geometric characteristics of the studied multi-
 477 channel systems. The goals of these analyses are to understand how channel network
 478 structure varies among different systems and to analyze the extent to which scale
 479 influences the internal organization of these channel networks. We present results for
 480 the four case studies for which channel networks were extracted with LowPath (Figs. 6
 481 and 7).

482 The number of links in the composite network detected in a given δ scale generally
 483 decreases as the scale fraction value increases for each case study (Fig. 8a). The
 484 Waimakariri has the most links across scales, which is likely due to the relatively high
 485 resolution of the topography relative to the width of the braid belt. The estuary
 486 model has generally the least number of channel links for a given δ value due to the
 487 low number of channels detected. The channel network extracted for the Waimakariri
 488 has significantly more links than that of the braided river model (noted as BR model
 489 in Fig. 8a) and the same is true for the Western Scheldt versus the estuary model (Fig.
 490 8a). The difference in number of links at a given δ value between natural and model
 491 systems is about one order of magnitude.

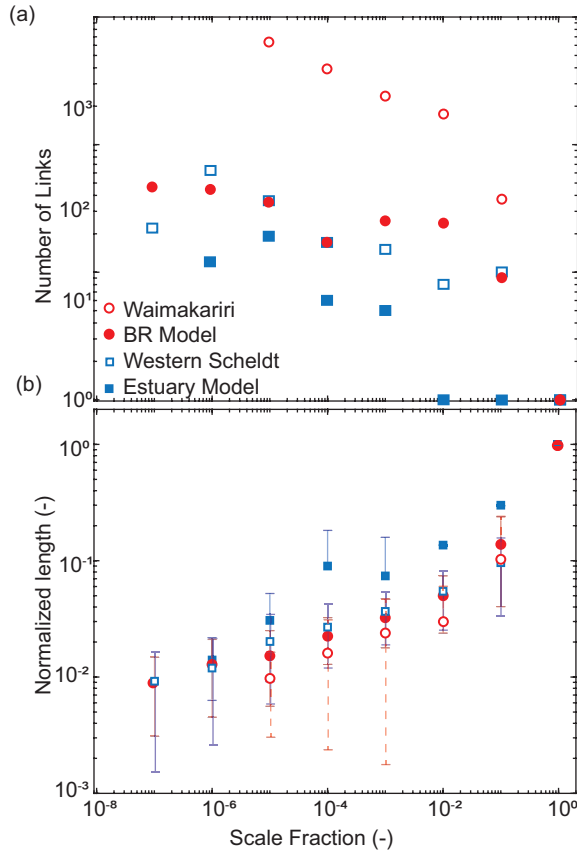
492 Within differential networks, the number of nodes detected at a given scale is
 493 generally twice the number of links detected at that scale, since a link has a starting
 494 and ending node. Multiple links originating from or ending on shared nodes may
 495 decrease this total. The inverse relation between node number and δ does exhibit some
 496 variability and there are examples where increasing δ values do not cause a decrease in
 497 node number. This is likely due to the inherent variability in natural systems and the
 498 choice of threshold for δ values. At the upper threshold of δ values there are always
 499 two nodes detected for the single “main” channel.

505 The length of each link in the composite network is calculated from the geometric
 506 information provided by the topographic surface. For each link i at a given scale $\delta = j$,
 507 the normalized length is calculated as:

$$\bar{L}_{\delta=j,i} = \frac{L_{\delta=j,i}}{L_{LP}} \quad (1)$$

508 where L is the length of the link denoted with a subscript i , the subscript j is the delta
 509 scale of interest, and L_{LP} is the length of the single link extracted at the maximum δ
 510 scale (i.e., the lowest path). Likewise, we introduce another normalization to account
 511 for the difference in δ thresholds among the case studies. For each case site, the Scale
 512 Fraction, is calculated as the scale of interest δ, i divided by the largest sand fraction
 513 scale δ_{max} . The values for both Scale Fraction and $\bar{L}_{\delta=j,i}$ range between 0 and 1.
 514 Performing these normalizations allows for systems of much different spatial scales to
 515 be quantitatively compared.

516 The normalized link length is positively related with scale fraction and appears
 517 to follow power-law increase behavior (Fig. 8b). The exponent on the power relation



500 **Figure 8.** (a) The number of links per scale fraction. (b) The normalized length for links for
 501 each data set across the range of delta scales. The sand fraction scales are presented as fractions
 502 of the largest scale. The symbols represent the medians of the normalized link length distribu-
 503 tions and the error bars represent the ranges. The mean length of links generally increases with
 504 increasing δ . The data appears to follow a power-law decay (see text for details).

518 is 0.23 for the braided river model, 0.27 for the estuary model, 0.24 for the Western
 519 Scheldt, and 0.35 for the Waimakariri River. The magnitude of normalized length is
 520 mostly similar among the case studies throughout the range of scale fractions con-
 521 sidered. However, the estuary model normalized length tends to consistently plot at
 522 higher values than those of the other cases, especially at the scale fraction of 10^{-4} ,
 523 where the normalized length for the estuary model is nearly an order of magnitude
 524 greater than the other three cases.

525 The frequency distributions of slope-corrected channel bed elevations for the
 526 composite network of each case study are displayed in Fig. 9. Depth distributions
 527 are constructed by extracting depth values for each pixel that lies under a link at a
 528 given sand function scale. The depth distributions are partitioned into contributions
 529 from each δ scale tested to determine how channel bed elevation changes with scale
 530 (those classifications are presented qualitatively in Fig. 9). In the Waimakariri River
 531 channel network, elevations associated with small δ values are generally higher than
 532 those associated with larger δ values (Fig. 9a). In the Waimakariri River example,
 533 this transition from higher to lower elevations as δ increases is fairly gradual which
 534 results in a fairly symmetrical, unimodal distribution shape. Additionally, in the
 535 Waimakariri River, there are a higher frequency of elevations associated with small δ
 536 values. This is due to the large number of channels detected at small δ scales present
 537 in the Waimakariri River channel network. Higher δ scales have relatively few low
 538 elevation values. This pattern of sequentially decreasing elevation with scale is clear
 539 for Waimakariri River channel network.

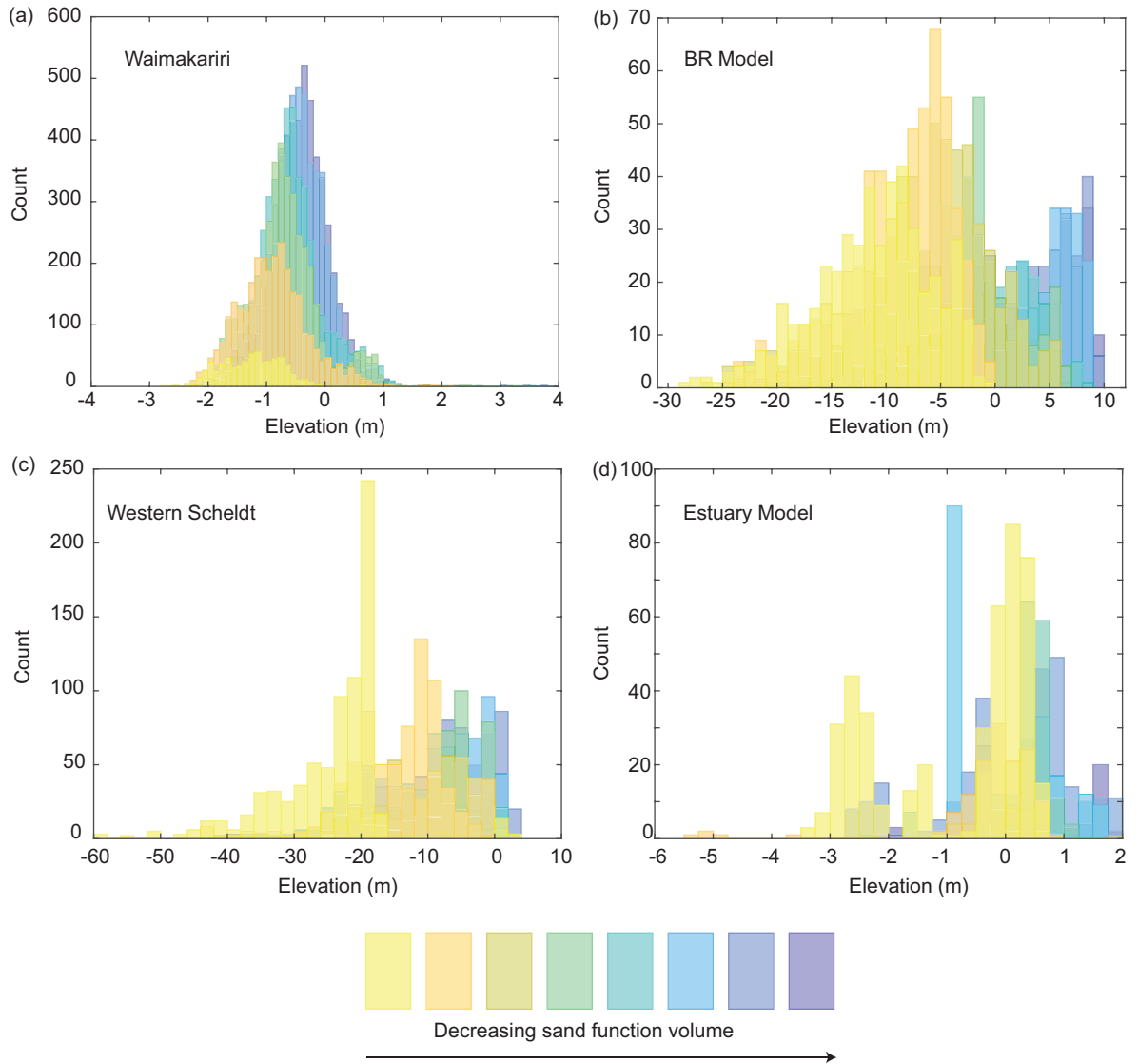
542 The slope-corrected elevation frequency distribution of the braided river model
 543 channel network exhibits the behavior of decreasing elevations as δ increases (Fig. 9b),
 544 but the pattern of decreasing frequency in elevation counts from low to high δ values is
 545 not present as it is in the Waimakariri River system (Fig. 9a). While the overall shape
 546 of the elevation distribution appears to be bimodal, the distributions of elevation at
 547 each individual δ scale is unimodal. The largest δ scale occupies a large portion of the
 548 overall network distribution, which suggests that the main channel is relatively long
 549 compared to the cumulative length of channels detected at small scales. However, like
 550 the Waimakariri River channel network, the links associated with large δ values are
 551 found at lower elevations than those identified at small δ values.

552 The channel network elevation distributions for the Western Scheldt and the es-
 553 tuary model display different behavior. For the Western Scheldt, the channel network
 554 elevation distribution follows a similar pattern of low elevation for high δ values and
 555 there is a stark increase in elevation frequency at the largest δ scale around an eleva-
 556 tion of $z = -20\text{m}$ (Fig. 9c), which is likely due to channel bed maintenance through
 557 dredging activities in the estuary. There is also a fairly wide range of elevations at
 558 which the largest δ scale link exists. The frequency of elevations is fairly uniform
 559 across smaller δ scales in the Western Scheldt. In the estuary model, the elevation
 560 distribution for the highest δ scale is bimodal, which is unique among the cases stud-
 561 ied (Fig. 9d). Additionally, the second highest δ value contains some links, albeit at
 562 a very low frequency, with the lowest elevation values around $z = -5\text{m}$, which again
 563 breaks with the general trend observed in the other case studies.

564 5 Discussion

565 5.1 Comparison among systems

566 The novelty of the presented analyses is the combination of a new network extrac-
 567 tion tool for bathymetric data and the objective comparison between network topology
 568 and morphology of fluvial and tidal systems and of field data and numerical modeling.



540 **Figure 9.** Comparison among the depth distributions across sand function scales for each case
 541 study. The elevation values have been corrected for system slope, if necessary.

569 Our results indicate that there are some quantitative similarities between the structure
570 of braided rivers and estuaries for the cases examined in this text.

571 Visual inspection of our results indicate that the scales of the two channels down-
572 stream of a bifurcation are often not the same in the cases studied (see Figs. 6 & 7).
573 This result seems to align with the generally-accepted consensus that morphodynamically-
574 stable bifurcations must exhibit asymmetrical partitioning of water and sediment fluxes
575 due to geometric asymmetries between the bifurcate channels [Bolla Pittaluga *et al.*,
576 2003; Zolezzi *et al.*, 2006; Kleinhans *et al.*, 2007, 2008, 2013]. It is reasonable to argue
577 that the geometrical asymmetry associated with the differences in geometry between
578 the bifurcate channels is directly related to the volume of deposited sediment (i.e.
579 channel bar) separating the two channels. Though the discrepancy in scale between
580 bifurcate channels seems to coincide with the literature on bifurcation geometry, the
581 results presented here may be influenced by the calculation of δ within LowPath. In
582 an symmetrical bifurcation, LowPath will still slightly assign different δ values to the
583 bifurcate channels. In our analysis, we selected a range of δ values at intervals of one
584 order of magnitude to assign scales to channels. This large interval dampens the bias-
585 ing effects of the LowPath algorithm and increases the likelihood that scale differences
586 are due to geometric discrepancies among channels rather than systematic bias.

587 The division of channel segments into a range of scales with the physically mean-
588 ingful unit of sediment volume allows for scaling analysis. Scale invariance and power-
589 laws are often used in geomorphology in the search for mechanisms describing system
590 self-organization and scaling [Dodds and Rothman, 2000; Kleinhans *et al.*, 2005]. In
591 network analysis, a scale-free network is one whose degree (i.e., the number of con-
592 nections each node has with other nodes) distribution follows a power-law distribution
593 with an exponent between -2 and -3 [Albert and Barabási, 2002]. There is significant
594 spread in the decay of node number as a function of δ , and the slope of the decay
595 does not follow, in general, a power-law decay. Thus, the decrease of nodes as δ scale
596 increases (Fig. 8a) suggests that the configuration of channel networks in estuaries
597 and braided rivers (i.e., the topology) is not scale independent. This may be expected,
598 since channel networks in nature are chain-like [Marra *et al.*, 2014], and the connec-
599 tivity among channels is limited to those in proximity to one another. This causes
600 the network degree distribution to be fairly uniform: and cannot follow the power-law
601 distribution decay that constitutes a scale-free network. Conversely, the geometry of
602 the networks suggests some scale-invariant properties (Fig. 8b). The normalized length
603 of channel links increases as a power law with an exponent of around 0.30 for all the
604 cases tested. This suggests that the channel networks in estuaries and braided rivers
605 self-organize in a similar fashion, regardless of size of the system.

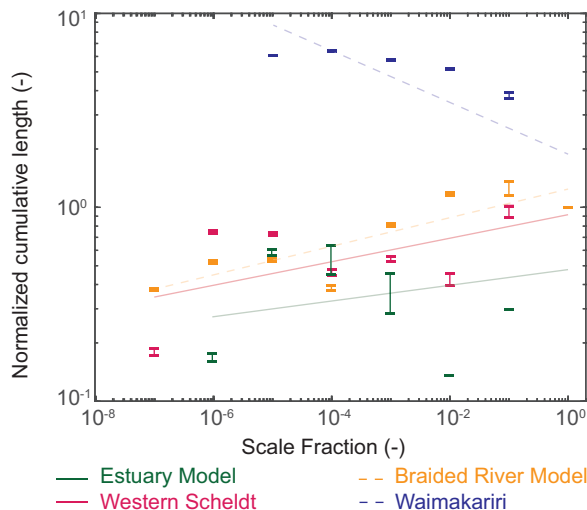
606 The length of channels at various scales obviously depends on the overall length
607 scale of the system in question. In Fig. 8b, the length of each network link was normal-
608 ized by the length of the largest δ scale channel and the normalized length distribution
609 was displayed to compare across systems of different sizes. This metric showed that
610 link length had a rough positive power relation with scale fraction. However, this
611 normalization averages out the effect of the total number of links detected at a given
612 δ scale, which can vary significantly among systems (Figs. 6,7). To address this, we
613 introduce the normalized cumulative length per δ scale as

$$\hat{L}_{\delta=j} = \frac{\sum_{i=1}^{i=N} L_{\delta=j,i}}{L_{\delta=max}} \quad (2)$$

614 where N is the total number of links at scale $\delta = j$. The normalized cumulative
615 lengths of the braided river model, estuary model, and Western Scheldt systems follow
616 a positive power relation with scale fraction (Fig. 10), but has a negative relation for

617 the Waimakariri (Fig. 10). The behavior of the normalized cumulative length scale
 618 with scale fraction for the Waimakariri is opposite of the trend presented in Fig. 8b,
 619 while both the normalized cumulative length and the normalized length show similar
 620 patterns for the three other systems.

621 We have two alternative hypotheses for the deviation of the Waimakariri net-
 622 work. First, the much longer collective length of smaller channels than the single main
 623 channel may point to an issue of topographic grid resolution. The dependence of ex-
 624 tracted channel network features, such as drainage density, on DEM resolution has
 625 long been established in catchment hydrology [Garbrech and Mart, 1994; Molnar and
 626 Julien, 2000; Ariza-Villaverde et al., 2015; Sangireddy et al., 2016b], and the phenom-
 627 ena simply depends on the ability of the extraction method to recognize channels and
 628 it should recognize smaller channels as grid resolution increases. Many small channels
 629 were detected for the Waimakariri system compared to the others (Fig. 3), which is
 630 likely due to the relatively fine resolution of the Waimakariri lidar used for channel net-
 631 work extraction (Table 1). Because high cumulative length of channels at small scales
 632 relative to the length of the main channel. Thus, for high resolution topographies,
 633 this result suggests that small scale channels dominate the behavior of the extracted
 634 channel network geometry distributions, while systems with lower resolution grids sug-
 635 gest main channel dominance. This may explain the prevalence of bi-modality in the
 636 depth distributions (Fig. 9b,c,d) and lack thereof in the depth distribution for the
 637 Waimakariri (Fig. 9a). The second hypothesis is that the larger collective length of
 638 smaller channels is a system characteristic. The Waimakariri River is much wider and
 639 shallower than the other systems, which leads to a higher braiding index. Regardless
 640 of system width, there is only one single main channel with a length of the order of
 641 the study reach length, but a higher degree of braiding leads to a higher collective
 642 channel length at smaller scales. This hypothesis is supported by the observation that
 643 the second-largest scale has already a nearly four times larger collective length, and
 644 the smallest scales do not become more than a factor two higher than that. The
 645 second-largest scale is not affected by the resolution of the lidar, which argues against
 646 the resolution hypothesis.



647 **Figure 10.** Normalized cumulative length for each tested system with a best fit line included
 648 for changes with scale fraction.

649 The depth distributions (Fig. 9) indicated that braided rivers tend to have more
 650 overlap among channel depths across scales (i.e., even large scale channels can be as

shallow as small scale ones), but the estuarine systems appeared to have a more bi-model depth distributions suggesting that a single, main channel tends to develop. Several hypotheses explain these trends. First, this is in qualitative agreement with much higher predicted braiding index in river bar theory than tidal bar theory *Leuven et al.* [2016], and also the difference between the modeled and natural braided river is qualitatively expected from their respective channel width-to-depth ratios [*Kleinhans and van den Berg*, 2011]. Another possible cause for the deeper estuarine channel is that the natural, mid-twentieth century channel depth in the Western Scheldt has been increased by several meters [*Verbeek et al.*, 1998], while the secondary and smaller channel depths decreased due to dredging for fairway maintenance as demonstrated by modeling compared to controls without dredging [*van Dijk et al.*, 2019]. A third hypothesis is that morphological models may have a tendency to erode channels and over-steepened the bars. Though the estuary model [*Braat et al.*, 2017] was run with a high bed slope effect parameter that prevents such erosion but also subdues bars and reduces the braiding index [*Baar*, 2019]. While this model exhibits bi-modality in the depth distribution, the relatively small number of channels available for extraction at any given timestep is likely the source of significant temporal variability in depth distributions. On the other hand, the braided river model had a much lower bed slope effect and showed runaway erosion of channel beds which caused very deep main channels and relatively steep channel banks, which likely caused the depth distributions to be unnaturally deep at large δ scales. The braided river model also exhibits depth detected at multiple scales, as in the Waimakariri, because channel depth is not the the only factoring determining δ . Bar height and distance between channels also play a role in determining the δ scale, so differences in these factors lead to channel depths being identified at a range of different scales. Finer resolution modeling with between channel resolution may be required to adequately compare model results to natural systems. Future work should include topographic re-sampling to assess the differences/similarities between numerical models and natural systems at equivalent spatial resolutions.

5.2 Comparison to other methods for channel network extraction

An earlier method based the channel extraction on simplified hydrodynamic modeling and it has been suggested that flow modeling is a better method for quantifying connectivity in channel networks with divergences and convergences than methods utilizing topography [*Limaye*, 2017]. This was largely correct before the present work, when older methods failed in systems with jumps in channel bed elevation (see Introduction). On the other hand, modeling connectivity accounting for the water surface elevation through flow modeling also has some clear advantages over topographic methods. Namely, hydrodynamic schemes can account for the effects of vegetation in determining landscape connectivity. Vegetation plays a major role in controlling water flow especially between channelized and floodplain (over-bank) environments [*Musner et al.*, 2014; *Hiatt and Passalacqua*, 2017; *Wright et al.*, 2018]) which has major effects on channel initiation, erosion, and deposition [*Temmerman et al.*, 2007; *Vandenbruwaene et al.*, 2011; *Nardin and Edmonds*, 2014; *Nardin et al.*, 2016]. Another advantage may be the ability of flow models to capture channel connectivity even when complete bathymetric information is unavailable [e.g., *Limaye*, 2017], which is not possible using topographic methods such as LowPath.

However, there are several distinct advantages of using the topographic method of LowPath versus simplified hydrodynamic models. Most importantly, LowPath relies only on the geomorphic signatures of the system (i.e., the channel network geometry) and is able to identify the channel thalweg in each network link by tracing the lowest elevation paths and is insensitive to local bed jumps. Furthermore, there are neither assumptions required of any hydrodynamic condition nor uncertain parameters such as hydraulic resistance. The recognized thalweg in particular is an important feature

704 of a channelized system. For example, stream-wise flow velocities are often highest
 705 above the channel thalweg and lateral flow structure is partly dictated by thalweg
 706 position and geometry relative to other channel features [Valle-Levinson *et al.*, 2003;
 707 Blanckaert, 2011; Zinger *et al.*, 2013; Konsoer *et al.*, 2016], which drives morphody-
 708 namic processes such as point bar deposition, channel bend erosion, chute cutoff [e.g.,
 709 van Dijk *et al.*, 2012]. Thus, proper and objective identification of channel thalwegs
 710 from topographic data is an important feature to capture for network extraction that
 711 has not been previously available in multi-threaded systems, because thalweg dynam-
 712 ics are important for multi-thread channel evolution [Li *et al.*, 2017]. Even outside of
 713 multi-thread channel applications LowPath represents an advancement in identifying
 714 thalweg geometry in single-thread systems, especially in pool-riffle channels that may
 715 have local minima in thalweg elevation that are filled via steepest-descent schemes but
 716 are captured with LowPath.

717 Furthermore, the stability and functioning of channel junctions in tidal systems
 718 are poorly understood, and the network allows testing of theory developed for rivers in-
 719 dependent of flow models. Relative channel depths (i.e., thalweg geometry) are defining
 720 characteristics for river bifurcation stability and discharge asymmetry [Edmonds and
 721 Slingerland, 2008; Kleinhans *et al.*, 2008, 2013; van Dijk *et al.*, 2014; Bolla Pittaluga
 722 *et al.*, 2015]. However, estuaries exhibit mutually evasive ebb- and flood-dominated
 723 channels connected at bifurcations, and it is unclear why these asymmetrical bifurca-
 724 tions form with a tidal phase dependence and how this affects propagation of changes
 725 through the network [Wang *et al.*, 2002; Kleinhans *et al.*, 2015; Leuwen *et al.*, 2018;
 726 van Dijk *et al.*, 2019].

727 Another distinct advantage of LowPath over hydrodynamic methods is the ca-
 728 pability to automatically and objectively decompose the extracted channel thalwegs
 729 into a topologically-coherent network of links and nodes that is represented by an ad-
 730 jacency matrix. While analyses of topological characteristics of estuaries and braided
 731 rivers in this paper are limited to relatively simple metrics like node count (Fig. 8),
 732 many recent studies have used network analyses of multi-thread channel networks
 733 in the geosciences to quantify channel network evolution, vulnerability, and system
 734 self-organization [Marra *et al.*, 2014; Tejedor *et al.*, 2015a,b, 2016, 2017, 2018]. Specif-
 735 ically, the pioneering work of Tejedor *et al.* [2015a,b] established a framework for quan-
 736 tifying a suite of metrics that quantify the structural and dynamic connectivities of
 737 river delta channel networks using spectral graph theory. The framework relies on the
 738 assumption that delta channel networks are purely distributary (i.e., all network links
 739 emanate from a single apex node and have seaward transport directions), which can-
 740 not be directly applied to systems like estuaries and braided rivers. Marra *et al.* [2014]
 741 first attempted to use graph theoretic metrics, specifically the betweenness centrality
 742 [Brandes, 2001], in a braided river system and identified the importance of channels
 743 within three distinct reaches of the Jamuna River. However, there still exists no rigor-
 744 ous framework for addressing topological and dynamic connectivity using graph theory
 745 for the non-distributary, chain-like multi-thread channel networks in braided rivers and
 746 estuaries. While LowPath represents an advancement in generating the topology of
 747 such channel networks, moving the needle forward on understanding dynamics of such
 748 channels networks will still require research to establish theoretical tools for network
 749 analyses similar to those presented by Tejedor *et al.* [2015a,b] for deltas.

750 Finally, development of methods that track network development through time
 751 would allow tremendous advances in model and data analyses. Though LowPath
 752 currently extracts channel networks at sequential timesteps, each extracted network is
 753 independent of the previous timestep. This presents a challenge for performing desired
 754 morphological analysis such as tracking the nodal point of a bifurcation through time,
 755 assessing avulsions, and tracking changes to individual channels. Further development
 756 of the network tool requires the possibility to define a single multi-temporal network

757 structure in both space and time and, for application on discrete data, such rigorous
 758 measures for similarity that shifting links and nodes are recognized correctly. In turn,
 759 the mathematical rules that correctly identify such shifts require phenomenological
 760 models of channel behaviour and/or may well capture such natural dynamics.

761 6 Conclusions

762 This paper presents a novel method for objectively and automatically extracting
 763 topologically-complete networks and geometry from multi-channel environments using
 764 only topography and bathymetry data.

765 The method, called LowPath, relies on extracting the lowest paths traversing a
 766 topography across a range of spatial scales, quantified by a new metric for volume-
 767 based channel separation in three-dimensional environments called the sand function.
 768 The methodology represents a significant advancement over classic steepest-descent-
 769 based algorithms for detecting channels from topography, which cannot handle flow
 770 divergences and bed steps, which are ubiquitous in multi-channel systems like braided
 771 river, deltas, estuaries, and alluvial fans. The method also provides an advantage over
 772 inundation-based approaches which cannot capture the full network topology of the
 773 extracted channel network. The new channel extraction method represents a unique
 774 and important tool for furthering our ability to quantitatively assess channel network
 775 structure and geometry in complex environment.

776 The LowPath method was applied to four case studies: the Western Scheldt
 777 estuary, a morphodynamic model of an alluvial estuary, the Waimakariri River, and a
 778 morphodynamic model of a braided river. The analyses of the case studies reveal that
 779 (1) the number of network links and nodes are inversely related to the sand function
 780 scale, (2) the relative lengths of links is positively related to the sand function scale and
 781 this relation follows a positive power law with an exponent of $0.23 - 0.35$, and (3) the
 782 elevations of links detected at high sand function scales are deeper than those detected
 783 at smaller scales. The quantitative and objective comparison of the detailed channel
 784 network allows fair comparisons between topological and geometrical characteristics of
 785 natural systems and those in numerical morphodynamic models, suggesting that highly
 786 braided systems have collectively longer secondary and smaller channel segments than
 787 main channel length, as opposed to lower-braided systems where the main channel has
 788 a higher length than the collective smaller channels. Furthermore the results suggest
 789 that the tendency to incise channels in the models differs from that in nature for
 790 braided rivers and estuaries.

791 Acknowledgments

792 In theoretical computer science, it is customary to list authors in alphabeti-
 793 cal order. Therefore, in reference [*Kleinhans et al.*, 2017], the author order does not
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