1 **A Review of Machine Learning Applications to Coastal Sediment Transport and**

2 **Morphodynamics**

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13 **Abstract**

14   A range of computer science methods under the heading of machine learning (ML) enables

15 the extraction of insight and quantitative relationships from multidimensional datasets. Here, we

16 review some common ML methods and their application to studies of coastal morphodynamics

17 and sediment transport. We examine aspects of 'what' and 'why' ML methods contribute, such

18 as 'what' science problems ML tools have been used to address, 'what' was learned when using

19 ML, and 'why' authors used ML methods. We find a variety of research questions have been

20 addressed, ranging from small-scale predictions of sediment transport to larger-scale sand bar

21 morphodynamics and coastal overwash on a developed island. We find various reasons justify

22 the use of ML, including maximize predictability, emulation of model components, smooth and

23 continuous nonlinear regression through data, and explicit inclusion of uncertainty. Overall the

24 expanding use of ML has allowed for an expanding set of questions to be addressed. After

25 reviewing the studies we outline a set of 'best practices' for coastal researchers using machine

26 learning methods. Finally we suggest possible areas for future research, including the use of

27 novel machine learning techniques and exploring 'open data' that is becoming increasingly

28 available.

29

30 **1. Introduction**

31   The amount of available data on coastal systems has increased dramatically in recent years,

32   ranging from topographic and bathymetric data (e.g., Turner et al., 2016), to compilations and

33   collections of sediment transport and physical forcing (e.g., Bolaños and Souza, 2010; Garel and

34   Ferreira, 2015; Nelson et al., 2013; van der Werf et al., 2009). Large spatial and temporal

35   extents, high resolution, and rapid turnaround from acquisition to availability means that the data

36   being produced enables expanded applications to coastal morphodynamic research. In particular,

37   since observational data has always been the foundation for developing empirical relationships or

38   testing quantitative models, the recent volume of data available, the intrinsic high dimensionality

39   and nonlinearity of underlying processes, and increased computing power, have all led to

40   renewed interest in empirical research.

41   A key example in this new wave of research is attempting to extract insights, predictions,

42   or quantitative relationships directly from multidimensional datasets using automated tools. This

43   'data-driven' route for science has been demonstrated to be a promising research direction (e.g.,

44   Anderson, 2008; Hey et al., 2008), and tools from a range of disciplines have been influential in

45   defining and tackling 'data-driven' science (e.g., Staltzer and Mentzel, 2016). In this review we

46   differentiate classic empirical work and this new wave of 'data-driven' work as being divided by

47   the computational methodology, as well as (potentially) the quantity, nonlinearity expressed in

48   the data, and high dimensionality. Our focus is on the new empirical work using machine

49   learning, the set of computer algorithms, methods and tools that implement a given task and use

50   data to optimize performance (e.g., reduction of error). In this manuscript we provide many

51   examples of successes in the use of machine learning for coastal research, but first we discuss the

52   rationale for this data-driven approach.

53   Data-driven research is inductive. As with other empirical work, data-driven research relies

54   on data to develop insight, predictions, or relationships. We acknowledge that empirical work

55   does not and cannot exist in a vacuum — theory and logic are critical parts of data analysis (e.g.,

56   Coveney et al., 2017; Crutchfeld 2014) and mathematical proofs show the lack of

57   generalizability of inductive statements (e.g., Popper and Miller, 1983). However, inductive

58   statements are part of the scientific workflow, and are unavoidable at certain junctures. Even

59   Newton expressed the utility of induction in 'Rule 4' in the 3rd edition of the Principia (Cohen et

60   al., 2016):

61

62   *"In experimental philosophy, propositions gathered from phenomena by induction should be*

63   *considered either exactly or very nearly true notwithstanding any contrary hypotheses, until yet*

64   *other phenomena make such propositions either more exact or liable to exceptions. "*

65

66   Coastal morphodynamics specifically and geomorphology in general have long histories

67   of induction, and developing empirical rules that are useful. Even when basic laws of physics can

68   be used, empirical expressions or rules of some form or another are always required to close an

69   equation set. For example, sediment transport rules, turbulent closure schemes, friction

70   coefficients, and wave breaking all rely on ad hoc rules, assumptions or empirical relations. If we

71   still need inductive rules, how should we build them? With the increased quantity of data, and

72   the improvements in computing power, coastal researchers have access to a wide range of

73   computer science tools from the subdiscipline of machine learning (ML) to develop inductive

74   statements and optimized predictions directly from data sets.

75   Much of the machine learning work we discuss in this review is inherently focused on

76   identifying and exploiting correlations and patterns in data. Assigning causation can be less clear

77   in some coastal morphodynamic systems because of multiple scales (ripples, megadunes, bars,

78   shoreline), and feedbacks between scales (bars impact shoreline, and vice versa) that interact in

79   both space and time (e.g., Murray et al., 2014a, 2014b; Sherman, 1995; Short et al., 1985;

80   Werner, 1999; Winant et al., 1975). However, correlation is valuable for prediction because of

81   the concept of analogy (Lorenz, 1969a; 1969b) — knowing how a coastal system evolved when

82   it was in the same configuration but at a previous time can lead to predictions about how the

83   system might evolve in the future (i.e., seasonal dynamics of sediment transport; Aubrey, 1979;

84   Plant et al., 1999; Plant et al., 2006; Splinter et al. 2011; Yates et al., 2009). A data-driven

85   approach can help to elucidate this behavior by examining previously collected data, and

86   developing a model focused on how the system will evolve based on past instances.

87   Because empirical approaches rely on the data to make predictions about a system, data-

88   driven work may only be strictly applicable within the range of the data used to develop the

89   predictor — unless the prediction scheme can be argued to be more generally valid. This is a

90   limit of all inductive, empirical techniques, though it is rarely mentioned in more traditional

91   empirical studies (i.e., any study that uses linear regression to predict beyond the bounds of the

92   data). Furthermore, this caveat is likely applicable to all modeling studies because new processes

93   or feedbacks can exist that are not included within the model. A morphodynamicist might argue

94   that, if a given model is built from conservation laws, the model should be able to predict outside

95   of the range of conditions where the model has been tested. This argument also holds for data-

96   driven work — the data used to construct the model adheres to conservation laws, therefore

97   predictions (built directly from data) might also adhere to these physical constraints outside of

98   the range of data used to build the model. Our point here is to suggest to readers that data-driven

99   work should not be disregarded because it is not built from 'laws' — data-driven work is based

100   on data, which obey conservation laws.

101   While there are a number of aspects of coastal science that can and do benefit from

102   machine learning, we focus here on predictions of coastal sediment transport, coastal

103   morphology, and coastal morphodynamics. The review here is focused on supervised learning,

104   specifically regression tasks using continuous data (as opposed to classification tasks).

105   Supervised learning involves input and output data that are linked (such as wave forcing and a

106   given morphological configuration) with the goal of developing a function to relate the input to a

107   corresponding output and emulating physical processes relationships that are either poorly

108   understood or complex and difficult to capture with deterministic models. Excluded here are

109   prediction of forcing and fluid phenomena when no reference to sediment transport is given or

110   studies focused on engineering and structures.

111   Previous ML work written for an Earth and Environmental Science audience has focused

112   primarily on introducing ML algorithms, in the form of both books (Hsieh, 2006) and papers

113   (Chau, 2006; Valentine and Kalnins, 2016). This previous work serves a key role in connecting

114   coastal scientists to ML tools (e.g., Jones and Maccarone, 2013). Our work intends to move the

115   purview of these previous reviews, which focused on introducing ML algorithms, explaining ML

116   algorithms, and providing a few select examples to review. In this document, we do provide a

117   brief introduction to the most common machine learning techniques that have been used in

118   coastal sediment transport and the steps needed to start a ML project (Section 2). However, our

119   focus is on comprehensively reviewing previous machine learning work on coastal

120   morphodynamics such that these works can be recognized, compared, and used to build future

121   ML efforts. To this end we review and discuss more than 60 papers under three separate

122   headings: studies where ML is used to predict sediment transport (Section 3); studies where ML

123   is used to make a stand-alone morphodynamic model (Section 4); and studies where ML is

124 embedded or linked to a morphodynamic model (Section 5). Furthermore, we address 'why' ML

125 tools have been used in particular studies and what was learned by using ML methods. We

126 intend coastal morphodynamicists interested in ML to use these sections (3, 4, and 5) to assess

127 what research has been done (and what has not been done) at the time of this writing. This

128 comprehensive review of the coastal ML literature also permits us (in Section 6) to discuss

129 overarching topics, offer a set of best practices for open, reproducible, replicable machine

130 learning research and highlighting some future directions in coastal ML research primarily

131 focused on synthesis and intercomparison.

132

133 **2. Machine learning methods used in Coastal sediment transport and Morphodynamics.**

134 Before we review the uses of ML in coastal science, we introduce the ML methods such

135 that sections (Sections 2.1 - 2.6) provide basic information on each ML method. Within each of

136 these sections we provide relevant papers for readers who wish for more details regarding each

137 method

138

139 **2.1 Artificial Neural Network (ANN)**

140 Artificial Neural Networks (ANN) are commonly used algorithms in machine learning

141 because of their versatility. Many different fields of science have used ANNs for tasks such as

142 function fitting to classification. Applications in coastal sediment transport and

143 morphodynamics include multiple aspects of suspended sediment transport, sandbar

144 morphodynamics, and various studies of shoreline position — all mentioned in the following

145 sections. The most typical form of an ANN is represented by a series of layers: an input layer,

146 one or more hidden layers and an output layer. Each layer consists of a number of nodes

147 (artificial neurons). The input data is fed to the network via a node on the input layer (usually

148 each node represents an input variable) while, depending on the number of variables to be

149 predicted, the output layer could consist of one or more nodes. The hidden layer(s) contain a

150 somewhat arbitrary number of nodes chosen based on a mix between experience, empirical

151 formulas and systematic analysis. An idealized feed-forward ANN characterized by n input

152 nodes (the predictors or independent variables), m hidden nodes and one output node (the

153 prediction or dependent variable). Nodes are mathematically connected and transfer information

154 from the input variables to a node of the hidden layer:

155

156
$$h_j = f \cdot \left(a_j + \sum_{i=1}^{n} w_i x_i \right) \tag{1}$$

157

158 where x_i is the ith of n input variables, h_j the response of the jth neuron in the hidden layer, f is the

159 activation function (e.g., a sigmoid, an hyperbolic tangent, etc.), w_i is the connection weight

160 between x_i and h_j, and a_j is the bias for the jth hidden neuron. A further combination of the hidden

161 nodes, which is achieved by means of a new activation function (not necessarily the same as the

162 one used to link the input variables and the hidden layer) and new connection weights and biases,

163 connects the hidden layer to the output layer.

164   The biases and connection weights of the ANN are established through an optimization

165 algorithm that is applied to a dataset consisting of observed input and output variables. Various

166 algorithms can be used to perform this critical step, though it remains difficult to tell *a priori*

167 which optimization function will provide better results. Many of these algorithms are based on

168 the backpropagation of errors — the error at the output (prediction) layer is sent back through the

169 network to adjust and update the weights and biases.

170   ANNs are often portrayed as an example of a black-box predictor where the (usually) large

171 number of weights and biases obscures the role of individual variables. The architecture of

172 small-size ANNs can in fact be analyzed and various techniques have been developed to this aim

173 (e.g., Olden et al., 2004). LeCun et al. (2015) provide many helpful references and a relatively

174 recent review on ANN that focuses on current research themes (i.e., 'Deep Learning'; ANNs

175 with many hidden layers).

176

177   **2.2 Genetic Algorithms (GA) and Genetic Programming (GP)**

178   Genetic algorithms (GA; Holland, 1975) and genetic programming (GP; Koza 1992) are

179 related ML techniques that operate on rules based on natural selection. In the section below we

180 review the basics of genetic algorithms. For example, consider an equation with five free

181 parameters, where a given combination of specific values for each parameter can be compressed

182 into a single string of length 5. The string of parameter values is also related to the solution of the

183 equation using these 5 specific values. Each solution is also related to an associated error (the

184 value of the equation using the 5 parameters vs. some measured value). Now consider a

185   population of such strings (not just one), each with their own unique combination of values for

186   each of the 5 parameters. The genetic algorithm routine works by operating on these strings

187   using evolutionary rules. Given an initial set of strings (a population), there is an error associated

188   for each string. The strings with the smallest error are retained; the strings with the most error are

189   discarded. New strings are developed by mutation (changing values in a given string) and by

190   reproducing — recombining two strings to make a novel new string. By using these

191   'evolutionary' rules, the routine will search over the solution space and tend to converge on

192   solutions that are globally optimal. Parameters in the evolutionary rules and techniques in

193   applying those rules are tunable (e.g., number of predictors in the population, mutation percent,

194   crossover rules, number of generations, number of discarded or kept predictors for each

195   generation, etc.). Genetic algorithms can be used in tandem with artificial neural networks — for

196   example to find the appropriate weights and biases, as well as network architecture (e.g., Yao,

197   1999). Further helpful entries into the GA literature can be found in D'Ambrosio et al. (2013),

198   Mitchell (1995) and Mitchell (1998).

199   Building on the population approach of genetic algorithms, genetic programming (GP;

200   Koza, 1992) takes the idea a step further. The population is not strings of parameter values to be

201   input into a fixed equation but instead a population of equations with mutable form and length.

202   Given a set of mathematical operators (+,-,*,/), and a set of input variables (e.g., forcing

203   conditions) a GP routine works to find equations using these building blocks (input variables,

204   constants, and mathematical functions) — this is a symbolic regression problem. One issue with

205   GP is the development of large, complex functions that have small error compared to small, less

206   complex functions that have larger error but might be more physically interpretable. Therefore

207   routines may offer more than one solution, and instead offer many solutions to the problem

208   which fall along the Pareto front — a line in error-complexity space that defines how prediction

209   error decreases with the solution complexity (a measure of the size of the predictor that

210   incorporates the mathematical operators, variables, and constants). The act of choosing a

211   predictor from this front introduces subjectivity in the routine, though GP algorithms have shown

212   the ability to find physically meaningful results from data streams. Aside from the work of Koza

213   (1992) introducing the technique, the book by Poli et al. (2008), and work by Babovic and

214   Keijzer (2000), Olden et al. (2008), Schmidt and Lipson (2009), and O'Neill et al. (2010) have

215   proven helpful to us.

216

217   **2.3 Bayesian Networks (BN)**

218   Bayesian networks (BN) implement a form of probabilistic prediction that explicitly

219   resolves the conditional probabilities that link variables to one another, albeit in a discretized

220   fashion. Statistical operations include marginalization over a subset of a larger distribution, for

221   instance, when the data are used to provide constraints (Charniak, 1991). And, as the name

222   suggests, Bayesian estimation (Cooper and Herskovits, 1992; Malakoff, 1999) can be

223   implemented to solve problems that typically require data assimilation (Wikle and Berliner,

224   2007). For example, to estimate coastal erosion that is assumed to be influenced by dune

225   morphology, geology, and sea-level rise (Plant et al., 2016) the probabilistic relationship can be

226   expressed as:

227         $P(E_i) = \sum_{G,D,SLR} P(E_i | D, G, SLR)\, P(D | G, SLR)\, P(G, | SLR)\, P(D)\, P(SLR)$, (2)

228   where left side of the equation is describing the probability that a certain amount of erosion, E_i, is

229   experienced. The right side of the equation is the product of the conditional probability of that

230   amount of erosion occurring, given the morphologic state of coastal dunes (D) and geologic

231   setting (G) and a sea-level rise rate (SLR). The probability is integrated over all the states, which

232   may be constrained by data. This is the marginalization operation. Some of the terms on the

233   right side of equation (2) defining the erosion probability may themselves have dependencies

234   that can be solved using Bayes rule:

235         $P(D_i) = \sum_E P(E | D_i, G, SLR)\, P(D_i)/P(E)$, (3)

236   where the first term on the right side of the equation (2) is inverted. Bayes rule and

237   marginalization can take place simultaneously in a Bayesian network, implying that there is no

238   real distinction between a forward implementation that emulates a deterministic model (e.g., a

239   partial differential equation) and an inverse model.

240   The approach models probabilities directly, as opposed to modeling the process-variables

241   as is done in the other ML examples. This is useful if knowing the uncertainties is a primary

242   modeling requirement. A disadvantage is that the model must learn the conditional probabilities

243   that describe the correlations between variables, and this comes with a cost of increasing free

244   parameters that grows as the number of states raised to the number of variables. Furthermore the

245   uncertainty present in the resulting model only reflects the uncertainty that is found within the

246   data. We have found general papers by Aguilera et al. (2011), Chen and Pollino (2012), and

8

247   Uusitalo (2007) to be useful in learning techniques and applications of BN.

248

249   **2.4 Regression Trees (RT)**

250   Regression trees (RT) separate prediction tasks into a series of binary splits, leading to a

251   branching, tree-like structure (e.g., De'ath and Fabricius, 2000; Hastie et al. 2009). One

252   advantage of these tree-based approaches is that they easily allow users to assess the relative

253   influence of the input variables. Trees are visually appealing and reading through a RT model

254   can be straightforward, especially when the tree is short.

255   An example of a regression tree-based algorithm is recursively splitting the dataset into

256   groups. The details of each split are determined via a given metric, such as minimizing the sum

257   of squares of each group. A variety of rules exist for both growing trees (i.e., how many

258   recursive splits) and pruning trees (removing splits). Additionally, other algorithms can be

259   attached to tree based methods to improve accuracy, specifically 'Boosting'. Boosting routines

260   merge many small regression tree models that are built sequentially, with misfit data sequentially

261   given more weights so trees progressively focus on poorly predicted data (Elith et al., 2008). We

262   have found the works of De'ath and Fabricius (2000), De'ath (2007), Olden et al. (2008), and

263   Hastie et al., (2001), useful for learning about these tree based approaches.

264

265   **2.5 Nonlinear forecasting (NF)**

266   Though it may not strictly be classified as a ML method, nonlinear forecasting (NF) has

267   an affinity to machine learning methods, so we discuss it in this context. Nonlinear forecasting is

268   built from autoregressive models for predicting time series:

269

270   $S_t = a_0 + \sum_{i=1}^{m} a_i S_{t-(i\Delta t)}$ (4)

271

272   where a_0 through a_m are coefficients, S is the variable of interest, t is time, and m is the number of

273   past time instances (with temporal spacing of Δt) used to develop an evaluation of S at time t. If

274   the coefficients a_0 through a_m are constant for the entire time series, the model is global and

275   linear. If the coefficients vary as a function of S, then the model is nonlinear, (i.e., only locally

276   linear). Coefficients and their variation as a function of S can be determined through nearest

277 neighbor approaches. There are additional ways to introduce nonlinearity, such as deciding a

278 specific nonlinear function for the right hand side of (4), or incorporating a threshold.

279   In situations where there is a dependence on initial conditions and external forcing, the

280 system can be modeled using approaches such as input-output models (Casdagli, 1991). Adding

281 external forcing inputs to the autoregressive framework is the basis of ARX models

282 (AutoRegressive model with eXogenous inputs):

283

284 $S_t = a_0 + \sum_{i=1}^{m} a_i\, S_{t-(i\Delta t)} + \sum_{k=1}^{n} b_k\, Q_{t+(k\Delta t)}$ (5)

285

286 where Q represents an external forcing signal, b_1 through b_n are coefficients, and k is the number

287 of past instances (with temporal spacing Δt) used to develop the model. Coefficients again can

288 vary as to make the model nonlinear (via locally linear sections). Other modifications to this

289 framework include NARX models (Nonlinear AutoRegressive models with eXogenous inputs),

290 which adjust the functional form of the right hand side of the multiple linear regression equation

291 (5). For example, a tuned neural network can be used as the right hand side of (5), an example of

292 a NARX model.

293   Key recent papers to understand the technique and application of nonlinear time series

294 analysis, nonlinear forecasting, and other related work (under the heading of 'Empirical Dynamic

295 Modeling') are Casdagli (1989), Chang et al. (2017), Farmer and Sidorowich (1987), Kantz and

296 Schreiber (2004), Packard et al. (1980), Sugihara et al. (2012), Sugihara and May (1990), Ye and

297 Sugihara (2016), and finally Takens (1981), who provided much of the theoretical background

298 on which the techniques are based.

299

300 **3. Applications to Coastal Sediment transport**
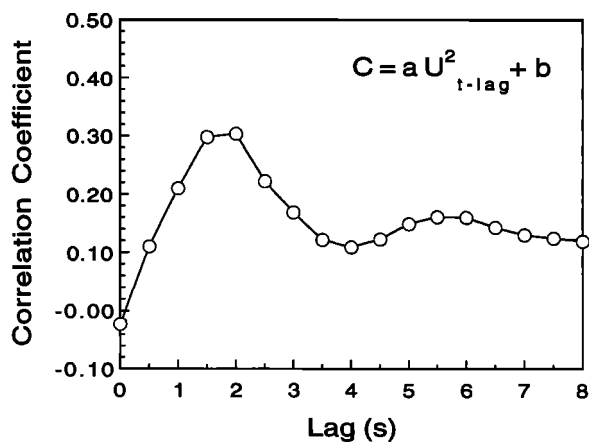
301   We have now reviewed the most used ML techniques in coastal morphodynamics and

302 sediment transport studies. The availability of coastal sediment transport data, and the lack of a

303 single 'perfect' predictor (for a given sediment transport relation) has lead to the hope that ML

304 will provide a more viable, optimal sediment transport equation — a motivation for many of the

305 works that we review in this section. Authors frequently want to develop a predictor that is either

306 more generally valid (better prediction with a large set of data) or more specifically valid (better

307 prediction with a small set of data specifically collected for a given setting/condition). Authors of

308   the studies reviewed below all test their ML prediction scheme against established predictors

309   from the literature (i.e., previous empirical or theoretical sediment transport prediction schemes).

310   The newly developed ML techniques often performs better than the traditional scheme using the

311   error metric selected by the authors, a phenomena we discuss in Section 6.1.

312   **3.1 Suspended Sediment Concentration**

313   Predictions of suspended sediment concentration are a fundamental test of theoretical and

314   statistical understanding of sediment mobility and transport that control morphologic evolution

315   on a wide range of spatial and temporal scales. Time-varying sediment concentrations have been

316   predicted using several ML methods. Jaffe and Rubin (1996) used nonlinear forecasting

317   techniques to predict suspended sediment concentration based on instantaneous water velocity

318   (with and without higher order velocity terms) and various water velocity history terms (e.g.,

319   velocity at the previous time step, etc.). A notable aspect of this study is the investigation of the

320   appropriate time lag in water velocity to maximize the correlation with sediment transport

321   (Figure 1) an insight that may have transferability to other studies on time lags in coastal

322   systems.

323

The plot shows: $C = a\,U^2_{t\text{-}lag} + b$, with axes "Correlation Coefficient" (y-axis) and "Lag (s)" (x-axis).

324

325   *Figure 1: A plot from Jaffe and Rubin (1996), who used nonlinear forecasting to predict*

326   *suspended sediment concentration under waves. The plot above exhibits the changing*

327   *correlation between suspended sediment and wave forcing with changing lag time on the wave*

328   *forcing term.*

329

330   As an extension to this work, Yoon et al. (2013) used an ANN to predict time-dependent

331   suspended sediment concentration as a function of various hydrodynamic parameters both inside

332   and outside the surf zone. With such a large dataset and many measured variables, Yoon et al.

333   (2013) was able to use the ANN to identify the hydrodynamic parameters (and combinations of

334   parameters) that are most predictive in different regions of the laboratory surfzone. Using a GP

335   routine, Kizhisseri et al. (2005) used both synthetic and field data to produce expressions for

336   suspended sediment concentration based on instantaneous fluid velocity (and higher powers of

337   velocity). In a rare example of a reported unsuccessful ML application in coastal

338   morphodynamics, the prediction of suspended sediment concentration using field data lead to

339   poor performance (i.e., a large absolute error for the prediction; Kizhisseri et al., 2005). Oehler et

340   al. (2011) used both BRT and ANN to develop predictors for near bed suspended sediment

341   reference concentration based on water depth, median grain size, mean wave period at the bed,

342   wave orbital amplitude at the bed, and significant wave orbital speed at the bed. The BRT model

343   was superior to ANN (Figure 2), which we highlight because many studies do not compare ML

344   derived predictors developed from multiple ML routines. Oehler et al. (2011) provides a clear

345   example that this work should be done, and will inform future researchers wondering about

346   which ML method to use to predict suspended sediment reference concentration. Goldstein et

347   al., (2014) used the same dataset and developed a GP routine to construct a predictor for

348   reference concentration. This predictor was specifically derived for use in a numerical model of

349   inner shelf bedforms (discussed further in Section 5), and is an example of a predictor developed

350   to work in a specific (multiple grain size) setting. At a larger scales, Teodoro et al. (2007) used

351   an ANN on remotely sensed images of the surf zone to predict total suspended matter in the

352   water column along the coast of Portugal based on satellite remote sensing data (calibrated with

353   field measurements of seawater reflectance). This work highlights the potential for predicting

354   suspended sediment concentration using the high temporal and spatial resolution remote sensing

355   products available, which could potentially be linked to global measures of shoreline change

356   (e.g., Luijendijk et al., 2018).

357
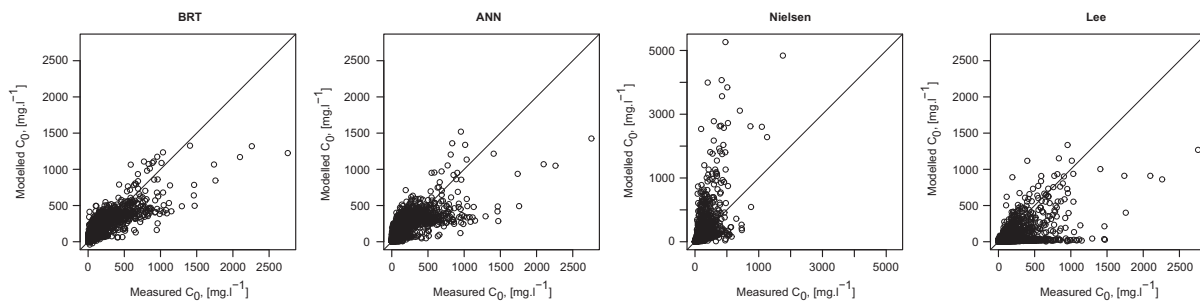
Figure 2: A figure from Oehler et al. (2011) exhibiting the performance of a BRT and ANN

model for suspended sediment reference concentration compared to two more traditional

prediction schemes.

3.2 Suspended Sediment Flux

Scaling up from instantaneous concentration to alongshore-directed suspended sediment

flux has been the focus of several studies. Using an ANN, van Maanen et al. (2010) predicted the

depth integrated alongshore sediment transport using water depth, wave height, wave period and

alongshore current velocity. Analyzing the parameterized ANN also allowed van Maanen et al.

(2010) to understand which parameters held the most explanatory power (alongshore current of

velocity), and to understand when the predictor provided unphysical answers. Notably,

unphysical predictions were found when the ANN was given input parameters outside the range

of the training data, highlighting the importance of training models with extreme conditions.

Predictors for the net alongshore sediment transport rate based on wave height, wave period,

breaking wave angle, beach slope, and grain size have been developed using ANN (Kabiri-

Samani et al. 2011) and regression trees (Mafi et al. 2013). The ability for both ML methods to

produce successful predictors highlights the need for more comparative work between ML

methods.

3.3 Sediment Properties

Finally there have been ML studies of sediment properties (e.g., mean grain size, skewness,

kurtosis, fall velocity, etc.). Nylen et al. (2015) trained a decision tree to determine several

aspects of beach and dune sediment in Finland as a function of environmental variables (e.g.,

elevation, slope, curvature, local fetch, geography and climate conditions). Sediment parent

material (parameterized via geography) was found to be an important control on grain size and

sediment sorting, obscuring the role of local controls. Goldstein and Coco (2014) used a GP

383 routine to develop a predictor for noncohesive sediment settling velocity that incorporates fluid

384 kinematic viscosity, relative sediment density and sediment nominal diameter. The study focused

385 on the role of training dataset size and selection method while developing a prediction scheme

386 that performed better than two common equations.

387

388 **4. ML Morphological and Morphodynamic Models**

389 A variety of coastal morphology and morphodynamic models have been built using ML.

390 Many researchers use ML as an optimization tool — looking for better morphological prediction

391 with newly collected or existing data.

392 **4.1 Sandbars**

393 Sandbar morphology (e.g., the cross-shore position and alongshore uniformity) has been a

394 common focus of machine learning studies. Múnera et al. (2014) developed an ANN to

395 determine the correlation between sandbar morphology and a given wave climate, culminating in

396 in examining the nonlinear dependencies of bar position on past wave conditions (i.e., time-

397 lagged wave conditions). Lopez et al. (2017) used an ANN to determine the cross-shore bar

398 position given wave characteristics, sediment characteristics, and temporal data (month and day

399 information). Compared to a common formula to predict bar characteristics, the optimized ANN

400 had lower error. Komurcu et al. (2013) used an ANN to predict the geometric and shape

401 characteristics of experimentally simulated bars based on the wave height, wave period, bed

402 slope, and grain size. Tests were performed varying the split of training data/testing data. The

403 best fit model was trained with the largest amount of data, and had lower error compared to

404 literature formula. A similar study on experimental bar data was performed by Demirci et al.

405 (2015), using wave parameters, bed slope, and sediment characteristics to predict bar volume

406 using an ANN and multiple linear regression. The predictor derived from ANN outperformed the

407 multiple linear regression.

408 Of particular note is the work of Pape et al., (2007; 2010), who used a recurrent artificial

409 neural network to model the cross-shore position and temporal dynamics of sandbar crests.

410 Recurrent neural networks are ANNs that feed output predictions back to the input layer of the

411 ANN, making a forward in time morphodynamic model. Pape et al. (2007) modeled sandbar

412 position using relevant wave inputs and previous sandbar positions using a linear autoregressive

413 model with exogenous inputs and a recurrent neural network (i.e., a nonlinear autoregressive

414 model with exogenous inputs; NARX) trained using multiple techniques. All models exhibit

415 decaying performance as the prediction horizon (the prediction lead time) increases, but

416 nonlinear ANN models show slightly better results over long prediction timescales (Figure 3).

417 Assessment of prediction timescale is especially critical to understand if data-driven techniques

418 can be successful techniques for forecasting future morphology and morphodynamics, and

419 understanding how error compounds or decays through time in data-driven models. Additionally,

420 comparative work between data-driven methods is particularly interesting to the user of ML, and

421 can give insight into inherent predictability and nonlinearity in the study system. Pape et al.

422 (2010) continued this work, using two neural networks to model sandbar behavior and compared

423 results to a traditional cross-shore morphodynamic model. Both data-driven models showed

424 increased performance compared to the morphodynamic model, measured using the metric of

425 error over increasing prediction horizon.

426
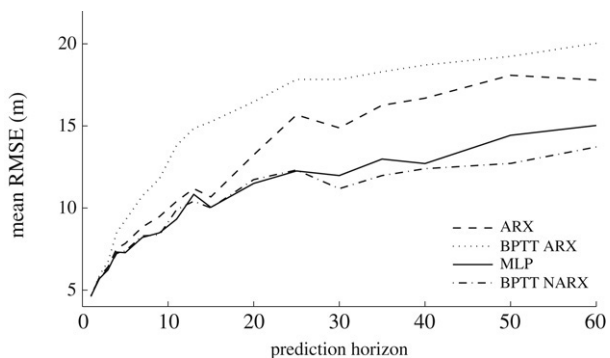
427

428 *Figure 3: The increase in sandbar position error for increasing prediction timescales using*

429 *data-driven models (from Pape et al., 2007). Error is minimized when using models based on*

430 *ANN (the 'MLP' and 'BPTT NARX' models).*

431

432 **4.2 Shoreline position and shore profile**

433 Various shoreline attributes have also been predicted using machine learning techniques.

434 Using an ANN to predict beach profiles (from the dunes to MSL) with wind and wave data,

435 Hashemi et al. (2010) also discusses the role of traning data that spans a wide range of conditions

436 to avoid error associated with out-of-sample predcition. Grimes et al. (2015) analyzed beachface

437 and shoreline timeseries data, using a GP and nonlinear forecasting to predict the dynamics of

438   intertidal beachface geometry and examine the role of internal dynamics vs. external controls

439   (i.e., forcing). Both Tsekouras et al. (2015) and Rigos et al. (2016b) described new methods to

440   formulate and train a novel ANN architecture to predict shoreline characteristics — Tsekouras et

441   al. (2015) examined shoreline erosion as a function of storm characteristics and bathymetry,

442   while Rigos et al. (2016b) investigated multiple shoreline positions and shoreline rotation given

443   hydrodynamic inputs and offshore reef morphology. Iglesias et al. (2009a; 2010) used an ANN

444   to predict the planform morphology of headland-bay-beach systems (including those with shore

445   protection structures). Iglesias et al. (2009a) tested multiple ANN architectures (number of

446   hidden layers and nodes) as well as different algorithms to train the ANN. The final ANN model

447   outperformed previously developed shoreline models, and error from the ANN model was

448   distributed across the shoreline as opposed to the previous models, which had concentrated zones

449   of high error. Iglesias et al. (2009b) extended this work by incorporating tidal range into the

450   ANN. After testing various ANN architectures and finding the best ANN predictor, Iglesias et al

451   (2009b) used the trained model to examine the interplay between tidal range and wave

452   parameters in controlling headland bay geometry. Loureiro et al. (2013) used a BN to

453   probabilistically determine the beach state classification (i.e., Wright and Short, 1984) given a

454   range of hydrodynamic data and sedimentological data. The study specifically found utility in

455   the uncertainty of prediction, an intrinsic part of the Bayesian estimation that was used to

456   develop probabilistic beach state predictions. At larger scales, Bayesian networks have also been

457   used to make probabilistic predictions of coastal morphology at large scales. Gutierrez et al.,

458   (2011) used a BN to develop shoreline change rate predictions for the US east coast based on

459   hydrodynamic, geologic and cross shore morphology of the coastline. Plant et al. (2016)

460   modified the BN of Gutierrez et al. (2011) to include and probabilistically predict shoreline

461   change as well as dune height for work in the Gulf of Mexico. Interestingly, the inclusion of

462   dune height as an input variable increases precision but predictions are not more accurate. Yates

463   and Le Cozannet (2012) also used the approach of Gutierrez et al. (2011) to probabilistically

464   assess future European coastal evolution (either erosion, stable or accretion) using

465   geomorphology, geology, mean tidal range, rate of sea level rise (RSLR), and mean significant

466   wave height. Stable coastlines are predicted with greater accuracy compared to erosive or

467   accreting coastlines, and the authors suggest that incorporating more local behaviors may resolve

468   this issue. Bulteau et al. (2015) use a Bayesian network to predict shoreline change on La

469   Réunion island from geomorphic setting, presence of an estuary, anthropogenic structures,

470   RSLR, and a function of wave energy. In addition to discussing why certain inputs are more

471   predictive than others (specifically local geomorphology), this study also specifically examines

472   areas of misprediction, and offers insight as to the unique situations when misprediction arises.

473   Lentz et al. (2016) use a BN to relate land cover classifications, current elevations, and expected

474   changes in RSLR to likelihood that coastal geomorphic settings would evolve to keep up with

475   sea-level rise or inundate. A BN approach was used specifically in this study because of its

476   probabilistic nature. Linking large scales and small scales, Gutierrez et al. (2015) predicted

477   decadal changes in barrier island geomorphology of Assateague Island, USA using both large-

478   scale (e.g., shoreline change rate, distance to an inlet) and small-scale morphologic features (e.g.,

479   dune height, beach width) in a Bayesian network.

480   In addition to looking at long term shoreline changes, event scale work has also used BNs

481   for prediction. Wilson et al. (2014) built on previous work by Lentz and Hapke (2011) to predict

482   the beach volume changes resulting from storm events on Fire Island NY, USA with a BN.

483   Predictions were improved in this network by including anthropogenic impacts on the beach

484   (nourishment in this location) and adjusting the hydrodynamic inputs to the model (runup

485   elevation vs., impact hours). This highlights the potential role of using several different inputs

486   that may be viewed as quantifying the same process (wave-driven erosion), but may vary in

487   correlation with the desired output (beach volume change). Beuzen et al. (2017) compared the

488   use a BNs of different size (2 vs. 3 input nodes) to predict shoreline retreat as a consequence of

489   storm events and preexisting beach characteristics (state, slope, width) at Collaroy-Narrabeen

490   Beach in SE Australia. Building on this work, Beuzen et al. (2018) examined the use of BNs as

491   both predictive tools (high performance on testing data) and descriptive tools (high performance

492   on training data) for storm-driven shoreline change. Beuzen et al. (2018) notes that BNs built for

493   descriptive purposes can be used to gain insight on underlying processes that produce the data,

494   including causality.

495   Bayesian networks have also focused on emulating process-based models of storm erosion

496   that are particularly computationally intensive—Poelhekke et al. (2016) used a BN as an

497   emulator for the detailed process based model XBeach (Roelvink et al. 2009). By developing a

498   set of forcing conditions for XBeach and running the model for each forcing condition,

499   Poelhekke et al. (2016) trained the BN to predict morphodynamic impacts (overwash depth, flow

500   velocity, and erosion) on Praia de Faro, Portugal, a developed barrier island. The goal of the

501   work is to develop a quick method to emulate the XBeach for use in an early warning system.

502   Plomaritis et al. (2017) extended the work of Poelhekke et al. (2016) and a BN on disaster risk

503   reduction (Jager et al., 2017) to assess the impact of risk reduction measures on morphodynamic

504   impacts on the Ria Formosa Barrier system of Portugal. Again the BN served as mechanism to

505   emulate process based model runs.

506   **4.3 Dune Erosion**

507   BN studies of coastal dune erosion from storm events have also found value in explicitly

508   developing probabilistic prediction —Plant and Stockdon (2012) used a BN to predict dune crest

509   elevation changes, dune crest position change, and shoreline position change as a function of

510   dune base elevation, storm induced mean water level, and storm induced run-up (Figure 4).

511   Observations of dune erosion do not always match predictions perfectly, but do fall within the

512   confidence intervals of the probabilistic method — this highlights the utility of probabilistic

513   predictions toward enhancing prediction accuracy and certainty. Palmsten et al. (2014) used the

514   network from Plant and Stockdon (2012) as well as a simplified model structure to develop

515   probabilistic predictions of dune position change along the Gold Coast in Queensland, Australia.

516   Of note in this study is the attempt to use the trained model from Plant and Stockdon (2012),

517   with no modifications or additional training, for a new site — prediction was not skillful with

518   this model, however the ability for ML models to be generalized and extrapolated to new sites is

519   an important test for any coastal ML models. den Heijer et al (2012) performed a similar test

520   using a Bayesian network that was designed to emulate an existing volumetric dune erosion

521   model. The trained model was not able to successfully extrapolate beyond the range of the

522   training data.
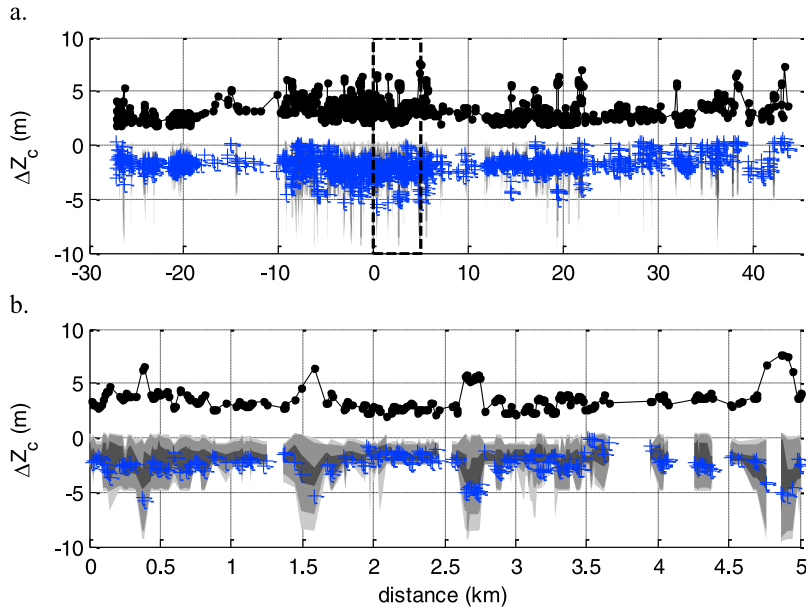
523

524 *Figure 4: Figure from Plant and Stockdon (2012), who used a Bayesian network to make*

525 *predictions of foredune crest elevation change (ΔZ_c). Initial dune height is shown in black,*

526 *observations are blue +, and predictions from the BN are shown as shaded area ranging from*

527 *50% (dark) to 95% (light) confidence interval.*

528

529   **4.4 Cliffs and Rocky Coastlines**

530   Much of the previous work has focused on low-sloped sandy coastlines, though there has

531 been work on rocky coastlines. Dickson and Perry (2015) used several regression tree

532 approaches to identify the controls on coastal cliff landsliding (e.g., distance to fault, bedding

533 dip, aspect, etc.). Multiple methods converged on the same two controlling variables, a benefit

534 when comparing multiple ML methods. Hapke and Plant (2010) used a BN to develop a

535 relationship between short term cliff erosion rate of rocky coastlines of the southern California,

536 US, and underlying geology, cliff height, cliff slope, and a metric based on hours the cliff is

537 subject to wave attack, and long term erosion rate of the cliffs.

538   **4.5 Wave Ripples**

539   Shifting from the coastline to smaller scale morphology, Yan et al. (2008) built an ANN to

540 predict wave generated ripple size (length and height) based on sedimentological and

541 hydrodynamic conditions. Data were from both field and lab studies, and the ANN results were

542 compared to four other empirical models. The ANN results provide more accurate predictions

19

543   based on 3 statistical measures (scatter index, correlation coefficient, and mean geometric

544   deviation) than the empirical models. Also studying wave-generated ripple geometry, Goldstein

545   et al., (2013) used a GP routine to construct an equation for wave generated ripple height,

546   wavelength, and steepness using sediment grain size and near bed orbital excursion. The new

547   machine learning scheme produced more accurate predictions compared to traditional predictors.

548   This predictor was ultimately used as a component within a larger numerical model (Goldstein et

549   al., 2014).

550   **4.6 Flora and Fauna**

551   We can find very few coastal morphodynamic/morphology studies that focus on machine

552   learning with flora and fauna. Coco et al. (2011) used ANN to predict the change in elevation of

553   intertidal flats based based on seagrass (*Zostera noltii*) shoot density, leaf length, leaf area index,

554   wave height, wind speed, sand content of the bed sediment, and sediment dry density. Gieder et

555   al. (2014) used a Bayesian network to predict piping plover (*Charadrius melodus*) nest presence

556   based on a Bayesian network that included barrier island morphology. Building on this work,

557   Zeigler et al. (2017) used data collected from a variety of practitioners using a phone application

558   to provide data to a BN to predict piping plover (*Charadrius melodus*) nest location. These three

559   studies highlight a potential future direction for coupling coastal morphodynamics to the

560   dynamics of flora and fauna.

561   **4.7 Detection of Bars and Shoreline in images**

562   Detection of morphological features from video images has also employed regression-

563   based ML. Kingston et al. (2000) used an ANN to model the difference between sandbar position

564   and video intensity maxima with additional inputs of wave height and tide level. Additionally,

565   the model developed by Kingston et al. (2000) showed success against other methods (Plant et

566   al., 2007). Related work has focused on detecting the shoreline in video observations with a

567   variety of ANN architectures (Alvarez-Ellacuria et al., 2011; Rigos et al., 2016).

568

569   **5. Hybrid ML Morphodynamic models**

570   Machine learning methods do not need to operate alone, and can be linked with

571   morphodynamic models to create what we refer to as 'hybrid' models, after the atmosphere and

572   ocean models by Krasnapolsky and Fox-Rabinovitz (2007), and Krasnopolsky (2013). There are

573   several reasons for a hybrid models (Goldstein and Coco, 2015): ML components can serve as

574 'emulations' of complex routines or equations to speed up the computational process; data-

575 driven parameterizations can serve as model components when parameterizations have ample

576 data but no single optimal expression — perhaps there are multiple competing formulations;

577 more data might be anticipated in the near term future, and the parameterizations might be

578 'volatile', subject to change as new data is collected; lastly, hybrid models offer a degree of

579 specificity to a model. Adding a ML predictor is way of incorporating a bespoke prediction

580 scheme, which can be useful for modeling a specific setting where data was collected.

581   Three coastal morphodynamic models have combined genetic programming routines to aid

582 in various aspects of modeling. Goldstein et al., (2014) incorporated a GP derived suspended

583 sediment reference concentration predictor and equilibrium wave orbital ripple morphology

584 predictor (Goldstein et al., 2013) into a model of inner shelf sorted bedforms. The model

585 previously had been built using theoretical and empirical parameterizations of these processes,

586 but data from inner shelf sorted bedforms was used to develop new parameterizations and

587 produce a refined model. The goal of the modeling work was to add more specificity to the

588 process parameterizations in settings with mixed grain sizes. Limber et al. (2014) and Limber

589 and Murray (2014) used a GP derived expression as a component in nonlinear dynamical system

590 model for rocky coastline evolution. The GP routine was used to develop an expression that

591 emulated the output of a wave ray tracing model, thus summarizing the wave model results into a

592 single smooth continuous equation amenable to further numerical work and phase plane analysis.

593 Finally, Goldstein and Moore (2016) developed a nonlinear dynamical model of coastal dunes

594 subject to storms by combined an empirical formulation of coastal foredune growth with a

595 parameterization for dune erosion built using a GP from data reported in the literature. The GP

596 routine was used to fit a smooth continuous equation to a set of data to facilitate numerical

597 analysis.

598   Bayesian networks have been used as subcomponents for a variety of coastal models. Plant

599 et al. (2014) used a Bayesian network to estimate overwash probability of a berm from

600 hydrodynamic and wind conditions. This overwash probability was linked to a (non-BN) model

601 of berm morphology. At larger space and time scales, both Passeri et al. (2016) and Bilskie et al.

602 (2016) use the BN of Plant et al. (2016) — itself an extension of Gutierrez et al. (2014) —as a

603 model component to predict century-scale shoreline change and dune height change as a function

604 of SLR scenarios and geological constraints for the Gulf of Mexico. Bilskie et al. (2016) used the

605 BN as a component in a model of Hurricane impacts under different SLR scenarios while Passeri

606 et al. (2016) used the BN as a component of a model to simulate tidal hydrodynamics under SLR

607 scenarios. Both Passeri et al. (2016) and Bilskie et al. (2016) mention that the Bayesian network

608 was used because it is computationally efficient for the long time and large space scales that

609 were modeled. Passeri et al. (2016) also discuss limitations to the BN component — the lack of

610 historic data to train the BN limited its use in bays and estuaries, and large scale barrier island

611 processes such as rollover of back barrier shoreline migration and nourishment also were not

612 encoded in the BN (but included as rules in the larger model). van Verseveld et al. (2015) used

613 the process based model XBeach to simulate a storm event impacts on a developed barrier island.

614 Hydrodynamic and morphodynamic output from the model was used as input for a Bayesian

615 network, which predicted the damage to buildings. van Verseveld et al. (2015) notes that BN

616 require a significant amount of data, but much was available for this research question, enabling

617 a data driven approach. The use of multiple inputs (flooding, scour, wave height) and the

618 probabilistic nature of the BN were also advantages in this research.

619   Many coastal morphodynamic models have several free parameters that must be 'tuned' for

620 a given field site or use case (e.g., Apotsos et al., 2008, Lin and Sheng, 2017; Murray et al.,

621 2016; Pinksy et al., 2013; Plant and Holland, 2011; Stephens et al., 2011, Stockdon et al., 2014).

622 When the number of free parameters is large and potentially interrelated, machine learning can

623 be used to find optimal parameters. Knaapen and Hulscher (2002) developed a model for sand

624 wave growth and saturated morphology, with best-fit model parameters are found using of a GA

625 routine. Ruessink (2005) tuned nearshore model parameters using a genetic algorithm coupled to

626 a local optimization routine (downhill simplex). Komurcu et al. (2008) used a GA to determine

627 the values for coefficients in two highly nonlinear functions that predict experimentally produced

628 bar geometry based on the wave height, wave period, bed slope and grain size.

629   We have so far discussed ML components that are internal to morphodynamic models

630 (hybrid models) and ML that is used to tune models. ML can also be used to analyze model

631 results and provide insight into model output. Lazarus et al. (2011) use nonlinear forecasting to

632 quantify the nonlinearity of timeseries output generated by a model of human – coastline

633 interaction.

634 **6. Discussion**

635   We have identified a wide range of ML applications to sediment transport, morphologic,

636 and hybrid coastal prediction problems. This provokes questions, such as how to select an

637 appropriate ML method to suit a particular problem, what sort of comparisons of ML can be

638 made to more standard approaches, what are the common principles that can be applied to these

639 applications, and where does this lead. These topics are discussed below.

640   **6.1 Which ML technique and how much data?**

641   We have reviewed commonly used ML techniques in the field of coastal morphodynamics,

642 and investigated their applications across a range of scales. Figure 5 is a schematic representation

643 of our workflow. Some of the steps in this workflow are decisions (selecting an algorithm,

644 determining if more data is needed, etc.) and may require significant investment of thought. With

645 many possible tools, we are often asked about the best ML routine to use for a given type of

646 problem. Unfortunately in most instances we cannot definitively answer this question a priori,

647 but we can offer some insights to readers wondering where to start. A researcher may have a

648 preference for a given learning routine based on the type or quantity of data, an intuition

649 regarding what worked best on a similar problem, or the form of a desired outcome. Guiding

650 questions can be used to determine the ML routine for a given problem: If probabilistic answers

651 are required, researchers could focus on Bayesian networks. If multiple free parameters exist for

652 a fixed, immutable equation, then a GA can be employed. If a specific smooth equation is

653 needed (e.g., to be used in an analytical model), an ANN or GP can be used. If functional form

654 and input dependencies are needed, a solution from GP can be attempted. Ambiguity over

655 picking a ML approach for a given dataset highlights the need for a larger empirical study where

656 many ML approaches are each attempted on an array of problems to determine (empirically) if

657 there are optimal techniques for a given research question. Examples of this approach can be

658 seen in other disciplines — work by Olson et al. (2017) and Hansen et al. (2013). Below (section

659 6.3) we offer a set of best practices for coastal researchers who aspire to make their ML results

660 usable for ML comparison.

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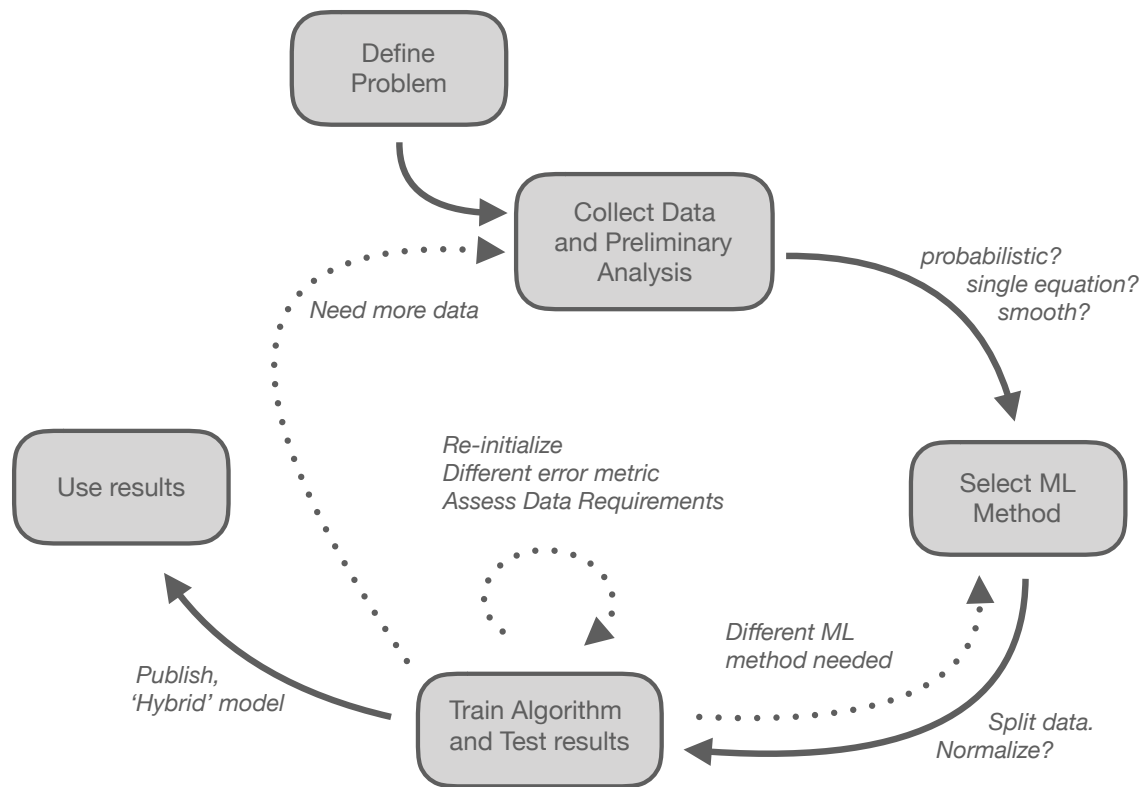
662
Figure 5: A schematic of our workflow. Work starts with 'Define Problem' —new or published

data — and progresses by following the filled arrows. Dotted arrows represent escapes from this

workflow for various reasons

666

It remains unclear how much data a researcher needs to perform meaningful ML analysis
and produce a useful predictor. For example, Beuzen et al. (2017) investigated the amount of
data needed to successfully parameterize a BN of shoreline change as a function of storm events,
and suggested that the number likely depends on network complexity (degrees of freedom, or
independent variables) and the signal 'clarity', likely a measure of signal to noise in the dataset.
Goldstein and Coco (2014) and Tinoco et al. (2015) investigated the impact of adding data for
GP prediction, finding that very little data was needed to train the model, and more data might
actually provide degraded prediction for low-complexity models (Figure 6). It is unclear if this
relationship holds for other machine learning routines or prediction tasks, but could point the
way in minimizing training data and maximizing the data used to test the resultant ML derived
predictor. Similar to 'which algorithm', we expect that empirical guidance is most valuable, and

678   further studies might shed light on how much data is really needed to make optimal predictions

679   for a given problem, with a given prediction technique. Providing justification for a given

680   amount of data, or a given ML technique — especially quantitative justification — is particularly

681   valuable for future researchers to determine what techniques and data quantities work for a given

682   problem, and what can be learned (or what we are unable to learn) using a given approach and

683   given set of data.
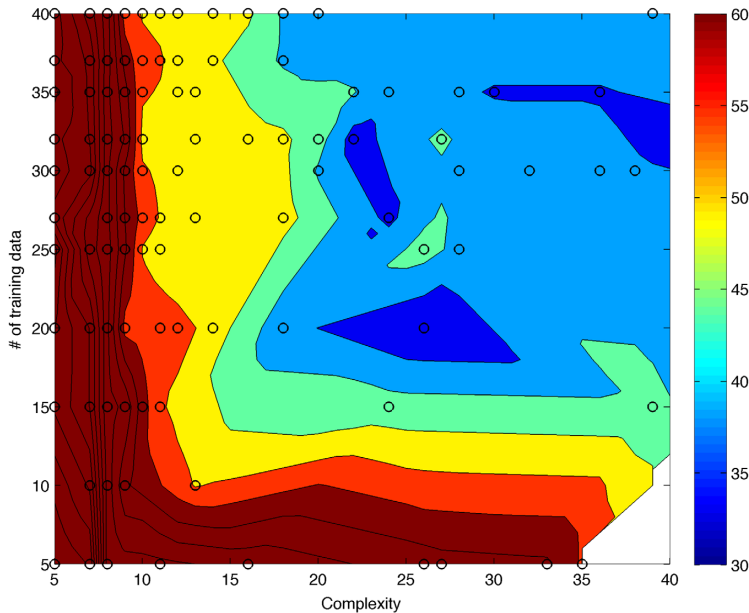
684

685   *Figure 6: A plot from Goldstein and Coco (2014) that displays GP solutions (open circles) of*

686   *differing complexity developed by changing the size of the training data. The colormap is a*

687   *measure of error, and suggests that continuing to increase the size of training data does not*

688   *always yield decreases in error of the final solution.*

689

690   Beyond the amount of data needed for a ML analysis, all machine learning methods require

691   that data be split into discrete parts — with one part of the data used for developing the model

692   ('training data'), while the remaining data are reserved outside the algorithm to test the

693   developed model ('testing data'). The most important aspect of the data splitting is that users do

694   not test the learned predictor with the training data (e.g., Domingos, 2012) — the testing data

695   should not be seen by the ML algorithm as it is trained, testing must occur using a new, unseen

696   portion of the data. There are enhancements beyond this simple two-part split (i.e., it is common

697   to use additional subsets in the training process as 'validation' to limit overfitting), but for this

698   moment it is important that some portion of the data is used in the model building phase, and

699   some portion of data is used in the model testing phase.

700   In many of the studies reviewed in this paper the data are split randomly. While random

701   selection can be used, there are many methods to select a data for training and testing that are

702   advantageous for developing generalizable predictor. For example, it is often easier to acquire

703   data for coastal studies in controlled lab settings under weak forcing, and there may be few data

704   points in field conditions (with complexities such as mixed grain sizes, irregular waves, etc.) or

705   under extreme forcing (i.e., storms). Extracting training data by randomly sampling a full dataset

706   may omit the critical information from the training data, for example extreme conditions (e.g.,

707   Passarella et al., 2018). There are many intentional sampling strategies from splitting data into

708   training and testing that have not seen wide adoption in coastal community — we believe that

709   adoption of these techniques will lead to more generalizable ML predictors. For examples of data

710   selection routines, see Galelli et al. (2014) on evaluating input value selection routines, and

711   previous work by Bowden et al. (2002), Bowden et al. (2012), Camus et al. (2011a; 2011b), May

712   et al. (2010), Tinoco et al. (2015), Splinter et al. (2013).

713

714   **6.2 When does ML perform better than more traditional methods?**

715   As we state in the sediment transport modeling section, the ML studies we review often

716   outperform more traditional prediction schemes that are based on derivations from 'first

717   principles' (i.e., conservation laws) and schemes based on more classic curve fitting techniques

718   (e.g., linear regression). It remains unclear why this is the case. One possibility is that we are

719   only aware of published ML studies, which bias us into believing ML provides only positive

720   results. Or perhaps developing a new ML predictor might outperform a non-ML predictor

721   because of flexibility — many ML routines can develop predictors that do not conform to a set

722   basis function. For example, more traditional regression techniques work well when data

723   conforms to a set functional form (a line, or a curve) and obeys the many generalizing

724   assumptions (i.e., normally distributed). A researcher therefore performs dimensional reduction

725   or transformation to first get data into this functional form, then fits the data with a known basis

726   function (a line, a parabola, etc.). ML techniques offer more flexibility because the basis function

727   for many techniques is highly adaptable — i.e., a neural network, which has many free

728   parameters and can be trained to fit lines or curves.

729   We have discussed many of the studies that develop ML predictors for the same

730   phenomena (e.g., suspended sediment transport flux, bar geometry, ripple wavelength). Even

731   when multiple studies examine the same research question, the comparison between ML

732   predictors is often impossible because each study uses different datasets, the method to split and

733   testing data is often not clear, or information regarding the final predictor is not provided (e.g.,

734   for cases where ANN are used, the weights and biases may not be provided). Therefore it is

735   difficult to truly compare ML methods and the resulting predictors. For instances, it is difficult to

736   compare the ripple predictors developed by Yan et al. (2008) with a ANN and the ripple

737   predictors developed by Goldstein et al. (2013) with a GP. After reviewing the work of ML in

738   coastal morphodynamics and sediment transport we are left instead with the knowledge that

739   the studies reviewed here can be understood as a 'proof of concept' for ML being able to develop

740   accurate predictions for a given dataset. In this way, we suggest that ML might point the way

741   toward the being valuable for developing bespoke prediction routines for a given site, a given

742   dataset, or a given purpose. In some cases, more accurate prediction might be needed because of

743   a specific research question or prediction task. An example is work by Goldstein et al. (2014),

744   where a near bed suspended sediment reference concentration prediction scheme was developed

745   from data collected in fields of sorted bedforms, and then used in a model of sorted bedforms to

746   predict sorted bedform dynamics.

747   **6.3 A set of practices for Coastal ML research**

748   If researchers using ML aspire to make their results reproducible, transferable, and useful

749   to future researchers (e.g., intercomparison projects, helping to determine which algorithm is

750   best, or how much data is needed), we offer a set of practices here that would aid in this goal. 1)

751   Provide the data with the paper, or link to an open archive. 2) Unequivocally state the degree to

752   which the training data and testing data are separate, that the testing data was not seen by the

753   machine learning algorithm, and that the training data was not used to test the success of the

754   developed model. 3) Clearly describe the technique used to split the data into training and

755   testing, the percentage of data used for each group, and if possible, the actual data split into

756   groups. 4) Report the final model in its entirety (e.g., weights, biases and architecture for ANN;

757   binary splits for a tree model, etc.). 5) Define the metrics that are used to test the models and

758   define levels required to be successful. 6) Compare results to other models to provide

759   benchmarks for improvements and the relative value of ML vs. theoretically developed models.

760   7) Compare ML model to newly collected data sets as a test to determine whether there are
761   sufficient data for a particular model and whether the model is locally or generally applicable.

762   The goal with this set of best practices is to steer ML papers toward being usable and
763   reproducible by the community. We understand that for a variety of reasons, these practices may
764   not be possible under all circumstances, but if authors would like their ML work be built upon,
765   tested, and refined, these practices aid in that goal. Very few studies that we review adhere to all
766   of these practices. However we offer this guidance here to help advance the understanding and
767   reuse of ML research in the coastal community, and we hope that all future work is performed
768   with an eye toward reuse and reproducibility by others.

769

770   **6.4 Future directions**

771   Data-driven research relies on the existence of data. Beyond the collection and ad hoc
772   sharing of data, the trend in publication of data is a major factor in the continued adoption of
773   data-driven science. Data publication is enabled by the existence of repositories — Figshare,
774   Zenodo, Data Dryad, Pangaea, and others identified by the re3data.org project (Pampel et al.,
775   2013) — as well as data journals, publications that focus exclusively on descriptions of the data
776   (from collection to access) such as Earth System Science Data (Pfeiffenberger and Carlson,
777   2011), Earth and Space Science (Hanson, 2014), Geoscience Data (Allan, 2014), and Scientific
778   Data (Scientific Data, 2014). The continued collection and release of data will enable more data-
779   driven work to occur in coastal settings.

780   In addition to data, ML research relies on ML algorithms and techniques. We have only
781   discussed ML techniques that have been used in coastal settings, but this in no way is an
782   exhaustive list of techniques. First, many common techniques — such as Support Vector
783   Machines — have seen only minimal usage in coastal morphodynamics problems; though they
784   have been used for coastal classification routines (Hoonhout et al., 2015) and in oceanographic
785   contexts (Li et al., 2013). Second, many newer techniques may not yet have been applied to
786   coastal research, such as recent advances in ANN architecture and training (e.g., Deep Learning;
787   LeCun et al., 2015), or newer probabilistic techniques (Ghahramani, 2015). There is a world of
788   new algorithms and techniques that can be brought over from the ML community — researchers
789   might find it profitable to look for new techniques within the ML literature to make sure we are
790   not missing out on the revolutionary advances in data-driven tools.

791   Finally, ML learning techniques can be thought of as new additions to the coastal

792   researchers bag of tools — providing new insights during data analysis (e.g. Tinoco et al., 2015;

793   Beuzen et al., 2018). ML techniques could be taught alongside other more common data analysis

794   techniques (e.g., Fourier transforms, wavelets; Zdeborova, 2017) since ultimately the goal is the

795   same with any of these tools and techniques — to find and extract new knowledge or insight

796   from data.

797   In light of our general requests to continue publishing data for reuse, the continued

798   adoption of new algorithms, and to teach these modern methods to students, we also see three

799   specific areas for growth in Coastal ML research. First, to provide guidance for which methods

800   perform best for which problems, a more structured comparison projects between ML techniques

801   using the identical data set (and data split) is required. Comparative work of this nature will help

802   all researchers decide which ML has a high chance of success for a given problem. This may also

803   help us to further understand a given coastal problem. Second, we identify an opportunity to use

804   ML on timeseries, especially when systems may have memory and/or storage effects. The work

805   of Pape et al (2010) is a rare example, however new advances in neural network architecture

806   (i.e., long short-term memory) has the potential to allow for more accurate time series prediction

807   even when systems have strong autocorrelation, thresholds, and memory dynamic (e.g.,

808   shorelines, bars, bedforms, etc.). See Kratzert et al. (2018) as an example of the power of long

809   short-term memory networks in hydrological time series prediction. Third, uncertainty derived

810   from ML can further be incorporated into models. A clear possibility is to use probabilistic ML

811   based predictions (from Bayesian networks, or other novel techniques such as Gaussian

812   Processes) creatively in numerical models. An example is to use the probabilistic nature of these

813   predictors as 'stochastic parameterizations' (e.g., Berner et al., 2017), whereby some aspect of an

814   otherwise deterministic numerical model is made probabilistic, and models may then be able to

815   generate ensemble predictions using identical forcing and initial conditions.

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