



1 **Statistical modeling of the long-range dependent structure of barrier island framework**
2 **geology and surface geomorphology**

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33 **Abstract**

34 Shorelines exhibit long-range dependence (LRD) and have been shown in some environments to
35 be described in the wavenumber domain by a power law characteristic of scale-independence.
36 Recent evidence suggests that the geomorphology of barrier islands can, however, exhibit scale-
37 dependence as a result of systematic variations of the underlying framework geology. The LRD of
38 framework geology, which influences island geomorphology and its response to storms and sea
39 level rise, has not been previously examined. Electromagnetic induction (EMI) surveys conducted
40 along Padre Island National Seashore (PAIS), Texas, USA, reveal that the EMI apparent
41 conductivity σ_a signal and, by inference, the framework geology exhibits LRD at scales up to 10^1
42 to 10^2 km. Our study demonstrates the utility of describing EMI σ_a and LiDAR spatial series by a
43 fractional auto-regressive integrated moving average process that specifically models LRD. This
44 method offers a robust and compact way for quantifying the geological variations along a barrier
45 island shoreline using three parameters (p,d,q) . We discuss how ARIMA $(0,d,0)$ models that use a
46 single parameter d provide a quantitative measure for determining free and forced barrier island
47 evolutionary behavior across different scales. Statistical analyses at regional, intermediate, and
48 local scales suggest that the geologic framework within an area of paleo-channels exhibits a first-
49 order control on dune height. The exchange of sediment amongst nearshore, beach and dune in
50 areas outside this region are scale-independent, implying that barrier islands like PAIS exhibit a
51 combination of free and forced behaviors that affect the response of the island to sea level rise.

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63 **1 Introduction**

64 Barrier island transgression in response to storms and sea level rise depends to varying degrees on
65 pre-existing geologic features. The traditional assumption of uniform sand at depth and alongshore
66 cannot explain many of observations (e.g., Belknap and Kraft, 1985; Houser, 2012; Lentz and
67 Hapke, 2011; McNinch, 2004; Riggs et al., 1995). Models of barrier island evolution are required to
68 ascertain the degree to which the island is either *free* (such as a large sand body) or *forced* (i.e.
69 constrained) by the underlying geology. In a free system, small-scale undulations in the dune line
70 reinforce natural random processes that occur within the beach-dune system and are not influenced
71 by the underlying geologic structure. In a forced system, the underlying geologic structure establishes
72 boundary constraints that control how the island evolves over time. Spatial variation in the dune line
73 impacts the overall transgression of the island with sea-level rise. Transgression is accomplished
74 largely through the transport and deposition of beach and dune sediments to the backbarrier as
75 washover deposits during storms (Houser, 2012; Morton and Sallenger Jr., 2003; Stone et al.,
76 2004).

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78 1.1 Framework geology controls on barrier island evolution

79 The dynamic geomorphology of a barrier island system is the result of a lengthy, complex and
80 ongoing history that is characterized by sea level changes and episodes of deposition and erosion
81 (e.g., Anderson et al., 2015; Belknap and Kraft, 1985; Rodriguez et al., 2001). Previous studies
82 demonstrate that the underlying geological structure, otherwise termed *framework geology*, of barrier
83 islands plays a considerable role in the evolution of these coastal landscapes (Belknap and Kraft,
84 1985; Evans et al., 1985; Kraft et al., 1982; Riggs et al., 1995). For example, antecedent structures
85 such as paleo-channels, ravinement surfaces, offshore ridge and swale bathymetry, and relict
86 transgressive features (e.g., overwash deposits) have been suggested to influence barrier island
87 geomorphology over a wide range of spatial scales (Hapke et al., 2010; Hapke et al., 2016; Houser,
88 2012; Lentz and Hapke, 2011; McNinch, 2004). In this study, the term “framework geology” is
89 specifically defined as the topographic surface of incised valleys, paleo-channels, and/or the depth to
90 ravinement surface beneath the modern beach.

91 As noted by Hapke et al. (2013), the framework geology at the **regional scale** (> 30 km)
92 influences the geomorphology of an entire island. Of particular importance are the location and size



93 of glacial, fluvial, tidal, and/or inlet paleo-valleys and channels (Belknap and Kraft, 1985; Colman et
94 al., 1990; Demarest and Leatherman, 1985), and paleo-deltaic systems offshore or beneath the
95 modern barrier system (Coleman and Gagliano, 1964; Frazier, 1967; Miselis et al., 2014; Otvos and
96 Giardino, 2004; Twichell et al., 2013). At the regional scale, nonlinear hydrodynamic interactions
97 between incident wave energy and nearshore ridge and swale bathymetric features can generate
98 periodic alongshore variations in beach-dune morphology (e.g., Houser, 2012; McNinch, 2004)
99 that are superimposed on larger-scale topographic variations as a result of transport gradients
100 (Tebbens, et al., 2002). At the **intermediate scale** (10 - 30 km), feedbacks between geologic
101 features and relict sediments of the former littoral system (e.g., Honeycutt and Krantz, 2003;
102 Riggs et al., 1995; Rodriguez et al., 2001; Schwab et al., 2000) act as an important control on
103 dune formation (Houser et al., 2008) and offshore bathymetric features (e.g., Browder &
104 McNinch, 2006; Schwab et al., 2013). Framework geology at the **local scale** (≤ 10 km), induces
105 meso ($\sim 10^1 - 10^2$ m) to micro-scale (< 1 m) sedimentological changes (e.g., Murray and Thieler,
106 2004; Schupp, et al., 2006), variations in the thickness of shoreface sediments (Brown and
107 Macon, 1977; Miselis and McNinch, 2006), and spatial variations in sediment transport across
108 the island (Houser and Mathew, 2011; Houser, 2012; Lentz and Hapke, 2011).

109 To date, most of what is known regarding barrier island framework geology is based on
110 studies done at either intermediate or local scales (e.g., Hapke et al., 2010; Lentz and Hapke, 2011;
111 McNinch, 2004) whereas few studies exist at the regional scale for United States coastlines (Hapke et
112 al., 2013). The current study focuses on barrier islands in the US and we do not consider work on
113 barrier islands in other regions. Assessments of framework geology at regional and intermediate
114 spatial scales for natural and anthropogenically-modified barrier islands are essential for improved
115 coastal management strategies and risk evaluation since these require a good understanding of the
116 connections between subsurface geology and surface morphology. For example, studies by Lentz and
117 Hapke (2011); Lentz et al., (2013) at Fire Island, New York suggest that the short-term
118 effectiveness of engineered structures is likely influenced by the framework geology. Extending
119 their work, Hapke et al. (2016) identified distinct patterns of shoreline change that represent
120 different responses alongshore to oceanographic and geologic forcing. These authors applied
121 empirical orthogonal function (EOF) analysis to a time series of shoreline positions to better
122 understand the complex multi-scale relationships between framework geology and contemporary



123 morphodynamics. Gutierrez et al. (2015) used a Bayesian network to predict barrier island
124 geomorphic characteristics and argue that statistical models are useful for refining predictions of
125 locations where particular hazards may exist. These examples demonstrate the benefit of using
126 statistical models as quantitative tools for interpreting coastal processes at multiple spatial and
127 temporal scales (Hapke et al., 2016).

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129 1.2 Statistical measures of coastline geomorphology

130 It has long been known that many aspects of landscapes exhibit similar statistical properties
131 regardless of the length or time scale over which observations are sampled (Burrough, 1981). An
132 often-cited example is the length L of a rugged coastline (Mandelbrot, 1967), which increases
133 without bound as the length G of the ruler used to measure it decreases, in rough accord with the
134 formula $L(G) \sim G^{1-D}$, where $D \geq 1$ is termed the fractal dimension of the coastline. Andrieu
135 (1996), however, has identified limitations of the self-similar coastline concept, suggesting that a
136 coastline may contain irregularities that are concentrated at certain characteristic length-scales
137 owing to local processes or structural controls. Recent evidence from South Padre Island, Texas
138 (Houser and Mathew, 2011), Fire Island, New York (Hapke et al., 2010), and Santa Rosa Island,
139 Florida (Houser et al., 2008) suggests that the geomorphology of barrier islands is affected to
140 varying degrees by the underlying framework geology and that this geology varies, often with
141 periodicities, over multiple length-scales. The self-similarity of the framework geology and its
142 impact on the geomorphology of these barrier islands was not examined explicitly.

143 Many lines of evidence suggest that geological formations in general are inherently rough
144 (i.e., heterogeneous) and contain multi-scale structure (Bailey and Smith, 2005; Everett and
145 Weiss, 2002; Radliński et al., 1999; Schlager, 2004). Some of the underlying geological factors
146 that lead to self-similar terrain variations are reviewed by Xu et al. (1993). In essence, competing
147 and complex morphodynamic processes, influenced by the underlying geological structure,
148 operate over different spatiotemporal scales, such that the actual terrain is the result of a complex
149 superposition of the various effects of these processes (see Lazarus et al., 2011). Although no
150 landscape is strictly self-similar on all scales, Xu et al. (1993) show that the fractal dimension, as
151 a global morphometric measure, captures multi-scale aspects of surface roughness that are not



152 evident in conventional local morphometric measures such as slope gradient and profile
153 curvature.

154 With respect to coastal landscapes, it has been suggested that barrier shorelines are scale
155 independent, such that the wavenumber spectrum of shoreline variation can be approximated by
156 a power law at alongshore scales from tens of meters to several kilometers (Lazarus et al., 2011;
157 Tebbens et al., 2002). However, recent findings by Houser et al. (2015) suggest that the beach-
158 dune morphology of barrier islands in Florida and Texas is scale-dependent and that
159 morphodynamic processes operating at swash (0-50 m) and surf-zone (< 1000 m) scales are
160 different than the processes operating at larger scales. In this context, scale-dependence implies
161 that a certain number of different processes are simultaneously operative, each process acting at
162 its own scale of influence, and it is the superposition of the effects of these multiple processes
163 that shapes the overall behavior and shoreline morphology. This means that shorelines may have
164 different patterns of irregularity alongshore with respect to barrier island geomorphology, which
165 has important implications for analyzing long-term shoreline retreat and island transgression.
166 Lazarus et al. (2011) point out that deviations from power law scaling at larger spatial scales
167 (tens of km) emphasizes the need for more studies that investigate large-scale shoreline change.
168 While coastal terrains might not satisfy the strict definition of self-similarity, it is reasonable to
169 expect them to exhibit long-range dependence (LRD). LRD pertains to signals in which the
170 correlation between observations decays like a power law with separation, i.e. much slower than
171 one would expect from independent observations or those that can be explained by a short-
172 memory process, such as an autoregressive-moving-average (ARMA) with small (p, q) (Beran,
173 1994; Doukhan et al., 2003).

174

175 1.3 Research objectives

176 This study performed at Padre Island National Seashore (PAIS), Texas, USA utilizes
177 electromagnetic induction (EMI) apparent conductivity σ_a responses to provide insight into the
178 relation between spatial variations in framework geology and surface morphology. Two
179 alongshore EMI surveys at different spatial scales (100 km and 10 km) were conducted to test
180 the hypothesis that, like barrier island morphology, subsurface framework geology exhibits LRD.
181 The σ_a responses, which are sensitive to parameters such as porosity and mineral content, are



182 regarded herein as a rough proxy for subsurface framework geology (Weymer et al., 2015). This
183 assumes, of course, that alongshore variations in salinity and water saturation, and other factors
184 that shape the σ_a response, can be neglected to first order. A corroborating 800 m ground-
185 penetrating radar (GPR) survey, providing an important check on the variability observed within
186 the EMI signal, confirms the location of a previously identified paleo-channel (Fisk, 1959) at ~ 5
187 – 10 m depth. The overall geophysical survey design allows for a detailed evaluation of the long-
188 range-dependent structure of the framework geology over a range of length scales spanning
189 several orders of magnitude. We explore the applicability of autoregressive integrated moving-
190 average (ARIMA) processes as statistical models that describe EMI and Light Detection and
191 Ranging (LiDAR) spatial data series. This paper introduces the use of a generalized fractional
192 ARIMA (0, d ,0) process (Hosking, 1981) that is specifically designed to model LRD for a given
193 data series using a single differencing non-integer parameter d . The parameter d can be used in
194 the present context to discriminate between *forced*, scale-dependent controls by the framework
195 geology; i.e., stronger LRD ($d \rightarrow 0.5$) and *free* behavior that is scale-independent; i.e., weaker
196 LRD ($0 \leftarrow d$). In other words, it is the particular statistical characteristics of the framework
197 geology LRD at PAIS that we are trying to ascertain from the EMI σ_a signal, with the suggestion
198 that σ_a measurements can be used similarly at other sites to reveal the hidden LRD characteristics
199 of the framework geology.

200

201 **2 Background and regional setting**

202 2.1 Utility of electromagnetic methods in coastal environments

203 Methods to ascertain the alongshore variability of framework geology, and to test long-range
204 dependence, are difficult to implement and can be costly. Cores provide detailed point-wise
205 geologic data; however, they do not provide laterally continuous subsurface information (Jol et
206 al., 1996). Alternatively, geophysical techniques including seismic and GPR provide spatially
207 continuous stratigraphic information (e.g., Buynevich et al., 2004; Neal, 2004; Nummedal and
208 Swift, 1987; Tamura, 2012), but they are not ideally suited for LRD testing because the data
209 combine depth and lateral information at a single acquisition point. Moreover, GPR signals
210 attenuate rapidly in saltwater environments whereas seismic methods are labor-intensive and
211 cumbersome. On the other hand, terrain conductivity profiling is an easy-to-use alternative that



212 has been used in coastal environments to investigate fundamental questions involving;
213 instrument performance characteristics (Delefortrie et al., 2014; Weymer et al., 2016),
214 groundwater dynamics (Stewart, 1982; Fitterman and Stewart, 1986; Nobes, 1996; Swarzenski,
215 and Izbicki, 2009), and framework geology (Seijmonsbergen et al. 2004; Weymer et al. 2015).
216 Previous studies combining EMI with either GPR (Evans and Lizarralde, 2011) or coring
217 (Seijmonsbergen et al. 2004) demonstrate the validity of EM measurements as a means to
218 quantify alongshore variations in the framework geology of coastlines.

219 In the alongshore direction, Seijmonsbergen et al. (2004) used a Geonics EM34™ terrain
220 conductivity meter oriented in the horizontal dipole mode with intercoil separation and station
221 spacing both of 20 m. This configuration provides an exploration depth of roughly 15 m. A 14.5
222 km-length EMI transect was collected along the backbeach crossing a former outlet of the Rhine
223 River, Netherlands to evaluate alongshore variations in subsurface lithology. The survey was
224 conducted in an area that was previously characterized by drilling and these data were used to
225 calibrate the σ_a measurements. The results from the study suggest that coastal sediments can be
226 classified according to σ_a signature. The range of σ_a values was categorized into three groups. The
227 first group of low σ_a 20 – 45 millisiemens per meter (mS/m) with low-variability amplitudes was
228 interpreted as beach sands. The second group of medium σ_a values (20 – 90 mS/m) with large
229 variability corresponded to clay and peat layers of varying thickness. A third group of high σ_a values
230 (60 – 190 mS/m) with large variability was interpreted as clay-rich brackish channel deposits. The
231 authors suggest that high σ_a values occur in areas where the underlying conductive layer is thick and
232 close to the surface. Although Seijmonsbergen et al. (2004) suggest that EMI surveys are a rapid,
233 inexpensive method to investigate subsurface lithology they also acknowledge that variations in
234 salinity as a result of changing hydrologic conditions, storm activity and/or tidal influence confound
235 the geological interpretation and should be investigated in further detail (see Weymer et al., 2016).

236 The challenge on many barrier islands and protected National Seashores is obtaining
237 permission for extracting drill cores to validate geophysical surveys. At PAIS, numerous areas
238 along the island are protected nesting sites for the endangered Kemp's ridley sea turtle,
239 migratory birds, while other areas comprise historic archeological sites with restricted access.
240 Thus, coring is not allowed and only non-invasive techniques, such as EMI/GPR are permitted.
241



242 2.2 Regional setting

243 North Padre Island is part of a large arcuate barrier island system located along the Texas Gulf of
244 Mexico coastline and is the longest undeveloped barrier island in the world. The island is one of
245 ten national seashores in the United States and is protected and managed by the National Park
246 Service, a bureau of the Department of the Interior. PAIS is 129 km in length, and is an ideal
247 setting for performing EMI surveys because there is minimal cultural noise to interfere with the
248 σ_a signal, which as stated earlier we regard as a proxy for alongshore variations in framework
249 geology (Fig. 1). Additionally, the island is well-covered by high-resolution aerial LiDAR data.
250 The island is not dissected by inlets or navigation channels (excluding Mansfield Channel
251 separating north and south Padre Island), or modified by engineered structures (e.g., groynes,
252 jetties, etc.) that often interfere with natural morphodynamic processes (see Talley et al., 2003).
253 The above characteristics make the study area an exceptional location for investigating the
254 relationships between large-scale framework geology and surface morphology.

255 Relatively little is known about the framework geology at PAIS, especially its alongshore
256 variability. A notable exception is the information obtained from a series of coring and seismic
257 surveys conducted by Fisk (1959) in the central region of Padre Island ($\sim 27^\circ$ N). As described in
258 Weymer et al. (2015a; Fig. 3), locations of paleo-channels were established by Fisk (1959) based
259 on 3,000 cores and several seismic surveys. More than 100 borings were drilled to the top of the
260 late Pleistocene surface (tens of m depth) providing sedimentological data for interpreting the
261 depth and extent of the various paleo-channels. These cores were extracted ~ 60 years ago, but
262 the remnant Pleistocene and Holocene fluvial/deltaic features described in Fisk's study likely
263 have not changed over decadal time scales.

264 Geologic interpretations based on the Fisk (1959) data suggest that the thickness of the
265 modern beach sands is $\sim 2 - 3$ m, and they are underlain by Holocene shoreface sands and muds
266 to a depth of $\sim 10 - 15$ m (Brown and Macon, 1977; Fisk, 1959). The Holocene deposits lie upon
267 a Pleistocene ravinement surface of fluvial-deltaic sands and muds and relict transgressive
268 features. A network of buried valleys and paleo-channels in the central segment of the island, as
269 interpreted by Fisk (1959), exhibits a dendritic, tributary pattern. The depths of the buried valleys
270 inferred from seismic surveys range from $\sim 25 - 40$ m (Brown and Macon, 1977). These
271 channels have been suggested to incise into the Pleistocene paleo-surface and became infilled



272 with sands from relict Pleistocene dunes and fluvial sediments reworked by alongshore currents
273 during the Holocene transgression (Weise and White, 1980). However, the location and cross-
274 sectional area of each valley and paleo-channel alongshore is not well-constrained. It is also
275 possible that other channels exist other than those identified by Fisk (1959).

276 As presented in Weymer et al. (2015a), minima in the alongshore σ_a signal are spatially
277 correlated with the locations of these previously identified geologic features. This observation
278 provides an impetus for using EMI to map the known, and any previously unidentified, geologic
279 features alongshore. The observed beach-dune morphology and other metrics such as island
280 width are highly variable and controlled to an unknown extent by the framework geology both
281 within and outside the known paleo-channel regions. The fact that much of the framework
282 geology at PAIS is poorly known provides additional motivation for integrating subsurface
283 geophysical methods and surface observations to analyze, from a statistical standpoint, the key
284 geologic controls on island morphology within the study area.

285

286 **3 Methods**

287 A combination of geophysical, geomorphological, and statistical methods are used in this study
288 to quantify the relationships between framework geology and surface geomorphology at PAIS. A
289 description of the EMI, GPR, geomorphometry and statistical techniques is provided in the
290 following sections.

291

292 **3.1 Field EMI and GPR surveys**

293 Profiles of EMI σ_a responses typically are irregular and each datum represents a spatial averaging
294 of the bulk subsurface electrical conductivity σ , which in turn is a function of a number of
295 physical properties (e.g., lithology, porosity, water content, salinity, etc.). The “sensor footprint”,
296 or subsurface volume over which the spatial averaging is performed, is dependent on the
297 separation between the TX – RX coils (1.21 m in this study), and the transmitter frequency. The
298 horizontal extent, or radius, of the footprint can be more or less than the step-size between
299 subsequent measurements along the profile. The sensor footprint determines the volume of
300 ground that contributes to σ_a at each acquisition point, and as will be discussed later, the radius
301 of the footprint has important implications for analyzing LRD. The footprint radius depends on



302 frequency and ground conductivity, but is likely to be of the same order as, but slightly larger
303 than, the intercoil spacing. Two different station-spacings were used to examine the correlation
304 structure of σ_a as a function of spatial scale. An island-scale alongshore survey of ~ 100 km
305 length was performed using a 10 m station spacing (station spacing \gg footprint radius) such that
306 each σ_a measurement was recorded over an independently sampled volume of ground.
307 Additionally, a sequence of σ_a readings was collected at 1 m spacing (station spacing $<$ footprint
308 radius) over a profile length of 10 km within the Fisk (1959) paleo-channel region of the island.
309 This survey design allows for comparison of the long-range-dependent structure of the
310 framework geology over several orders of magnitude ($10^0 - 10^5$ m).

311 The 100-km-long alongshore EMI survey was performed during a series of three field
312 campaigns, resulting in a total of 21 (each of length ~ 4.5 km) segments that were collected
313 during October 9 – 12th, 2014, November 15 – 16th, 2014, and March 28th, 2015. The EMI σ_a
314 responses were stitched together by importing GPS coordinates from each measurement into
315 ArcGIS™ to create a single composite spatial data series. The positional accuracy recorded by a
316 TDS Recon PDA equipped with a Holux™ WAAS GPS module was found to be accurate within
317 ~ 1.5 m. An additional 10 km survey was performed along a segment of the same 100 km survey
318 line in one day on March 29th, 2015, to determine whether varying hydrologic conditions in both
319 space and time, which are discussed below, play a deleterious role in resolving the framework
320 geology. This second composite data series consists of 8 stitched segments.

321 The same multi-frequency GSSI Profiler EMP-400™ instrument was used for each
322 segment. All transects were located in the backbeach environment ~ 25 m inland from the mean
323 tide level (MTL). This location was chosen to reduce the effect of changing groundwater
324 conditions in response to nonlinear tidal forcing, which may be significant closer to the
325 shoreline. The sensor has reduced ability to detect lateral changes in the underlying geology
326 during wet conditions such as during or immediately after significant rainfall events, or at high
327 tide near the shoreline, since electrical conductivity increases rapidly with water content. The
328 transect locations also avoid the large topographic variations (see Santos et al., 2009) fronting the
329 foredune ridge that can reduce the efficiency of data acquisition and influence the EMI signal. In
330 a companion study, Weymer et al. (2016) demonstrated that the σ_a signal at the beachfront exhibits
331 a step-like response over the course of a tidal cycle; however, this effect is less pronounced



332 further inland where the surveys in the present study were collected. Their study shows that the
333 difference between high-tide and low-tide EMI σ_a measurements is as large as 50 mS/m at the
334 backbeach, but this difference is less than 9% of the range of σ_a variations observed ($\sim 50 - 600$
335 mS/m) along the entire length of the island. As will be shown later, there is not a direct
336 correlation between high tide and high σ_a values. Thus, we assume the tidal influence on the EMI
337 signal can be neglected over the spatial scales of interest in the present study. Nevertheless, the
338 duration and approximate tidal states of each survey was documented in order to compare with
339 the EMI signal (see Weymer et al., 2016). Tidal data were accessed from NOAA's Tides and
340 Currents database (NOAA, 2015b). Padre Island is microtidal and the mean tidal range within the
341 study area is 0.38 m (NOAA, 2015a). A tidal signature in EMI signals may become more significant
342 at other barrier islands with larger tidal ranges.

343 For all surveys, the EMI profiler was used in a vertical dipole orientation with TX and
344 RX coils aligned in the (P-mode) direction parallel to the profile line (Weymer et al., 2016).
345 Measurements were made at a constant step-size to simplify the data analysis; for example,
346 ARIMA models require that data are taken at equal intervals (see Cimino et al., 1999). The EMI
347 profiler was carried at a height of 0.7 m above the ground to mitigate noise from the mainly non-
348 metallic debris on the beach that unfortunately is scattered along the island (Weymer et al.,
349 2016). Although the sensor is capable of recording three frequencies simultaneously (see GSSI,
350 2007), we choose herein to focus on data collected at 3 kHz, resulting in a depth of investigation
351 (DOI) of $\sim 3.5 - 6.4$ m over the range of conductivities found within the study area (Weymer et
352 al., 2016; Table 1.). Because the depth of the modern beach sands is $\sim 2 - 3$ m or greater (see
353 Brown and Macon, 1977; page 56, Figure 15), variations in the depth to shoreface sands and
354 muds is assumed to be within the DOI of the profiler, which may not be captured at the higher
355 frequencies also recorded by the sensor (i.e., 10, and 15 kHz).

356 An 800 m GPR survey was performed on August 12th, 2015 across one of the paleo-
357 channels previously identified Fisk (1959) located within the 10 km EMI survey for comparison
358 with the σ_a measurements. We used a Sensors and Software PulseEKKO Pro[®] system for this
359 purpose. A survey grade GPS with a positional accuracy of 10 cm was used to match the
360 locations and measurements between the EMI/GPR surveys. Data were acquired in reflection
361 mode at a nominal frequency of 100 MHz with a standard antenna separation of 1 m and a step-



362 size of 0.5 m. The instrument settings resulted in a DOI of up to 15 m. Minimal processing was
363 applied to the data and includes a dewow filter and migration (0.08 m/ns), followed by AGC gain
364 (see Neal, 2004). Given The theory and operational principles of GPR are discussed in many
365 places (e.g. Everett, 2013; Jol, 2008) and will not be reviewed here.

366

367 3.2 Geomorphometry

368 Topographic information was extracted from aerial LiDAR data that were collected by the Army
369 Corps of Engineers (USACE) in 2009 as part of the West Texas Aerial Survey project to assess
370 post-hurricane conditions of the beaches and barrier islands along the Texas coastline. This
371 dataset is the most recent publicly available LiDAR survey of PAIS and it provides essentially
372 complete coverage of the island. With the exception of Hurricane Harvey, which made landfall
373 near Rockport, Texas as a Category 4 storm in late August, 2017, Padre Island has not been
374 impacted by a hurricane since July 2008, when Hurricane Dolly struck South Padre Island as a
375 Category 1 storm (NOAA, 2015a). The timing of the LiDAR and EMI surveys in this study
376 precede the impacts of Hurricane Harvey, and it is assumed that the surface morphology across
377 the island at the spatial scales of interest (i.e., $10^1 - 10^2$ km) did not change appreciably between
378 2009 and 2015.

379 A 1-m resolution DEM was created from 2009 LiDAR point clouds available from
380 NOAA's Digital Coast (NOAA, 2017). The raw point cloud tiles were merged to produce a
381 combined point cloud of the island within the PAIS National Seashore. The point clouds were
382 processed into a continuous DEM using the ordinary kriging algorithm in SAGA GIS, which is
383 freely available open-source software (www.saga-gis.org/); and subsequent terrain analysis was
384 conducted using an automated approach involving the relative-relief metric (Wernette et al.,
385 2016). Relative relief is a measure of topographic position of the center pixel compared to the
386 minimum and maximum pixel elevations within a given computational window. Several other
387 morphometrics including beach width, dune height, and island width were extracted from the
388 DEM using a recently developed automated multi-scale approach (see Wernette et al., 2016).
389 This technique extracts the open-water shoreline (in this case the Gulf of Mexico shoreline) and
390 backbarrier shoreline based on elevation thresholds and uses them to calculate beach and island
391 width referenced to mean sea-level (MSL). Dune metrics including dune crest, dune heel, and



392 dune toe elevations are calculated based on the average relative relief (RR) to determine where
393 the dune begins, crests, and ends along every shore-normal profile in a DEM. This process is
394 repeated for all such profiles at a 1 m spacing along the entire length of PAIS to generate a
395 continuous dataset of alongshore dune height and volume. A detailed description of the
396 procedure for extracting each metric is provided in Wernette et al. (2016).

397 Each morphometric feature was extracted by averaging the RR values across window
398 sizes of 21 m x 21 m, 23 m x 23 m, and 25 m x 25 m. The choice of window size is based on
399 tacit *a priori* knowledge and observations of the geomorphology in the study area. Larger
400 window sizes will better capture smoother beach and dune features by reducing sensitivity to the
401 fine-scale variability induced by measurement error inherent in LiDAR-derived DEMs, as well
402 as natural terrain irregularities (Wernette et al., 2016). Each DEM series is paired with the σ_a
403 profile by matching the GPS coordinates (latitude and longitude) recorded in the field by the
404 EMI sensor. Cross-sectional DEM profiles oriented perpendicular to the shoreline were analyzed
405 every 10 m (y-coordinate) along the EMI profile to match the same 10 m sampling interval of the
406 σ_a measurements. The terrain variations along each cross-shore profile are summed to calculate
407 beach and island volume based on the elevation thresholds mentioned above. Dune volume is
408 calculated by summing the pixel elevations starting at the dune toe, traversing the dune crest, and
409 ending at the dune heel. In total, six DEM morphometrics were extracted as spatial data series to
410 be paired with the EMI data, each having an identical sample size ($n = 9,694$), which is
411 sufficiently large for statistical ARIMA modeling.

412

413 3.3 Statistical methods

414 Although the procedures for generating the EMI and LiDAR datasets used in this study
415 are different, the intended goal is the same; to produce spatial data series that contain similar
416 numbers of observations for comparative analysis using a combination of signal processing and
417 statistical modeling techniques. The resulting signals comprising each data series represent the
418 spatial averaging of a geophysical (EMI) or geomorphological (DEM) variable that contains
419 information about the important processes-form relationships between subsurface geologic
420 features and island geomorphology that can be teased out by means of comparative analysis
421 (Weymer et al., 2015a). Because we are interested in evaluating these connections at both small



422 and large spatial scales, our first approach is to determine the autocorrelation function and Hurst
423 coefficient (self-similarity parameter) H and hence verify whether the data series are
424 characterized by short and/or long-range memory (Beran, 1992; Taquu et al., 1995). LRD occurs
425 when the autocorrelation within a series, at large lags, tend to zero like a power function, and so
426 slowly that the sums diverge (Doukhan et al., 2003). LRD is often observed in natural time series
427 and is closely related to self-similarity, which is a special type of LRD.

428 The degree of LRD is related to the scaling exponent, H of a self-similar process, where
429 increasing H in the range $0.5 < H \leq 1.0$ indicates an increasing tendency towards such an effect
430 (Taquu, 2003). Large correlations at small lags can easily be detected by models with short-
431 memory (e.g., ARMA, Markov processes) (Beran, 1994). Conversely, when correlations at large
432 lags slowly tend to zero like a power function, the data contain long-memory effects and either
433 fractional Gaussian noise (fGn), or ARIMA models may be suitable (Taquu et al., 1995). The
434 R/S statistic is the quotient of the range of values in a data series and the standard deviation
435 (Beran, 1992, 1994; Hurst, 1951; Mandelbrot and Taquu, 1979). When plotted on a log/log plot,
436 the resulting slope of the best-fit line gives an estimate of H , which is useful as a diagnostic tool
437 for estimating the degree of LRD (see Beran, 1994). For a given number of observations $X_1, X_2,$
438 $\dots X_n$, a partial sum sequence is defined by $S_m = X_1 + \dots + X_m$, for $m = 0, 1, \dots$ and $m < n$ (with S_0
439 $= 0$). The R/S statistic is then calculated by (see Samorodnitsky, 2007):

$$440 \quad \frac{R}{S}(X_1, \dots, X_n) = \frac{\max_{0 \leq i \leq n} (S_i - \frac{i}{n} S_n) - \min_{0 \leq i \leq n} (S_i - \frac{i}{n} S_n)}{\sqrt{\left(\frac{1}{n} \sum_{i=1}^n (x_i - \frac{1}{n} S_n)^2\right)}} \quad (1)$$

441 where, S_n/n is the mean of the sample. It has been suggested that R/S tends to give biased
442 estimates of H , too low for $H > 0.72$ and too high for $H < 0.72$ (Bassingthwaigthe and Raymond,
443 1994), which was later confirmed by Malamud and Turcotte (1999). Empirical trend corrections
444 to the estimates of H can be made by graphical interpolation, but are not applied here because of
445 how the regression is done. The R/S analysis in this study was performed using signal analysis
446 software AutoSignal™ to identify whether a given signal is distinguishable from a random,
447 white noise process and, if so, whether the given signal contains LRD. The H value is calculated
448 by an inverse variance-weighted linear least-squares curve fit using the logarithms of the R/S and



449 the number of observations, which provides greater accuracy than other programs that compute
450 the Hurst coefficient.

451 Two of the simplest statistical time series models that can account for LRD are fGn and
452 ARIMA. In the former case, fGn and its “parent” fBm are used to evaluate stationary and
453 nonstationary fractal signals, respectively (see Eke et al., 2000; Everett and Weiss, 2002). Both
454 fGn and fBm are governed by two parameters: variance σ^2 ; and the scaling parameter, H (Eke et
455 al., 2000). A more comprehensive class of time series models that has similar capability to detect
456 long-range structure is ARIMA. Because fGn and fBm models have only two parameters, it is
457 not possible to model the short-range components. Additional parameters in ARIMA models are
458 designed to handle the short-range component of the signal, as discussed by Taqqu et al. (1995)
459 and others. Because the EMI data series presumably contain both short-range and long-range
460 effects, we chose to use ARIMA as the analyzing technique.

461 ARIMA models are used across a wide range of disciplines and have broad applicability
462 for understanding the statistical structure of a given data series as it is related to some physical
463 phenomenon (see Beran, 1992, 1994; Box and Jenkins, 1970; Cimino et al., 1999; Granger and
464 Joyeux, 1980; Hosking, 1981; Taqqu et al., 1995). The statistical ARIMA model of a given data
465 series is defined by three terms (p,d,q), where p and q indicate the order of the autoregressive
466 (AR) and moving average (MA) components, respectively and d represents a differencing, or
467 integration term (I) that is related to LRD. The AR element, p , represents the effects of adjacent
468 observations and the MA element, q , represents the effects on the process of nearby random
469 shocks (Cimino et al., 1999; De Jong and Penzer, 1998). However, in the present study our series
470 are reversible spatial series that can be generated, and are identical, with either forward or
471 backward acquisition, unlike a time series. Both p and q parameters are restricted to integer
472 values (e.g., 0, 1, 2), whereas the integration parameter, d , represents potentially long-range
473 structure in the data. The differencing term d is normally evaluated before p and q to identify
474 whether the process is stationary (i.e., constant mean and σ^2). If the series is nonstationary, it is
475 differenced to remove either linear ($d = 1$) or quadratic ($d = 2$) trends, thereby making the mean
476 of the series stationary and invertible (Cimino et al., 1999), thus allowing determination of the
477 ARMA p and q parameters.



478 Here, we adopt the definitions of an ARMA (p,q), and ARIMA (p,d,q) process following
479 the work of Beran (1994). Let p and q be integers, where the corresponding polynomials are
480 defined as:

$$481 \quad \phi(x) = 1 - \sum_{j=1}^p \phi_j x^j, \tag{2}$$

$$483 \quad \psi(x) = 1 + \sum_{j=1}^q \psi_j x^j.$$

484
485 It is important to note that all solutions of $\phi(x_0) = 0$, and $\psi(x) = 0$ are assumed to lie outside
486 the unit circle. Additionally, let $\epsilon_t (t = 1, 2, \dots)$ be independent, and identically distributed
487 normal variables with zero variance σ_ϵ^2 such that an ARMA (p,q) process is defined by the
488 stationary solution of:

$$490 \quad \phi(B)X_t = \psi(B)\epsilon_t \tag{3}$$

491
492 where, B is the backward shift operator $BX_t = X_{t-1}, B^2X_t = X_{t-2}, \dots$ and, specifically, the
493 differences can be expressed in terms of B as; $X_t - X_{t-1} = (1 - B)X_t, (X_t - X_{t-1}) - (X_{t-1} -$
494 $X_{t-2}) = (1 - B)^2X_t \dots$ Alternatively, an ARIMA (p,d,q) process X_t is formally defined as:

$$496 \quad \phi(B)(1 - B)^d X_t = \psi(B)\epsilon_t \tag{4}$$

497
498 where, equation (3) holds for a d th difference $(1 - B)^d X_t$.

499 As mentioned previously, a more general form of ARIMA (p,d,q) is the fractional
500 ARIMA process, or FARIMA, where the differencing term d is allowed to take on fractional
501 values. If d is a non-integer value for some $-0.5 < d < 0.5$ and $\{x_t\}$ is a stationary process as
502 indicated by equation 4, then the model by definition is called a FARIMA process where d -
503 values in the range $0 < d < 0.5$ of are of particular interest herein because geophysically-relevant
504 LRD occurs for $0 < d < 0.5$, whereas $d > 0.5$ means that the process is nonstationary, but
505 nonintegrable (Beran, 1994; Hosking, 1981). A special case of a FARIMA process explored in



506 the current study is ARIMA (0d0), also known as fractionally-differenced white noise (Hosking,
507 1981), which is defined by Beran (1994) and others as:

508

$$509 \quad X_t = (1 - B)^{-d} \epsilon_t. \quad (5)$$

510

511 For $0 < d < 0.5$, the ARIMA (0d0) process is a stationary process with long-range structure and
512 is useful for modeling LRD. According to Hosking (1981), $\{x_t\}$ is called an ARIMA (0d0)
513 process and is of particular interest in modelling LRD as d approaches 0.5 because in such cases
514 the correlations and partial correlations of $\{x_t\}$ are all positive and decay slowly towards zero as
515 the lag increases, while the spectral density of $\{x_t\}$ is concentrated at low frequencies. As shown
516 later, different values of the d parameter provide further insight into the type of causative
517 physical processes that generate each data series. When $d < 0.5$, the series $\{x_t\}$ is stationary,
518 which has an infinite moving average MA representation that highlights long-range trends or
519 cycles in the data. Conversely, when $d > -0.5$, the series $\{x_t\}$ is invertible and has an infinite
520 autoregressive AR representation (see Hosking, 1981). When $-0.5 < d < 0$, the stationary, and
521 invertible, ARIMA (0d0) process is dominated by short-range effects and is antipersistent. When
522 $d = 0$, the ARIMA (000) process is white noise, having zero correlations and a constant spectral
523 density.

524 Following the methodology proposed by Box and Jenkins (1970), there are three phases
525 that characterize ARIMA modeling: *identification*, *estimation*, and *diagnostic testing*. The
526 primary task of the first phase is to identify the autocorrelation function(s) and any patterns in the
527 data (e.g., autocorrelation function, R/S analysis), and to manipulate the data (if necessary) to
528 achieve stationarity before an appropriate model is chosen (Linden et al., 2003). After an
529 appropriate model is selected (e.g., ARMA, ARIMA, etc.), statistical software is used in the
530 second phase to generate estimates of each model parameter (p, d, q) in order to achieve a good
531 model fit. Tasks included in the third phase involve examining the residual score, or root-mean-
532 square error (RMSE), to determine if there are patterns remaining in the data that are not
533 accounted for. Residual scores, or the mismatch between the values predicted by the model and
534 the actual values of the data series, should show that there are no significant autocorrelations



535 among the residuals (Linden et al., 2003). The best model fit is determined by the smallest
536 residual score, which is the sum of the squares of the residuals (i.e., RMSE).

537 Identification of an appropriate model is accomplished by finding small values of
538 elements p, d, q (usually between 0 – 2) that accurately fit the most significant patterns in the data
539 series. When a value of an element is 0, that element is not needed. For example, if $d = 0$ the
540 series does not contain a significant long-range component, whereas if $p = q = 0$, the model does
541 not exhibit significant short-range effects. If $p, d, q \neq 0$, the model contains a combination of both
542 short and long-memory effects.

543 Time series modeling is traditionally used for either forecasting future values or assigning
544 missing values within the data series. In this study, we are interested in determining the orders of
545 p, d, q not for forecasting or filling in missing data, but rather for gaining physical insight into the
546 structure of EMI σ_a responses, and since it is a proxy, the structure of the framework geology.
547 Different combinations of (p, d, q) provide insights into the degree or strength of LRD within a
548 data series and, in the present context in which EMI and DEM are jointly analyzed, the best-fit
549 (p, d, q) values can be used to discern how the various length-scales within the framework
550 geology and island morphology are related.

551

552 **4 Results**

553 4.1 Spatial data series

554 4.1.1 EMI and GPR surveys

555 The 100 km EMI survey (Fig. 2a) represents (to our knowledge) the longest continuous ground-
556 based survey using a terrain conductivity meter ever performed. The unprocessed (raw) EMI σ_a
557 responses show a high degree of variability along the island. To reduce the effect of instrument
558 drift caused by temperature, battery and other systematic variations through the acquisition
559 interval, a drift correction was applied to each segment, the segments were then stitched together,
560 following which a regional linear trend removal was applied to the composite dataset. High-
561 amplitude responses within the EMI signal generally exhibit a higher degree of variability
562 (multiplicative noise) compared to the low-amplitude responses. Higher σ_a readings correspond
563 to a small sensor footprint and have enhanced sensitivity to small-scale near-surface
564 heterogeneities (see Guillemoteau and Tronicke, 2015). Low σ_a readings suggest the sensor is



565 probing greater depths and averaging over a larger footprint. In that case, the effect of fine-scale
566 heterogeneities that contribute to signal variability is suppressed.

567 The 10 km alongshore survey is located within an inferred paleo-channel region (Fisk,
568 1959), providing some *a priori* geologic constraints for understanding the variability within the
569 EMI signal (Fig. 2b). Here, the sample size is $n = 10,176$, permitting a quantitative comparison
570 with the 100-km-long data series since they contain a similar number of observations. Unlike the
571 100 km survey, successive footprints of the sensor at each subsequent measurement point
572 overlap along the 10 km survey. The overlap enables a fine-scale characterization of the
573 underlying geological structure because the separation between the TX – RX coils (1.21 m), a
574 good lower-bound approximation of the footprint, is greater than the step-size (1 m).

575 The overall trend in σ_a for the 10 km survey is comparable to that of the 100 km survey,
576 where regions characterized by high and low amplitude signals correspond to regions of high and
577 low variability, respectively, implying that multiplicative noise persists independently of station
578 spacing. The decrease in σ_a that persists between $\sim 2.5 - 6$ km along the profile (Fig. 2b)
579 coincides in location with two paleo-channels, whereas a sharp reduction in σ_a is observed at \sim
580 8.2 km in close proximity to a smaller channel. Most of the known paleo-channels are located
581 within the 10 km transect and likely contain resistive infill sands that should generate lower and
582 relatively consistent σ_a readings (Weymer et al., 2015a). The low σ_a signal caused by the sand
583 indirectly indicates valley incision, since it is diagnostic of a thicker sand section, relatively
584 unaffected by the underlying conductive layers. Thus, it is reasonable to assume that reduced
585 variability in the signal is related to the framework geology within the paleo-channels, which we
586 now compare with a GPR profile.

587 To corroborate the capability of the EMI data to respond to subsurface geology, an 800 m
588 GPR survey confirms the location of a previously identified paleo-channel (Fisk, 1959) at $\sim 5 -$
589 10 m depth (Fig. 3). A continuous undulating reflector from $\sim 150 - 800$ m along the profile is
590 interpreted to be the surface mapped by Fisk (1959) who documented a paleo-channel at this
591 location with a depth of ~ 8 m. Although the paleo-surface is within the detection limits of the
592 GPR, it is likely that the DOI of the EMI data ($\sim 3 - 6$ m) is not large enough to probe
593 continuously along the contact between the more conductive ravinement surface and the less
594 resistive infill sands. Along the transect at shallower depths highlighted by the red box in the



595 lower radargram (Fig. 3), low EMI σ_a values correspond to fine stratifications in the GPR
596 section, which is common for beach sands with little clay content that are not saline-saturated.
597 The EMI highs between $\sim 450 - 530$ m coincide with parts of the GPR section that do not have
598 the fine stratification and this may indicate the presence of clay or saline water. Here, the high
599 conductivity zone for both the GPR and EMI is located within a recovering washover channel
600 overlying the paleo-channel that is evident in the satellite imagery in the upper-left panel of Fig.
601 3. The overwash deposits consisting of a mix of sand and finer-grained backbarrier sediments
602 likely mask the EMI sensors' ability to probe greater depths. Nonetheless, the high conductivity
603 zone represents a smaller ~ 100 m segment within the ~ 500 -m-wide paleo-channel, suggesting
604 that variations in the EMI responses outside this zone correspond to variations in the framework
605 geology imaged by GPR.

606

607 4.1.2 LiDAR-derived DEM morphometrics

608 The LiDAR-derived DEM spatial data series along the 100 km transect are presented in Fig. 4.
609 Each data series is shown with respect to the areal DEM of the study area where the approximate
610 locations of each closely-spaced paleo-channel are highlighted in gray. This visualization allows
611 a qualitative analysis of the spatial relationships between subsurface information encoded in the
612 σ_a signal, and surface morphology over the entire length of the barrier island.

613 The morphology of the beach-dune system, as well as island width, changes substantially
614 from north to south. In the paleo-channel region, beach width decreases considerably and is more
615 variable. Beach width generally increases towards the northern section of the island. The volume
616 of the beach tends to be lowest in the northern zone, varies considerably in the central part of the
617 island, then stabilizes and gradually decreases towards the south. These zones correspond to the
618 southern (0 – 30 km), central (30 – 60 km), and northern (60 – 100 km) sections of the island.
619 Alongshore dune heights are greater in the south, become more variable in the paleo-channel
620 region, and decrease in the north except for the area adjacent to Baffin Bay. Dune volume is
621 lowest in the northern section, intermittently increases in the central zone and slightly decreases
622 towards the south. The island is considerably narrower between Mansfield Channel and Baffin
623 Bay (see Fig. 2a), increasing in width significantly in the northern zone; island volume follows a
624 similar trend. Overall, σ_a values are lower northward of the paleo-channel region compared to the



625 southern zone where σ_a increases substantially. However, the lowest σ_a values are located within
626 the region of paleo-channels inferred by Fisk (1959) supporting previous findings in the study
627 area by Weymer et al. (2015a) that suggest a potential geologic control on alongshore
628 geomorphic features.

629 Each spatial data series (Fig. 4a – 4g) represents a different superposition of effects
630 caused by physical processes operating across a wide range of temporal and length scales
631 (Weymer et al., 2015a). Short-range fluctuations represent small-scale heterogeneities, whereas
632 long-range components capture variations in each metric at broader length scales. There is a high
633 degree of variability within each signal that is directly related to the complex geological and
634 geomorphological structure along the island. Within and outside the paleo-channel region,
635 general associations between the EMI σ_a response and DEM metrics can be made, as we now
636 show by ARIMA modeling. To conduct the ARIMA analysis, we chose to divide the island into
637 three zones based on the location of the known paleo-channels. As will be discussed later, the
638 tripartite zonation allows for a quantitative analysis of LRD at three spatial scales (regional,
639 intermediate, local) within and outside the area containing paleo-channels. It is important to note,
640 however, that the framework geology is likely to exhibit LRD regardless of the length-scale over
641 which it is observed.

642

643 4.2 Tests for LRD

644 4.2.1 Tests for LRD in EMI data series

645 Both EMI spatial data series appear to be nonstationary since the mean and variance of the data
646 fluctuate along the profile. A closer visual inspection reveals however that cyclicity is present at
647 nearly all spatial frequencies, with the cycles superimposed in random sequence and added to a
648 constant variance and mean (see Beran, 1994). This behavior is typical for stationary processes
649 with LRD, and is often observed in various types of geophysical time series (Beran, 1992), for
650 example records of Nile River stage minima (Hurst, 1951). A common first-order approach for
651 determining whether a data series contains LRD is through inspection of the autocorrelation
652 function, which we have computed in AutoSignal™ signal analysis software using a fast Fourier
653 transform (FFT) algorithm (Fig. 5a, 5d). Both EMI signals exhibit large correlations at large lags
654 (at km and higher scales), suggesting the σ_a responses contain LRD, or "long-memory effects" in



655 time-series language. The degree of LRD can be characterized by evaluating the scaling
656 exponent H (or Hurst coefficient) of a self-similar process. When plotted on a log/log plot, the
657 resulting slope of the best-fit line gives an estimate of H , where values approaching 1.0 indicate
658 dominant long-range effects (see Beran, 1994). Results from a rescaled range R/S analysis (Fig.
659 5b, 5e) indeed show high H -values of 0.85 ($r^2 = 0.98$) and 0.95 ($r^2 = 0.99$) for the 100 km and 10
660 km surveys, indicating a strong presence of LRD at both regional and local spatial scales.

661 The manner in which different spatial frequency (i.e. wavenumber) components are
662 superposed to constitute an observed EMI σ_a signal has been suggested to reveal information
663 about the causative multi-scale geologic structure (Everett and Weiss, 2002; Weymer et al.,
664 2015a; Beskardes et al., 2016). For example, the lowest-wavenumber contributions are
665 associated with spatially coherent geologic features that span the longest length scales probed.
666 The relative contributions of the various wavenumber components can be examined by plotting
667 the σ_a signal power spectral density (PSD). A power-law of the form $|\sigma_a(f)|^2 \sim f^\beta$ over several
668 decades in spatial wavenumber is evident (Fig. 5c, 5f). The slope β of a power-law-shaped
669 spectral density provides a quantitative measure of the LRD embedded in a data series and
670 characterizes the heterogeneity, or “roughness” of the signal. A value of $|\beta| > 1$ indicates a
671 series that is influenced more by long-range correlations and less by small-scale fluctuations
672 (Everett and Weiss, 2002). For comparison, a pure white noise process would have a slope of
673 exactly $\beta = 0$, whereas a slope of $\beta \sim 0.5$ indicates fractional Gaussian noise, i.e., a stationary
674 signal with no significant long-range correlations (Everett and Weiss, 2002). The β -values for the
675 100 km and 10 km surveys are $\beta = -0.97$, and $\beta = -1.06$, respectively. These results suggest that
676 both the 100 km and 10 km EMI signals contain long-range correlations. However, there is a
677 slightly stronger presence of LRD within the 10 km segment of the paleo-channel region
678 compared to that within the segment that spans the entire length of the island. This indicates that
679 long-range spatial variations in the framework geology are more important, albeit marginally so,
680 at the 10-km scale than at the 100-km scale. It is possible that the variability within the signal
681 and the degree of long-range correlation is also a function of the sensor footprint, relative to
682 station spacing. This is critically examined in section 4.3.

683

684 4.2.2 Tests for LRD in surface morphometrics



685 Following the same procedure as applied to the EMI data, we performed the R/S analysis for
686 each beach, dune, and island metric. The calculated H -values for the DEM morphometrics range
687 between 0.80 – 0.95 with large values of $r^2 \sim 1$, indicating varying, but relatively strong
688 tendencies towards LRD. Beach width and beach volume data series have H -values of 0.82 and
689 0.86, respectively. Dune height and dune volume H -values are 0.83 and 0.80, whereas island
690 width and island volume have higher H -values of 0.95 and 0.92, respectively. Because each data
691 series shows moderate to strong evidence of LRD, the relative contributions of short and long-
692 range structure contained within each signal can be further investigated by fitting ARIMA
693 models to each data set.

694

695 4.3 ARIMA statistical modeling of EMI

696 The results of the tests described in section 4.2.1 for estimating the self-similarity parameter H
697 and the slope of the PSD function suggest that both EMI data series, and by inference the
698 underlying framework geology, exhibit LRD. Therefore, we suggest that an ARIMA process
699 might be an appropriate model. The goal of our analysis is to estimate the p , d , and q terms
700 representing the order, respectively, of autoregressive (AR), integrated (I) and moving-average
701 (MA) contributions to the signal (Box and Jenkins, 1970). For the analysis, the ‘arfima’ and
702 ‘forecast’ statistical packages in R were used to fit a family of ARIMA (p,d,q) models to the
703 EMI σ_a data and island morphometrics (Hyndman, 2015; Hyndman and Khandakar, 2007;
704 Veenstra, 2012). Results of ten realizations drawn from a family of ARIMA (p,d,q) models and
705 their residuals (RMSE) are presented in Table 1. The worst fit (ARIMA 001) models are shown
706 for the 100 km and 10 km (Fig. 6a, 6c) surveys. The best fit (ARIMA 0d0) models for both the
707 100 and 10 km surveys are shown in Fig. 6b and 6d, respectively. For this analysis, the tests
708 include different combinations of p,d,q that model either short-range: ARIMA (100; 001; 101;
709 202; 303; 404; 505), long-range: ARIMA (010; 0d0), or composite short- and long-range
710 processes: ARIMA (111). It is important to note that AR and MA are only appropriate for “short-
711 memory” processes since they involve only near-neighbor values to explain the current value,
712 whereas the integration (the “I” term in ARIMA) models “long-memory” effects because it
713 involves distant values. Note that ARIMA was developed for one-way time series, in which the
714 arrow of time advances in only one direction, but in the current study we are using it for spatial



715 series that are reversible. Different realizations of each ARIMA (p,d,q) data series were
716 evaluated, enabling physical interpretations of LRD at regional, intermediate, and local spatial
717 scales. Determining the best-fitting model is achieved by comparing the residual score, or
718 RMSE, of each predicted data series relative to the observed data series, where lower RMSE
719 values indicate a better fit (Table 1).

720 Based on the residuals and visual inspection of each realization, two observations are
721 apparent: 1) both EMI data series are most accurately modeled by an ARIMA ($0d0$) process with
722 non-integer d , and 2) the mismatch between the data and their model fit is considerably lower for
723 the 10 km survey compared to the 100 km survey. The first observation suggests that the data are
724 most appropriately modeled by a FARIMA process; i.e., a fractional integration that is stationary
725 ($0 < d < 0.5$) and has long-range dependence (see Hosking, 1981). This implies that spatial
726 variations in framework geology at the broadest scales dominate the EMI signal and that small-
727 scale fluctuations in σ_a caused, for example, by changing hydrological conditions over brief time
728 intervals less than the overall data acquisition interval, or fine-scale lithological variations less
729 than a few station spacings, are not as statistically significant. Regarding the second observation,
730 the results suggest that a small station spacing (i.e., 1 m) is preferred to accurately model both
731 short and long-range contributions within the signal because large station spacings cannot
732 capture short-range information. The model for the 10 km survey fits better because both p (AR)
733 and q (MA) components increase with a smaller step-size since successive volumes of sampled
734 subsurface overlap. On the contrary, the sensor footprint is considerably smaller than the station
735 spacing (10 m) for the 100 km survey. Each σ_a measurement in that case records an independent
736 volume of ground, yet the dataset still exhibits LRD, albeit not to the same degree as in the 10
737 km survey.

738

739 4.4 ARIMA statistical modeling of island metrics compared with EMI

740 A sequence of ARIMA (p,d,q) models was also evaluated for the DEM morphometrics series to
741 find best fits to the data. The analysis comprised a total of 36 model tests (Table 2). The RMSE
742 values reveal that: 1) all data series are best fit by an ARIMA ($0d0$) process with fractional d , i.e.
743 a FARIMA process; 2) the ARIMA models, in general, more accurately fit the EMI data than the
744 DEM morphometric data; and 3) in all cases, the poorest fit to each series is the ARIMA (001),



745 or MA process. This, in turn, means that the differencing parameter d is the most significant
746 parameter amongst p , d and q . It is important to note that different values of d were computed
747 based on the best fit of each FARIMA model to the real data. A graphical representation of the
748 FARIMA-modeled data series for each DEM metric is shown in Fig. 7, allowing a visual
749 inspection of how well the models fit the observed data. Because each data series has its own
750 characteristic amplitude and variability, it is not possible to compare RMSE between tests
751 without normalization. The variance within each data series can differ by several orders of
752 magnitude.

753 Instead of normalizing the data, a fundamentally different approach is to compare the
754 EMI σ_a d -values with respect to each metric at regional, intermediate, and local scales (Table 3).
755 Higher positive d -values indicate of a stronger tendency towards LRD. It is reasonable to assume
756 that the degree of LRD may change over smaller intermediate and/or local scales, which implies
757 a breakdown of self-similarity. For a self-similar signal, d is a global parameter that does not
758 depend on which segment of the series is analyzed. In other words, the d -values should be the
759 same at all scales for a self-similar structure.

760 The results of the FARIMA analysis at the intermediate scale vary considerably within
761 each zone of the barrier island and for each spatial data series (Table 3). In the southern zone (0 –
762 30 km), EMI σ_a and beach volume have the strongest LRD ($d = 0.44$), whereas the other metrics
763 exhibit weak LRD (ranging from $d \sim 0 - 0.2$), which may be characterized approximately as a
764 white noise process. Within the paleo-channel region (30 – 60 km), all of the island metrics show
765 a moderate to strong tendency towards LRD ($0.3 \leq d \leq 4.2$), however, the EMI signal does not (d
766 = 0.11). In the northern zone (60 – 100 km) all data series contain moderate to strong LRD with
767 the exception of beach and island width.

768 A FARIMA analysis was also conducted at the local scale by dividing the island into 10-
769 km-segments, starting at the southern zone (0 – 10 km) and ending at the northern zone of the
770 island (90 – 100 km). A total of 70 FARIMA model realizations were evaluated and the resulting
771 d -values demonstrate that the EMI data segments show a stronger presence of LRD ($d > 0.4$)
772 within the paleo-channels (40 – 60 km) and further to the north (60 – 80 km) in close proximity
773 to the ancestral outlet of Baffin Bay. However, there is a low d -value (~ 0) for the 30 – 40 km
774 segment, which is located at the southern fringe of the Fisk (1959) paleo-channel region. These



775 findings indicate that there may be local and/or intermediate geologic controls along different
776 parts of the island, but that the framework geology dominates beach and dune metrics at the
777 regional scale.

778

779 **5 Discussion**

780 Although it has long been known that processes acting across multiple temporal and length
781 scales permit the shape of coastlines to be described by mathematical constructs such as power
782 law spectra and fractal dimension (Lazarus et al., 2011; Mandelbrot, 1967; Tebbens et al., 2002),
783 analogous studies of the subsurface framework geology of a barrier island have not been carried
784 out. For the first time, it is demonstrated that near-surface EMI geophysical methods are useful
785 for mapping barrier island framework geology and that FARIMA data series analysis is useful
786 for illuminating the spatial connections between subsurface geology and geomorphology. The
787 results of the FARIMA analysis and comparisons of the best-fitting d -parameters show that
788 beach and dune metrics closely match EMI σ_a responses *regionally* along the entire length of
789 PAIS, suggesting that the long-range dependent structure of these data series is similar at large
790 spatial scales. However, further evaluation of the d -parameters over smaller data segments
791 reveals that there are additional intermediate and local framework geology controls on island
792 geomorphology that are not present at the regional scale.

793 At the *intermediate* scale, a low EMI d -value ($d = 0.11$) suggests there is only a weak
794 framework-geologic control on barrier island morphometrics. A possible explanation is that the
795 paleo-channels, located within a ~ 30 km segment of the island, are not regularly spaced and on
796 average are less than a few km wide. This implies that the framework geology controls are
797 localized (i.e., effective in shaping island geomorphology only at smaller spatial scales). At the
798 *local* scale, relationships between the long-range-dependence of EMI and each metric vary
799 considerably, but the d -values demonstrate that the EMI data segments show a stronger presence
800 of LRD ($d > 0.4$) within the paleo-channels (40 – 60 km) and further to the north (60 – 80 km) in
801 close proximity to the ancestral outlet of the Baffin Bay. The two networks of paleo-channels
802 that are located just outside of the 30 – 40 km segment may explain the low EMI d -value ($d \sim 0$)
803 calculated for this segment. In other words, the channels do not occupy most of the 30 – 40 km
804 segment, thus resulting in a lower d -value. It is hypothesized that the alongshore projection of



805 the geometry of each channel is directly related to a corresponding variation in the EMI signal,
806 such that large, gradual minima in σ_a are indicative of large, deep channel cross-sections and
807 small, abrupt minima in σ_a represent smaller, shallow channel cross-sections. At shallower
808 depths within the DOI probed by the EMI sensor, variability in the σ_a signal may correspond to
809 changes in sediment characteristics as imaged by GPR (Fig. 3). Located beneath a washover
810 channel, a zone of high conductivity EMI σ_a responses between $\sim 450 - 530$ m coincides with a
811 segment of the GPR section where the signal is more attenuated and lacks the fine stratification
812 that correlates much better with the lower σ_a zones. The contrasts in lithology between the
813 overwash deposits and stratified infilled sands was detected by both EMI and GPR
814 measurements, suggesting that EMI is a useful tool for mapping variations in barrier island
815 framework geology.

816 It is argued herein that differences in the d parameter between EMI σ_a readings (our
817 assumed proxy for framework geology) and LiDAR-derived surface morphometrics provide a
818 new metric that is useful for quantifying the causative physical processes that govern island
819 transgression across multiple spatial scales. All of the calculated d -values in this study are
820 derived from ARIMA ($0d0$) models that fit the observations, and lie within the range of $0 < d <$
821 0.5 , suggesting that each data series is stationary but does contain long-range structure that
822 represents randomly-placed cyclicities in the data. For all models in our study, the d -values range
823 between ($\sim 0 - 0.50$), which enables a geomorphological interpretation of the degree of LRD and
824 self-similarity at different spatial scales. In other words, the d -parameter not only provides an
825 indication of the scale dependencies within the data, but also offers a compact way for analyzing
826 the statistical connections between free (weaker $d \sim 0$) or forced (stronger $d \sim 0.5$)
827 geomorphological evolution along the island.

828 Alongshore variations in beach width and dune height are not uniform in PAIS and
829 exhibit different spatial structure within and outside the paleo-channel region (Fig. 5). These
830 dissimilarities may be forced by the framework geology within the central zone of the island but
831 are influenced more by contemporary morphodynamic processes outside the paleo-channel
832 region. Once the dunes are initialized in part by the framework geology, stabilizing vegetation
833 may act as another important control on beach-dune evolution alongshore (Hesp, 1988). This
834 effect could be represented by higher-wavenumber components embedded within the spatial data



835 series. Beach and dune morphology in areas that are not controlled by framework geology (e.g.,
836 the northern and southern zones) exhibit more small-scale fluctuations representing a free system
837 primarily controlled by contemporary morphodynamics (e.g., wave action, storm surge, wind,
838 etc.). Because variations in dune height exert an important control on storm impacts (Sallenger,
839 2000) and ultimately large-scale island transgression (Houser, 2012), it is argued here that the
840 framework geology of PAIS acts as an important control on island response to storms and sea-
841 level rise. The forced behavior within the paleo-channel region challenges existing models that
842 consider only small-scale undulations in the dune line that are caused by natural randomness
843 within the system. Rather, we propose that dune growth is forced by the framework geology,
844 whose depth is related to the thickness of the modern shoreface sands beneath the beach. This
845 depth is the primary quantity that is detected by the EMI sensor.

846 Our findings extend previous framework geology studies from the Outer Banks, NC (e.g.,
847 Browder and McNinch, 2006; McNinch, 2004; Riggs et al., 1995), Fire Island, NY (e.g., Hapke
848 et al., 2010; Lentz and Hapke, 2011), and Pensacola, FL (e.g., Houser, 2012) where feedbacks
849 between geologic features and relict sediments within the littoral system have been shown to act
850 as an important control on dune growth and evolution. Nonetheless, most of these studies focus
851 on offshore controls on shoreface and/or beach-dune dynamics at either local or intermediate
852 scales because few islands worldwide exist that are as long and/or continuous as North Padre
853 Island. The current study augments the existing literature in that 1) it outlines a quantitative
854 method for determining *free* and *forced* evolution of barrier island geomorphology at multiple
855 length scales, and 2) it demonstrates that there is a first-order control on dune height at the local
856 scale within an area of known paleo-channels, suggesting that framework geology controls are
857 localized within certain zones of PAIS.

858 Further study is required to determine how this combination of free- and forced-behavior
859 resulting from the variable and localized framework geology affects island transgression.
860 Methods of data analysis that would complement the techniques presented in this paper might
861 include; spatiotemporal modeling, power spectral analysis, wavelet decomposition, bicoherence
862 analysis, and wavelet coherence. These approaches would provide important information
863 regarding:



- 864 1. Coherence and phase relationships between subsurface structure and island
865 geomorphology.
- 866 2. Non-linear interactions of coastal processes across large and small spatiotemporal
867 scales.

868 Quantifying and interpreting the significance of framework geology as a driver of barrier island
869 formation and evolution and its interaction with contemporary morphodynamic processes is
870 essential for designing and sustainably managing resilient coastal communities and habitats.

871

872 **6 Conclusions**

873 This study demonstrates the utility of EMI geophysical profiling as a new tool for mapping the
874 length-scale dependence of barrier island framework geology and introduces the importance of
875 statistical modeling of geophysical and geomorphological spatial data series by FARIMA
876 analysis to better understand the geologic controls on large-scale barrier island transgression.
877 The EMI and morphometric data series exhibit LRD to varying degrees, and each can be
878 accurately modeled using a non-integral parameter d . The value of this parameter diagnoses the
879 spatial relationship between the framework geology and surface geomorphology. At the *regional*
880 *scale* (~100 km), small differences in d between the EMI and morphometrics series suggest that
881 the long-range-dependent structure of each data series with respect to EMI σ_a is statistically
882 similar. At the *intermediate scale* (~ 30 km), there is a greater difference between the d -values of
883 the EMI and island metrics within the known paleo-channel region, suggesting a more localized
884 geologic control with less contributions from broader-scale geological structures. At the *local*
885 *scale* (10 km), there is a considerable degree of variability between the d -values of the EMI and
886 each metric. These results all point toward a forced barrier-island evolutionary behavior within
887 the paleo-channel region transitioning into a free, or scale-independent behavior dominated by
888 contemporary morphodynamics outside the paleo-channel region. The results from this study
889 suggest that the framework geology initially controls the development of the dunes at the local
890 scale within the paleo-channel region. This means that barrier island geomorphology at PAIS is
891 forced and scale-dependent, unlike shorelines which have been shown at other barrier islands to
892 be scale-independent (Tebbens et al., 2002; Lazarus et al., 2011). Our findings reveal that
893 shorelines may have different irregularity than island geomorphology, which suggests an



894 alongshore redistribution of sediment that shapes the shoreline toward a more dissipative state
895 over time. Without local variations in the framework geology alongshore, small-scale variations
896 in the shoreline will be masked by the large-scale transport gradients over long timescales. The
897 exchange of sediment amongst nearshore, beach and dune in areas outside the paleo-channel
898 region is scale independent, meaning that barrier islands like PAIS exhibit a combination of free
899 and forced behaviors that will affect the response of the island to sea level rise and storms. We
900 propose that our analysis is not limited to PAIS but can be applied to other barrier islands and
901 potentially in different geomorphic environments, both coastal and inland.

902

903 **Competing interests.** The authors declare that they have no conflict of interest.

904

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1162 **Tables**

1163 **Table 1.** Comparison of residuals (RMSE) of each ARIMA model for the 100 km and 10 km
1164 EMI surveys.

| | EMI (100 km) | EMI (10 km) |
|--------------------|---------------------|--------------------|
| ARIMA (100) | 18.4 | 8.14 |
| ARIMA (001) | 49.7 | 41.1 |
| ARIMA (101) | 15.6 | 6.65 |
| ARIMA (202) | 40.6 | 7.31 |
| ARIMA (303) | 40.5 | 7.22 |
| ARIMA (404) | 40.3 | 7.22 |
| ARIMA (505) | 40.2 | 7.29 |
| ARIMA (111) | 15.8 | 5.72 |
| ARIMA (010) | 18.5 | 8.15 |
| ARIMA (0d0) | 15.5 | 5.55 |

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1181 **Table 2.** Comparison of residuals (RMSE) of each ARIMA model for all spatial data series.
 1182 Note that the residuals for each DEM metric correspond to the analysis performed at the regional
 1183 scale (i.e., 100 km).

| | ARIMA (100) | ARIMA (001) | ARIMA (101) | ARIMA (111) | ARIMA (010) | ARIMA (0d0) |
|----------------------|----------------|----------------|----------------|----------------|----------------|----------------|
| Beach width | 13.4 | 14.9 | 13.0 | 13.1 | 14.8 | 13.0 |
| Beach volume | 44.8 | 50.5 | 43.1 | 43.1 | 49.1 | 42.7 |
| Dune height | 0.7 | 0.8 | 0.7 | 0.7 | 0.8 | 0.7 |
| Dune volume | 60.6 | 63.9 | 59.7 | 59.2 | 69.03 | 58.9 |
| Island width | 138.4 | 253.2 | 121.3 | 121.1 | 140.8 | 120.9 |
| Island volume | 271.3 | 611.4 | 244.3 | 244.1 | 273.9 | 243.3 |

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1202 **Table 3.** Summary table showing the computed *d* parameters that most appropriately model each
1203 ARIMA (0*d*0) iteration (i.e., lowest RMSE).

| Alongshore distance | Beach width | Beach volume | Dune height | Dune volume | Island width | Island volume | EMI σ_a |
|-----------------------|-------------|--------------|-------------|-------------|--------------|---------------|----------------|
| “Regional” | | | | | | | |
| 0-100 km | 0.38 | 0.42 | 0.34 | 0.32 | 0.13 | ~0.00 | 0.35 |
| “Intermediate” | | | | | | | |
| 0-30 km | ~0.00 | 0.44 | 0.13 | 0.20 | 0.03 | 0.18 | 0.44 |
| 30-60 km | 0.37 | 0.30 | 0.36 | 0.31 | 0.30 | 0.42 | 0.11 |
| 60-100 km | 0.26 | 0.41 | 0.35 | 0.46 | ~0.00 | 0.50 | 0.49 |
| “Local” | | | | | | | |
| 0-10 km | 0.41 | 0.39 | 0.20 | 0.21 | 0.09 | 0.18 | 0.36 |
| 10-20 km | 0.30 | 0.42 | 0.20 | 0.26 | 0.37 | ~ 0.00 | 0.36 |
| 20-30 km | 0.26 | 0.40 | ~ 0.00 | ~ 0.00 | 0.49 | ~ 0.00 | ~ 0.00 |
| 30-40 km | 0.47 | ~ 0.00 | 0.41 | 0.25 | 0.29 | 0.28 | ~ 0.00 |
| 40-50 km | 0.28 | 0.21 | 0.21 | 0.19 | 0.30 | 0.02 | 0.44 |
| 50-60 km | 0.03 | 0.31 | 0.23 | 0.32 | ~ 0.00 | 0.33 | 0.48 |
| 60-70 km | 0.16 | 0.37 | 0.29 | 0.34 | ~ 0.00 | 0.30 | 0.40 |
| 70-80 km | 0.47 | 0.34 | 0.43 | 0.26 | ~ 0.00 | 0.42 | 0.49 |
| 80-90 km | 0.27 | 0.19 | 0.42 | 0.39 | 0.01 | 0.02 | ~ 0.00 |
| 90-100 km | 0.13 | 0.13 | ~ 0.00 | 0.06 | 0.44 | 0.47 | 0.41 |

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1217 **Figure Captions:**

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1219 **Figure 1.** Location map and DEM of the study area at Padre Island National Seashore (PAIS),
1220 Texas, USA. Elevations for the DEM are reported as meters above sea level (masl). Field images
1221 from the northern (N), central (C), and southern (S) regions of the island showing alongshore
1222 differences in beach-dune morphology. Note: views are facing north for the northern and
1223 southern locations, and the central location view is to the south. Images taken in October, 2014.

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1225 **Figure 2.** 100 km (a) and 10 km (b) alongshore EMI surveys showing DEM's of study area and
1226 previously identified paleo-channel region by Fisk (1959). Channels are highlighted in red and
1227 green, where the green region indicates the location of the 10 km survey. 25 ft (7.6 m) contour
1228 intervals are highlighted with depths increasing from yellow to red and the center of the channels
1229 are represented by the black-dotted lines. For each survey, raw σ_a and zero-mean drift-corrected
1230 EMI responses are shown in grey and black, respectively. Tidal conditions during each EMI
1231 acquisition segment are shown below each panel. Low (lt) and falling tides (ft) are indicated by
1232 blue and light blue shades, respectively. High (ht) and rising tides (rt) are highlighted in red and
1233 light red, respectively.

1234

1235 **Figure 3.** Comparison of EMI σ_a responses from the 100 km survey with 100 MHz GPR data
1236 within one of the Fisk (1959) paleo-channels. The 800 m segment (A – A') crosses a smaller
1237 stream within the network of paleo-channels in the central zone of PAIS. The DOI of the 3 kHz
1238 EMI responses is outlined by the red box on the lower GPR radargram.

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1240 **Figure 4.** DEM metrics extracted from aerial LiDAR data. The sampling interval (step-size) for
1241 each data series is 10 m and the coordinates are matched with each EMI acquisition point. Each
1242 panel corresponds to a) beach width, b) beach volume, c) dune height, d) dune volume, e) island
1243 width, f) island volume, and g) EMI σ_a . The island is divided into three zones (red vertical lines)
1244 roughly indicating the locations within and outside the known paleo-channel region. A Savitzky-
1245 Golay smoothing filter was applied to all data series (LiDAR and EMI) using a moving window
1246 of $n = 250$ to highlight the large-scale patterns in each signal.

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1248 **Figure 5.** Autocorrelations of σ_a for the 100 km (a) and 10 km EMI surveys (d). *R/S* analysis for
1249 the 100 km (b) and 10 km surveys (e). PSD plots for the 100 km (c) and 10 km surveys (f).

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1251 **Figure 6.** Examples of the worst (6a, 6c) and best (6b, 6d) fit ARIMA models for the 100 and 10
1252 km EMI surveys. Model results are shown for the processed (drift-corrected) σ_a data. Residuals
1253 (RMSE) listed for each model gives the standard deviation of the model prediction error. For
1254 each plot, original data is in red and fitted (model) data is in blue.

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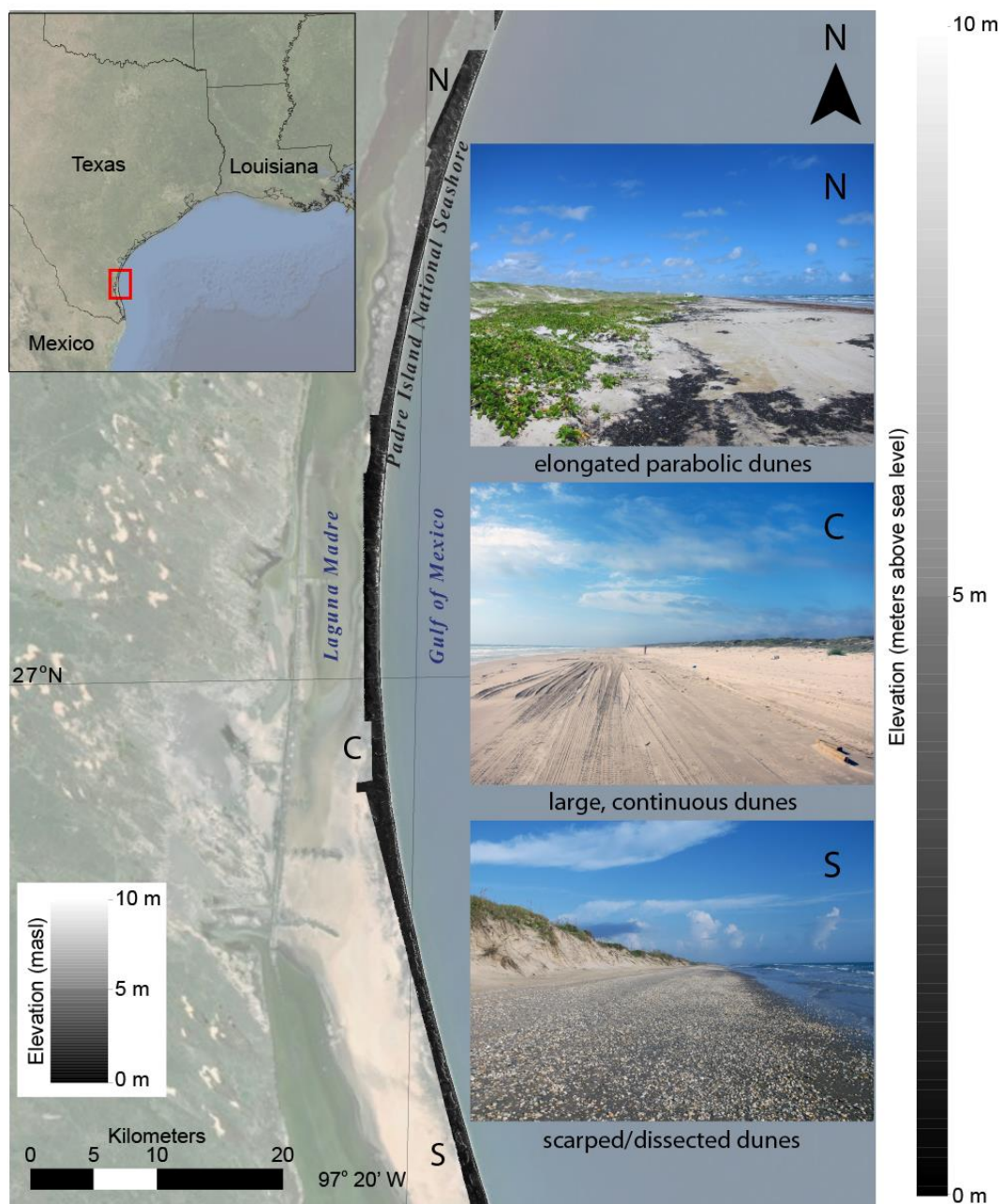
1256 **Figure 7.** Example of the best fit ARIMA (0d0) models for each LiDAR-derived DEM metric: a)
1257 beach width, b) beach volume, c) dune height, d) dune volume, e) island width, f) island volume.

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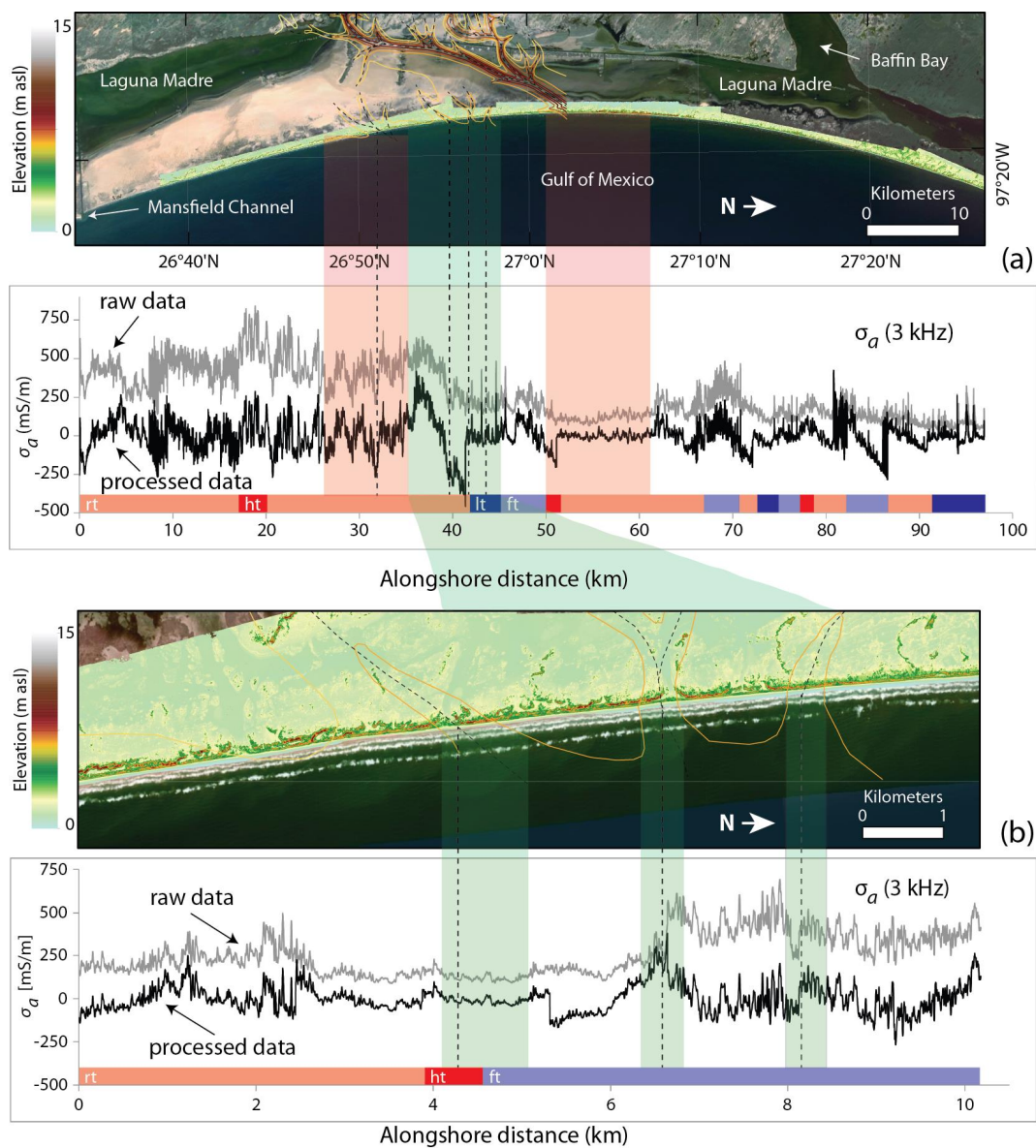
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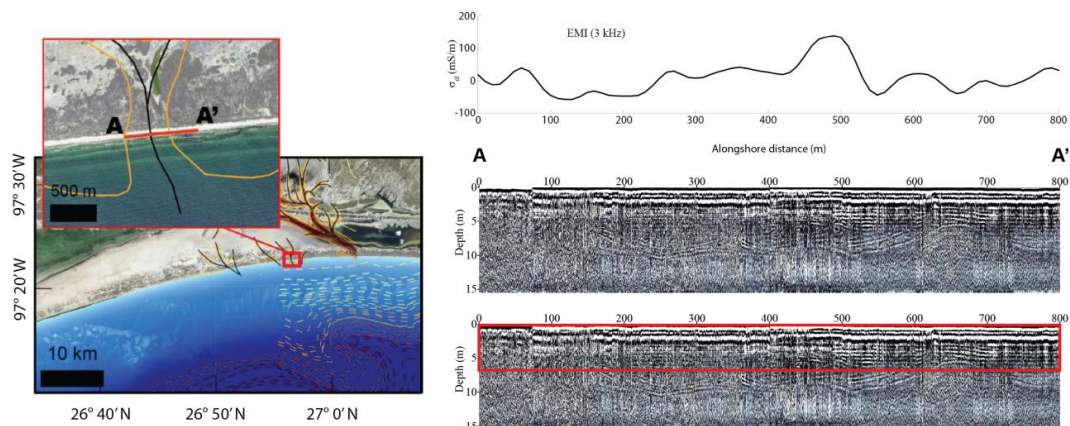
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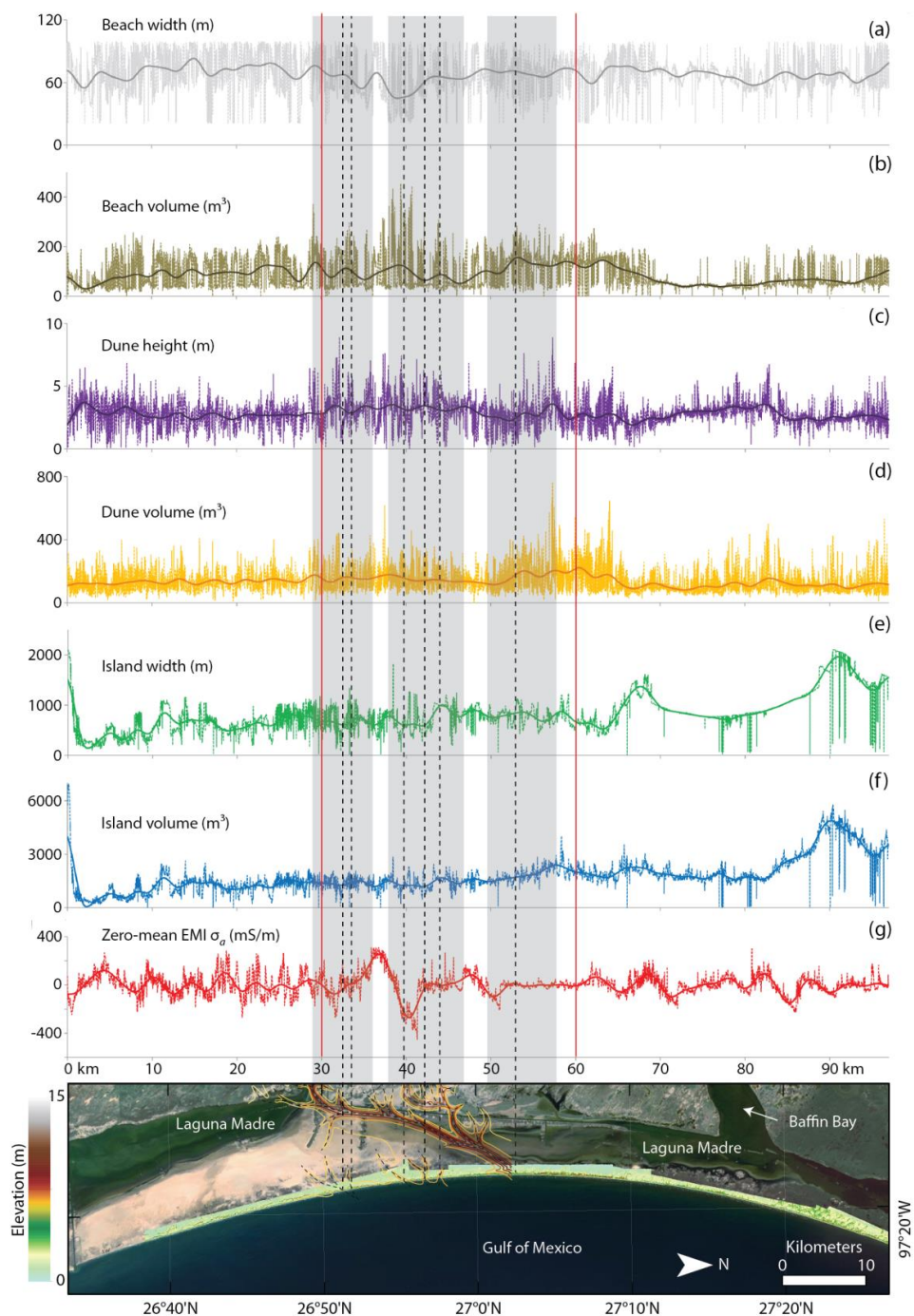
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Figure 2.



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Figure 3.



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Figure 4.

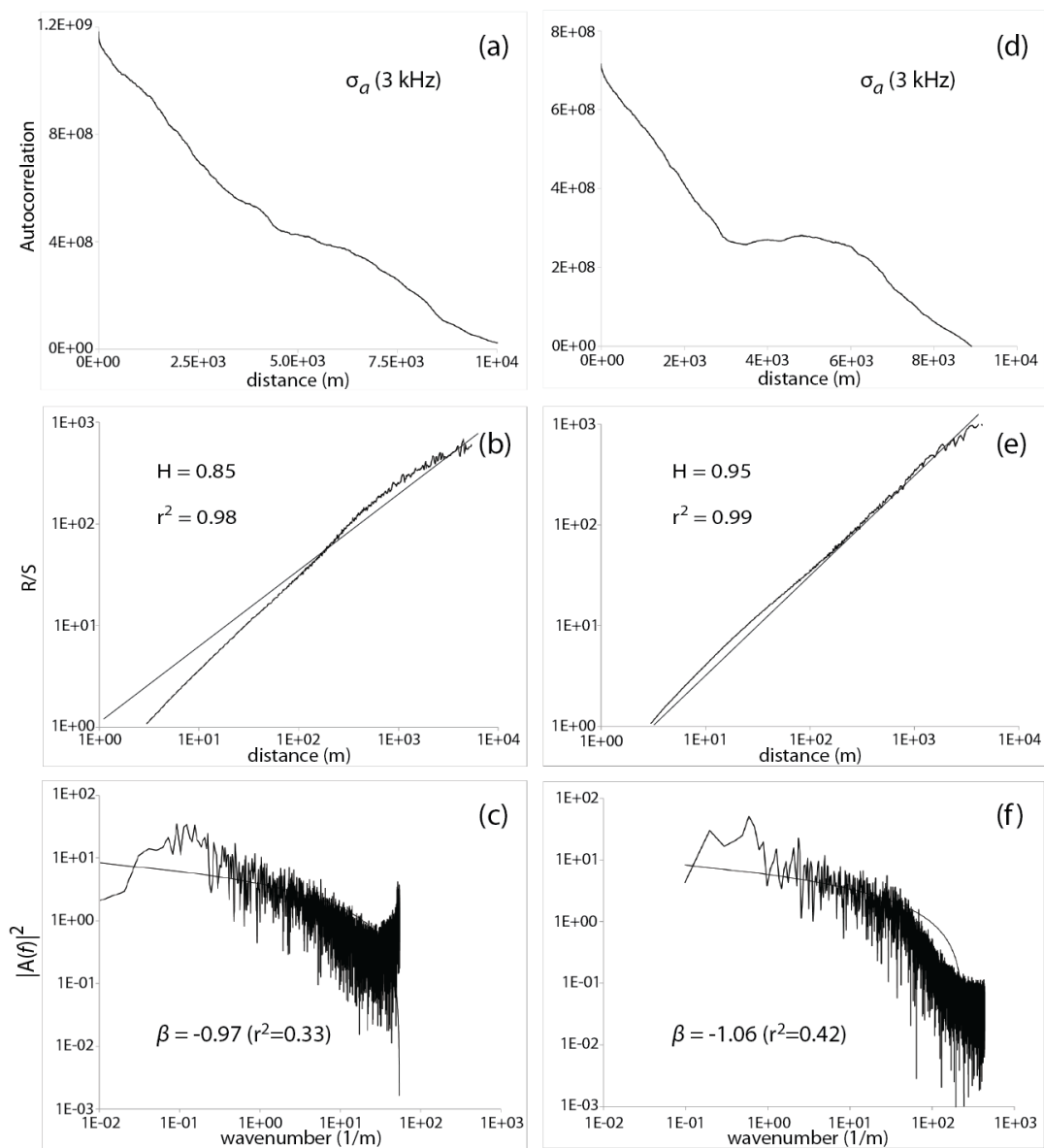
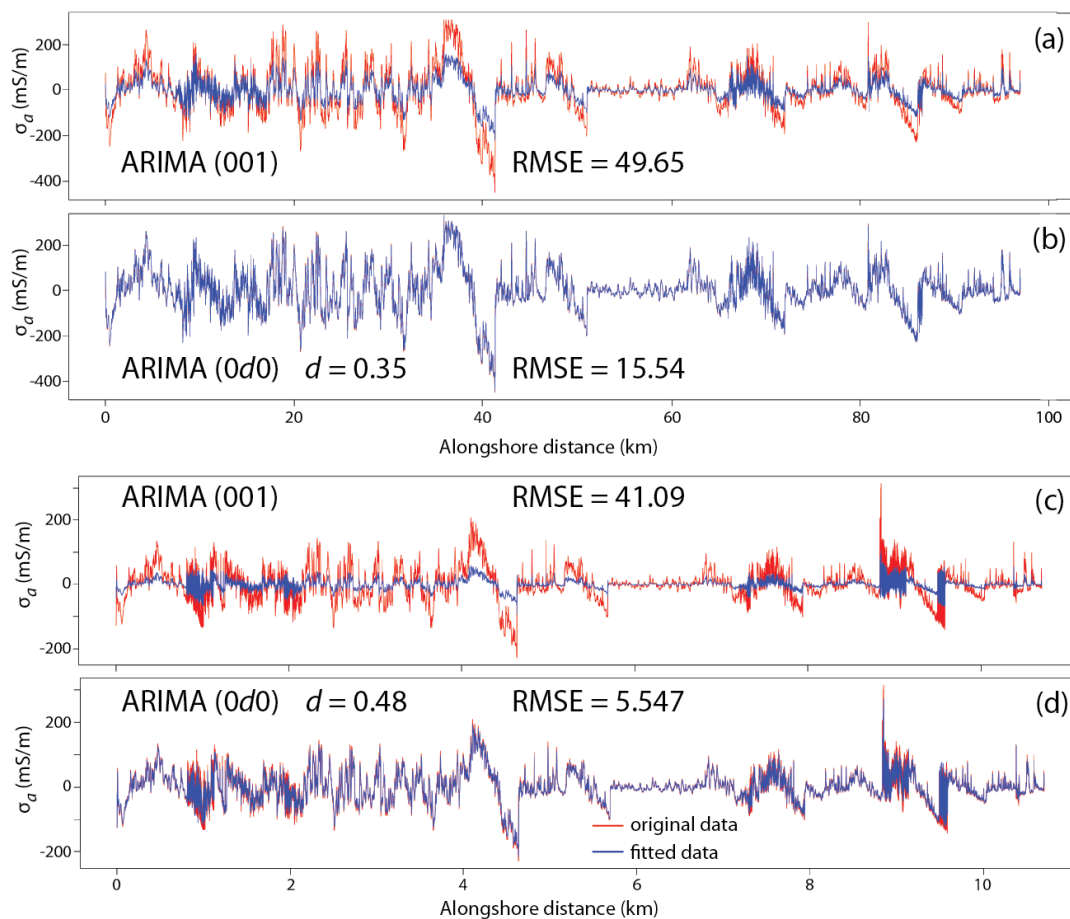


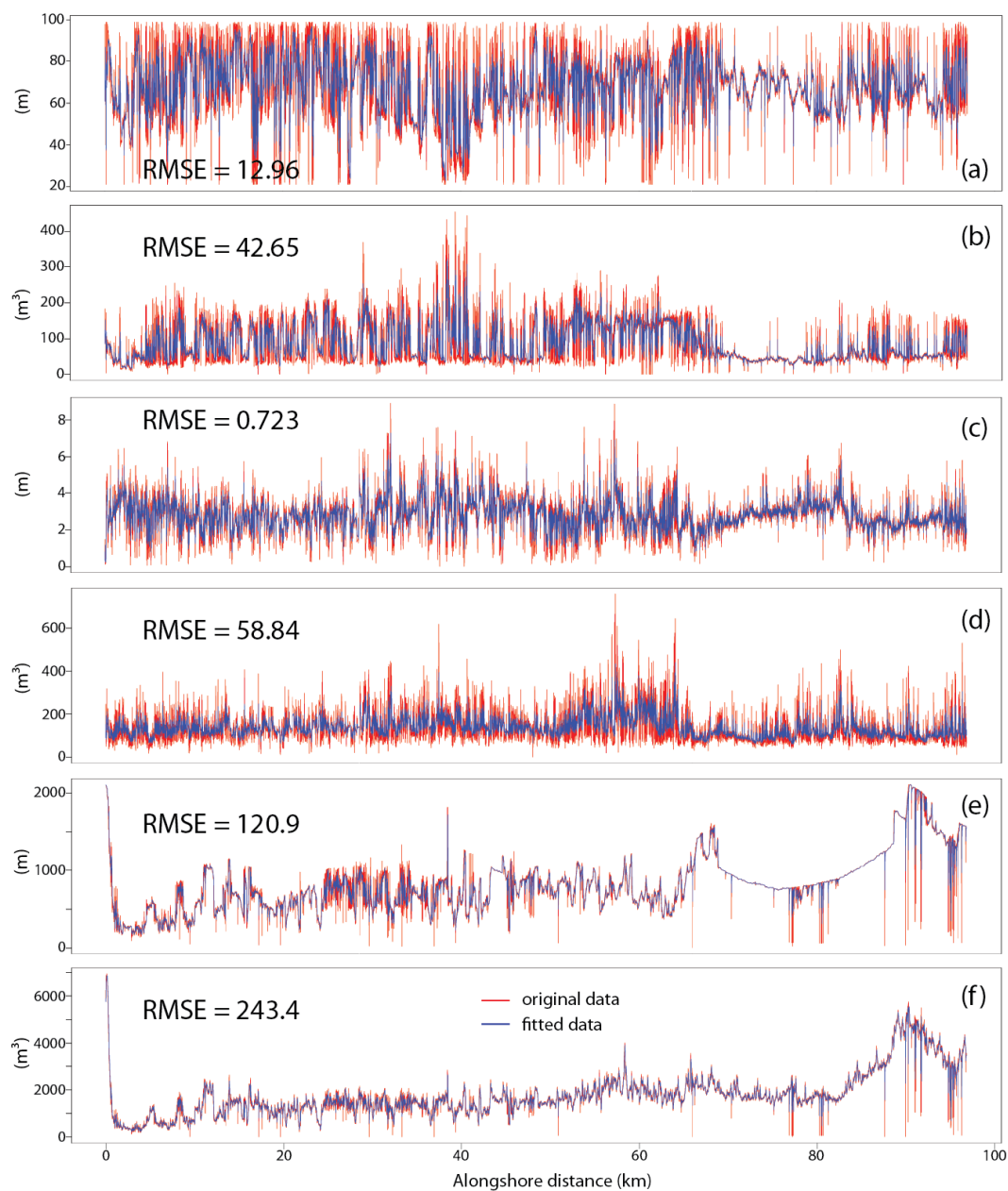
Figure 5.

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Figure 6.



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Figure 7.