Shoreline modelling on timescales of days to decades

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Impact statement

In the context of increased probability of coastal erosion and flooding associated with climate change, there is a pressing need to predict future shorelines at both short- (daily) and medium-term (decadal) timescales. Such predictions are essential for the assessment of the climate-resilience of the world's coastlines and the delivery of effective, economic and data-informed coastal management. Coastal managers currently lack these predictions and there are many different modelling approaches to inform where increased coastal protection, adaption measures or future infrastructure developments should be focussed. Promising modelling advances have recently been made, particularly in the context of reduced complexity models. This paper reviews various numerical modelling approaches to predicting shoreline and coastal morphological change, comments on some of the most promising methods used to-date, provides some guidance on model selection, and highlights important future research directions and challenges to progress.

Abstract

Climate change is resulting in global changes to sea level and wave climates, which in many locations significantly increase the probability of erosion, flooding and damage to coastal infrastructure and ecosystems. Therefore, there is a pressing societal need to be able to forecast the morphological evolution of our coastlines over a broad range of timescales, spanning days-to-decades, facilitating more focussed, appropriate, and cost-effective management interventions and data informed planning to support the development of coastal environments. A wide range of modelling approaches have been used with varying degrees of success to assess both the detailed morphological evolution and/or simplified indicators of coastal erosion/accretion. This paper presents an overview of these modelling approaches, covering the full range of the complexity spectrum, summarising the advantages and disadvantages of each method. A focus is given to reduced-complexity modelling approaches, including models based on equilibrium concepts, which have emerged as a particularly promising methodology for the prediction of coastal change over multi-decadal timescales. The advantages of stable, computationally-efficient, reduced-complexity models must be balanced against the requirement for good generality and skill in diverse and complex coastal settings. Significant obstacles are also identified, limiting the generic application of models at regional and global scales. Challenges include: the accurate long-term prediction of model forcing time-series in a changing climate, and accounting for processes that can largely be ignored in the shorter term but increase in importance in the long-term. Further complications include coastal complexities, such as the accurate assessment of the impacts of headland bypassing. Additional complexities include complex structures and geology, mixed grainsize, limited sediment supply, sources and sinks. It is concluded that with present computational resources, data availability limitations and process knowledge gaps, reduced-complexity modelling approaches currently offer the most promising solution to modelling shoreline evolution on daily-to-decadal timescales.

Keywords: modelling, shoreline-change, forecast, predictions, long-term, large-scale, climate-impacts, sea-level, projection.

Social media summary

This review details the most promising modelling approaches to shoreline changes in response to storms and longer-term climate change.

1 Introduction

Global climate change is expected to result in geographically widespread differences in; storm frequency and intensity (Dorland et al., 1999, Masselink et al., 2020); wave climate variability (Castelle et al., 2018, Scott et al., 2016, Chowdhury et al., 2019, Meucci et al., 2020, Morim et al., 2018, Morim et al., 2019); rising sea levels (Nicholls et al., 2014, Fox-Kemper et al., 2021) and significant morphological changes and impacts to vulnerable coastlines (Wiggins et al., 2019, Enríquez et al., 2017, Vousdoukas et al., 2020). The common assumption that the morphology remains unchanged during sea level rise is inaccurate for projecting coastal evolution on decadal and climate change timescales (Anderson et al., 2018b). Morphodynamic change can result in loss of land and infrastructure through erosion and can significantly change the likelihood of wave overtopping and flooding. Consequently, the development of methodological approaches for predicting morphodynamic change over daily-to-decadal timescales remains a topical and ongoing research focus for coastal scientists and engineers.

Whilst the focus of this paper is on shoreline modelling of sedimentary coastlines, it is important to recognise that this information can be derived from models of varying complexity, ranging from simple one-dimensional models that predict the shoreline evolution with time, to complex three-dimensional models of morphodynamic evolution. Coastal state indicators refer to a reduced set of parameters that enable a simplistic and quantitative description of the state and evolution of the coast (Davidson et al., 2007). Although shorelines are certainly an important state indicator (Boak and Turner, 2005, Davidson et al., 2007), it should also be recognised that shoreline definition is highly variable and not a unique example. Indicators like beach volume (Burvingt et al., 2018) or the momentary coastline position (Van Koningsveld et al., 2005), are among other useful state indicators relevant to coastal management (Davidson et al., 2007). This paper aims to review a range of modelling approaches, whilst retaining an emphasis on shoreline modelling.

Figure 1 illustrates the variety and the spatial/temporal scales of processes that shape coastal morphology. Also shown is the partitioning of the days-to-decades timescale addressed in this contribution into **short-** (days-to-weeks), **medium-** (months-to-decades) and **long-** term (>decades) categories, used throughout the following sections and – for convenience – simply referred to as short, medium and long timescales, without further elaboration. Cross-shore and longshore gradients in sediment fluxes, wave set-up and changing water levels are some of the principal processes driving coastal change at short-to-medium timescales on wave-dominated coastlines (Davidson et al., 2013), whereas, over longer timescales (multi-decadal/centurial), eustatic and isostatic sea level change may have a more significant influence on shoreline change. Eustatic sea level change refers to a global change in sea level, while isostatic (or 'relative') sea level change refers to localised changes in land height, relative to sea level (Rovere et al., 2016). Additionally, cross-shore processes often represent shorter time periods (days-to-months) relative to durations surrounding longshore processes (weeks-to-years) (Winter, 2012), although often overlap within the same categorised timescales. Thus, Figure 1 not only illustrates the typical time and space scales of hydro- and morpho- dynamic processes, but it also suggests the relative importance and need for consideration of these processes in morphodynamic models, providing an initial guide for both model development and choice. The morphology and dominating driving processes of coastal change also vary significantly between sites, presenting a variety of different challenges and requiring differing emphasis on underlying equations. For example, some models are restricted by their underlying physics to either cross-shore or longshore transport dominated coastlines.

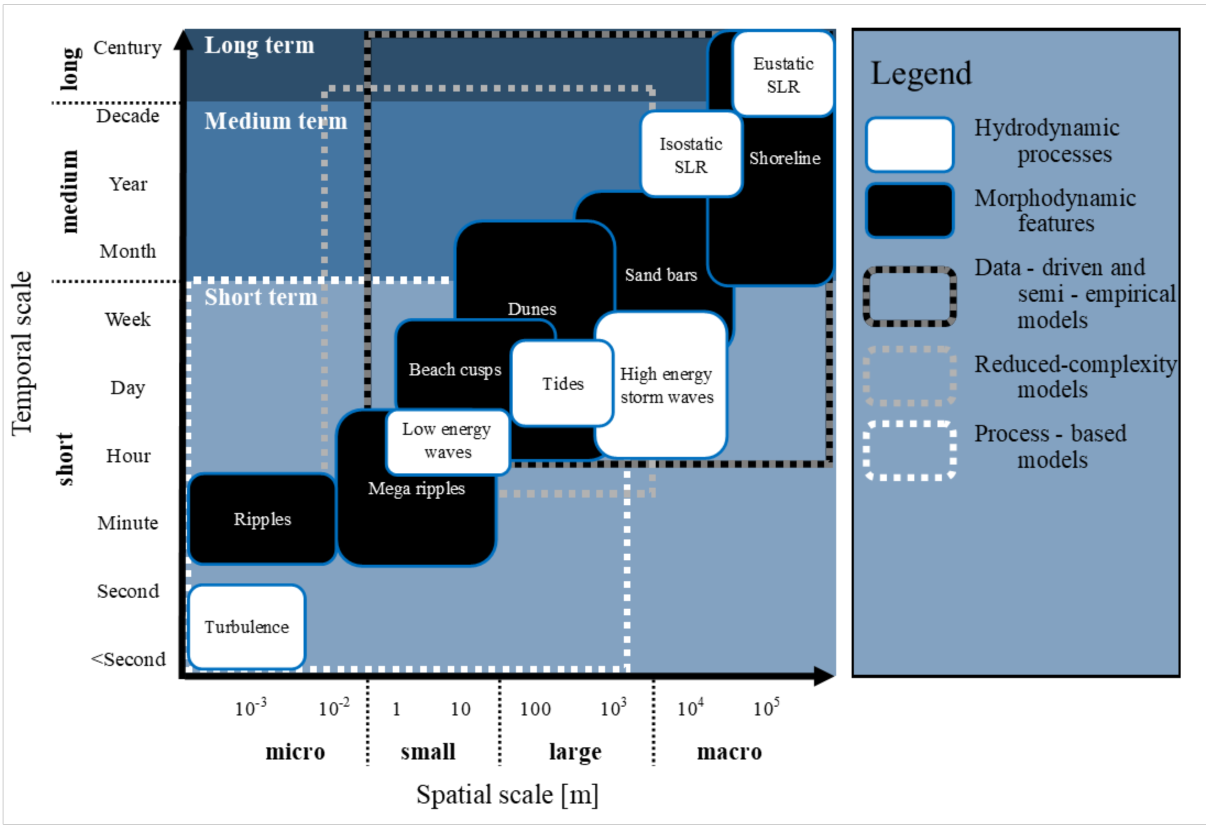

Figure 1. A schematic diagram representing approximate spatial and temporal modelling scales that are appropriate to hydrodynamic processes (white box) and morphodynamic features (black box). Typical temporal/spatial scales are represented for each model class (as described in Figure 2). Timescale classifications (short-to-long) are represented, referred to throughout the paper. SLR refers to sea level rise. Aspects of this figure have been modified from Fenster et al. (1993), Winter (2012)

A suggested classification of approaches to modelling coastal evolution is presented in Section 2, with special reference to equilibrium models in Section 3, which have emerged as particularly useful means of generating stable, computationally-efficient, long-term models of coastal processes. Sections 2 and 3 present the framework for a more general overview of shoreline modelling on timescales of days-to-decades in Section 4, followed by a discussion and concluding remarks on the future direction and challenges in shoreline modelling (Section 5).

2 The modelling complexity spectrum

Models of coastal morphodynamic evolution vary greatly in their complexity, computational demands, stability and prediction horizon. Each method has its own advantages/disadvantages, simplifications and assumptions. Therefore, classifying models can ensure that a model is appropriately selected based upon user requirements, the availability of calibration data and accepted best practices. Classification of coastal models (c.f. Wolinsky, 2009, Reeve et al., 2016, De Vriend, 1997) is becoming increasingly challenging as models are developed and combined. Models are generally classified based upon spatial (metres/kilometres), temporal scales (short-term/long-term), or dimensions (e.g., profile, depth-averaged coastal area, 3D models). As technology and process knowledge advances, new developments are based on coupling different models, each of which can resolve different temporal/spatial scales and/or processes.

Simple conceptual models of coastal evolution have been around for many decades (Bruun, 1988, Dean, 1977, Hanson and Kraus, 1989). In the 1990s, the advent of modern computers, better field measurements/coastal monitoring technology and improved coastal process understanding, led to a commonly adopted approach to predicting coastal change through the appropriate mathematical aggregation of small-scale processes into physics-based (process) models. Although this approach is fundamentally sound and incredibly powerful for predicting a range of hydrodynamic processes and shorter-term morphodynamic responses, it has been hindered in the area of medium-to-long term (years/decades) application by computational complexity (e.g., speed, stability and sensitivity to initial conditions), especially at regional spatial scales. The continual evolution of physics-based, process models and improved computational capabilities are now starting to mitigate some of these traditional limitations (O'Shea and Murphy, 2020, Van Der Wegen and Roelvink, 2008, Dastgheib et al., 2008), and may potentially be the best solution in the future. However, process models were challenged in the late 1990s by the arrival of an increasing number of high-quality, long-term, morphodynamic datasets and a more heretic approach to modelling coastal processes in the form of data-driven modelling (Hsu et al., 1994, Southgate, 2003), which omitted much of the process knowledge and was far more empirical. Some debate emerged in the community of coastal scientists as to the most productive method of predicting medium-to-long term coastal evolution. The quality and duration of such datasets continue to develop today, with better long-term monitoring in place in some areas (Turner et al., 2016, Senechal et al., 2009, Kroon et al., 2008, Castelle et al., 2020, Ludka et al., 2019) and improved technology, including coastal video monitoring systems (Holman et al., 1993, Smit et al., 2007, Kroon et al., 2007, Siegle et al., 2007, Davidson et al., 2007) and satellite data (e.g. Castelle et al., 2021, Vos et al., 2019a, Luijendijk et al., 2018, Vos et al., 2019b). However, the polarisation of modelling approaches has significantly blurred into a plethora of reduced-complexity models that attempt to combine the most impactful processes with the stability and computational efficiency of data-driven models.

Consistent with an anticipated broader evolution towards more reduced complexity models, it is therefore perhaps better to consider coastal morphodynamic models as a continuum. Figures 2 and 3 demonstrate such a complexity-spectrum and the appropriate application of the models. The 'bottom-up' approach to coastal modelling adopted by process models is positioned at the base of the diagram and represents the most complex and inclusive process models (Figure 2). The complexity spectrum progresses upwards through reduced-complexity and semi-empirical models to purely data-driven (top-down) models at the top. The advantages (green) and disadvantages (red) with progression up and down the complexity spectrum are indicated at each side of the diagram. Moving towards the top of the diagram, models become simpler, more stable and computationally efficient, with the potential for longer model runs. This progression (upwards) is accompanied by the negative effects (red) of reduced generality, an increased need for calibration data and reduced capacity to deal with system complexities (e.g., structures, complex geology and sources and sinks of sediment). Example models have been illustrated for each level of the complexity spectrum.

Figure 3 illustrates how the appropriate model choice trajectory is functionally dependent, (amongst other factors discussed previously), on both data availability and process knowledge. A high level of process understanding will facilitate process models with high fidelity, even in the absence of relevant calibration data. Conversely, in the absence of sufficient process understanding, but an abundance of relevant data, one may proceed with a data-driven modelling approach (Figure 2).

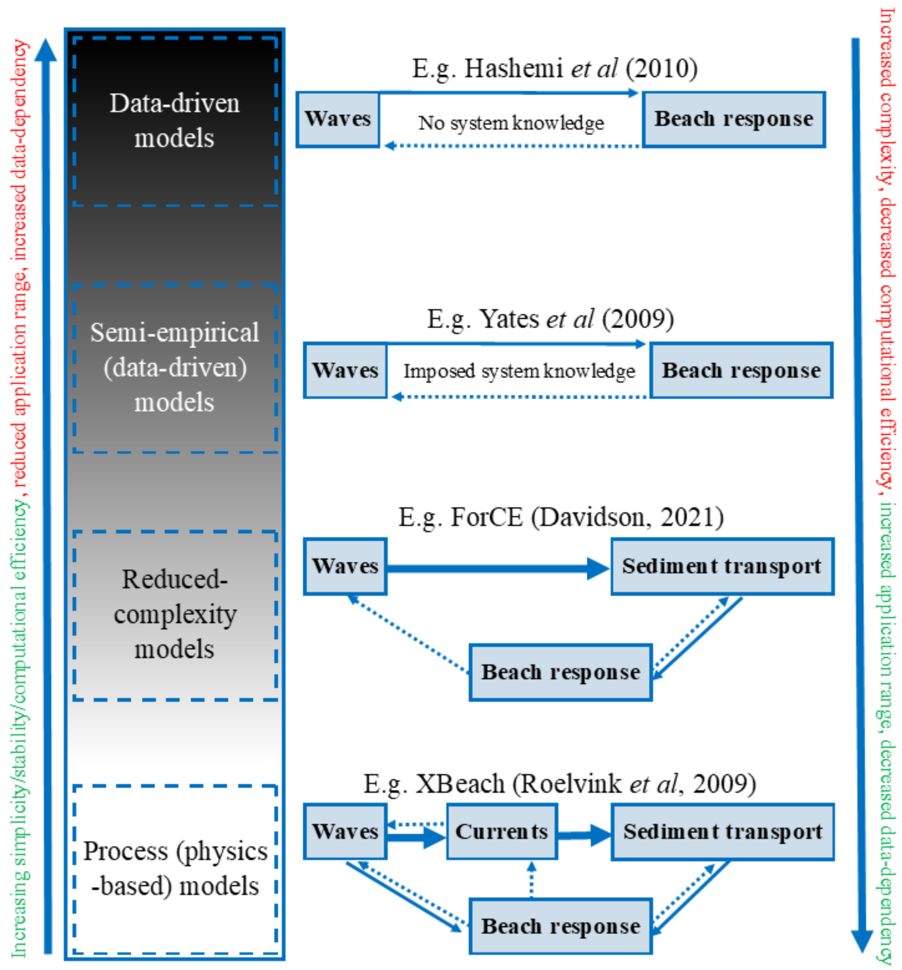

Figure 2. The morphodynamic modelling complexity spectrum (left), with corresponding simplified model examples on the right. Advantages/disadvantages are shown in green/red, respectively.

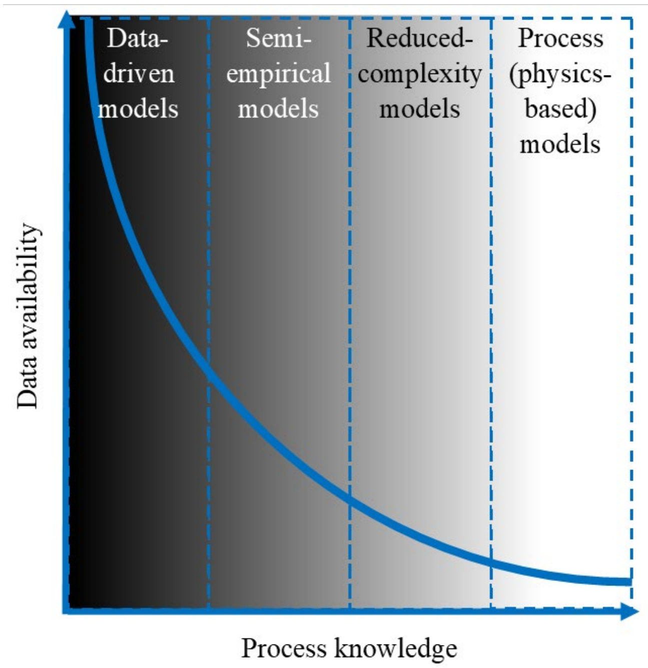

Figure 3. Schematic diagram demonstrating the relationship between typical model classifications (classified according to Figure 3), the availability of data and the current knowledge of processes.

3 Equilibrium concepts

Although beaches respond to, and are spatially translated by, eustatic and isostatic changes in sea level, they are remarkably persistent in time, often remaining for many centuries in the same location. The longevity of beaches and adaption to sea level change (e.g., raised beaches) strongly suggests that beaches are systems in a state of dynamic equilibrium. Therefore, it is not surprising that models with strongly embedded equilibrium concepts (Table 1) have been particularly successful in predicting a plethora of coastal morphodynamic processes. In the short-to-medium term (days-to-years), beaches can be modelled as systems that are perturbed around an underlying static equilibrium state. However, over the longer (multi-decadal) timescales, changes in sea level and wave climate demand a model that displays perturbations around a dynamic underlying equilibrium condition.

Equilibrium models are based upon the theory that the modelled process will vary temporally around a static or dynamically varying equilibrium value. Equilibrium models can be represented using the following simple generalisation:

$$\frac{d\zeta}{dt} = \mu\mathcal{F}[\psi_e - \psi]\,\chi + \text{ additional terms} \tag{1}$$

where $\frac{d\zeta}{dt}$ represents temporal change in some aspect of the beach morphology (e.g., shoreline position or beach volume), μ is a (tuneable) response rate parameter, $\mathcal{F}$ is a forcing term (usually related to incident waves), ψ is a dependent parameter (typically the shoreline location, dimensionless fall velocity or wave energy) and ψ_e is the long-term (or weighted) average of antecedent values of ψ. Note that in static equilibrium models, ψ_e is constant in time, but in dynamic equilibrium systems it varies temporally. In simple equilibrium models $\chi = 1$, whilst in more complex models, χ is a spatially varying shape function. Davidson and Turner (2009), for example, used χ to describe the cross-shore behaviour of morphological change in a profile model. The 'additional terms' in Equation 1 are stated in recognition that the model may have source or sink terms governed by other processes (e.g., sea level rise). A characteristic of equilibrium systems is that they trend asymptotically to the underlying equilibrium value with time under conditions of constant forcing ($\mathcal{F} = \text{constant}, \psi_e = \text{constant}$). The sign of the bracketed quantity in Equation 1 can be referred to as the disequilibrium and controls the direction of change (positive or negative), whilst the response rate and forcing term dictate the magnitude of the change.

Table 1 presents some illustrative, but not exhaustive, examples of published equilibrium models for a range of coastal phenomena, indicating the versatility and applicability of this class of model to nearshore systems. Equilibrium models are represented across a broad range of the complexity spectrum (Figure 2) (excluding pure data-driven models) and are most prevalent in the semi-empirical and reduced-complexity models, discussed in the following section. That said, embedding equilibrium concepts within process models to improve skill, stability and long-term predictions, are an ongoing area of research. Possibly one of the earliest examples of a model in the form of Equation 1 is the Wright et al. (1985) beach state prediction model (Table 1), which introduced the important concept of 'beach memory' and meant that future predicted beach states were crucially affected by antecedent wave conditions.

4 Modelling Approaches

Here, we use the complexity spectrum (Figure 2) as a framework for the discussion of a range of modelling approaches, starting with data-driven models and progressing to more complex

Table 1. Summary table of a selection of prominent models with (embedded) equilibrium components for a range of coastal processes. ***Key:*** *ζ - modelled variable, x – shoreline position, z – bed level, H, E, P, D – Wave height, energy, power and dissipation, c – Model tuning coefficient(s) (NB. including subscripts if more than one & values vary for each table row), Ω – dimensionless fall velocity, S – wave steepness, subscript e – represents equilibrium value. Other symbols are defined in the comment's column.*

Author	$\boldsymbol{\zeta(t)}$	$\boldsymbol{\mathcal{F}(t)}$	$\boldsymbol{\psi(t)}$	$\boldsymbol{\psi_e}$	**Comments**
Wright et al., 1985	Beach state (1-5)	Ω	$\Omega = H/\omega T$	$\Omega_e = \frac{\sum_{i=0}^{i=2\phi} 10^{i/\phi}\Omega_i}{\sum_{i=0}^{i=2\phi} 10^{i/\phi}}$	ϕ is the number of days before the prediction time and represents the '*beach memory*'.
Larson and Kraus, 1989	Sediment transport	c_1 *Sand transport rate coefficient*	$D + \frac{c_2}{c_1}\frac{dh}{dx}$ ε= slope transport rate coefficient	D_e Constant value specific to site/beach profile	SBEACH profile model which contains 4 distinct transport zones. This disequilibrium term operates in the surfzone.
Plant et al., 1999	Sandbar position	$c_1 H^2$	x_{bar}	$c_2 H$	Equilibrium bar position changes with H
Madsen & Plant, 2001	Beach gradient (β)	$c_1 H^p$	β	$\beta_e = f(H, L, D)$	p – variable exponent
Miller & Dean, 2004	Shoreline	$c = f(H \text{ or } \Omega))$	x	$x_e = f(W, B, H, \eta)$	Cross-shore transport only
Davidson & Turner, 2009	Profile	$c\ P^{0.5}\zeta(x,t)$	Ω	$\overline{\Omega}$	Here $\zeta(x,t)$ is a dimensionless cross-shore varying shape function
Yates et al., 2009	Shoreline	$c_1^{\pm}\ E^{0.5}$	E	$c_2 x + c_3$	Cross -shore transport only
Davidson et al., 2013	Shoreline	$c^{\pm}\ P^{0.5}$	Ω	$\Omega_e = \frac{\sum_{i=0}^{i=2\phi} 10^{i/\phi}\Omega_i}{\sum_{i=0}^{i=2\phi} 10^{i/\phi}}$	ShoreFor model, cross -shore transport only
Turki et al., 2013	Shoreline	$c\ \omega$	R	R_e	Longshore transport only. R= x-displacement at the embayment edge. ω is the rate of beach change = *f*(wave parameters and embayment geometry)
Stokes, et al., 2015	Sandbar rhythmicity	$c^{\pm}\ P^{0.5}$	Ω	$\Omega_e = \frac{\sum_{i=0}^{i=2\phi} 10^{i/\phi}\Omega_i}{\sum_{i=0}^{i=2\phi} 10^{i/\phi}}$	ShoreFor-type model
Prodger et al., 2016	Grainsize / sorting	c	S	$S_e = \frac{\sum_{i=0}^{i=2\phi} 10^{i/\phi} S_i}{\sum_{i=0}^{i=2\phi} 10^{i/\phi}}$	ShoreFor-type model based on wave steepness
Vitousek et al., 2017	Shoreline	One-line model with Yates et al., (2009) for cross-shore terms			Longshore & cross-shore processes
Burvingt et al., 2018	Beach volume	$c^{\pm}\ P^{0.5}$	Ω	$\Omega_e = \frac{\sum_{i=0}^{i=2\phi} 10^{i/\phi}\Omega_i}{\sum_{i=0}^{i=2\phi} 10^{i/\phi}}$	ShoreFor model applied to beach volume.
Robinet et al., 2018	Shoreline	One-line model with Davidson et al., (2013) for cross-shore terms.			Cellular one-line model
Davidson, 2021	Sediment transport	c_1	$D + \frac{c_2}{c_1}\frac{dz}{dx}$	$D_e(x) + \frac{c_2}{c_1}\beta_e$	ForCE model. Profile model like SBEACH.

physics-based process models. We detail a wide range of models beyond the traditional shoreline models, e.g., profile models, whereby a shoreline value may be extracted.

4.1 Data-driven models

Data-driven models are essentially a '*black box*' technology, mapping the forcing directly to morphodynamic response, with no imposed/intervening system knowledge. The key advantage of this approach is that gaps in system knowledge are no longer an obstacle to prediction and can be instead learned by an algorithm. Data-driven models involve making predictions of unseen/future coastal state based on empirical relationships between the model forcing and response timeseries, with no prior knowledge of the internal processes involved.

This class of model has grown in popularity alongside the emergence of long-term morphodynamic datasets. Manual methods of coastal monitoring, through in-situ survey for example, have previously taken considerable time and labour to generate, limiting the application of data-driven models to a small number of coastal locations. However, the volume of available coastal morphodynamic datasets has increased significantly in recent years, including data sources like coastal video systems and drone technology, and – most notably – satellite-derived shoreline data (e.g. Castelle et al., 2021, Vos et al., 2019a, Luijendijk et al., 2018), making the use of fully data-driven models a more realistic opportunity and opening the door for the emergence of machine-learning techniques.

Goldstein et al. (2019) presents a detailed review of such machine-learning techniques within the context of coastal applications. Goldstein et al. (2019) note that machine-learning models fundamentally differ from statistical/empirical models, as there are no assumptions or hypothesis about the structure of the relationship in the data, and instead there is an automated searching for rules and relationships. Additionally, in machine-learning, no restrictive assumptions about the data are made, for example, no specific distribution is required for residuals. Therefore, statistical and machine-learning modelling techniques are discussed separately in the following sections.

4.1.1 Statistical Models

Statistical models infer relationships between variables, to understand and extrapolate beyond the limits of the dataset. Morphodynamic datasets are often irregularly sampled in time, making decomposition of the signals using conventional spectral analysis difficult, leading early investigators to use Empirical Orthogonal Function (EOF) analysis to decompose the temporal evolution of different modes of morphology, whereby different modes can represent key beach processes (e.g., cross-shore/longshore transport), enabling analysis and prediction of coastal changes (e.g. Winant et al., 1975, Aranuvachapun and Johnson, 1978, Wijnberg and Terwindt, 1995, Reeve et al., 2001). Winant et al. (1975) were the first to apply this technique to coastal modelling, followed by an extension to 3-dimensions by Hsu et al. (1986) and Medina et al. (1992), using both cross-shore and longshore eigenfunctions to describe temporal morphological variations. Canonical Correlation Analysis (CCA) has been used in a similar fashion to study bar dynamics (Różyński, 2003) and to link beach profile evolution to wave forcing (Larson et al., 2000, Horrillo-Caraballo and Reeve, 2008, Horrillo-Caraballo and Reeve, 2010).

Bayesian networks (BN), a probabilistic graphical model that explicitly represents the conditional dependencies that link variables, have also been applied to shoreline prediction problems, with most developments occurring since the 1990s. Nodes within these networks represent variables, while arrows demonstrate the cause-effect relationships between associated nodal points. The simplicity of this approach means it is intuitive and provides a fast and computationally-efficient solution. Studies have demonstrated positive results, with BN shoreline models replicating up to 71% (Gutierrez et al., 2011) and 88% (Beuzen et al., 2018) of shoreline variability. Beuzen et al. (2018) developed a BN to model shoreline change during storm events at Narrabeen-Collaroy, Australia, tested against 10 years of data. Multiple BNs were investigated within the study, with the most successful model able to reproduce up to 88% of the variability in the training dataset. Plant and Stockdon (2012) developed a BN to predict barrier-island response to extreme conditions, predicting dune-crest elevation as a function of dune-base elevation, storm-induced mean water level and storm-induced extreme run-up. The computational-efficiency of BNs conveniently facilitates Monte Carlo simulations of shoreline change (Wikle and Berliner, 2007), which are now a popular technique within coastal literature.

4.1.2 Machine-Learning Models

Machine learning models are algorithms that enable the computer to 'learn' from a dataset, based on inferred relationships. Artificial Neural Networks (ANNs) are a prominent data-driven methodology which have been used to link wave information directly to shoreline (e.g. Alizadeh et al., 2011) and profile response (e.g. Hashemi et al., 2010). ANNs consist of a series of node layers connecting an input layer (here, wave parameters) to an output layer (beach response), via one or more hidden layers. During training, the relations between the input and output datasets are 'learnt' and the relationships quantified within the hidden layers. The term 'deep learning' is often used to describe ANNs, whereby the greater the number of hidden layers, the 'deeper' the learning.

There are various types of ANN, which have been applied to a wide range of coastal problems. ANNs may be classified due to their structure, data-flow direction or density of neurons. A Feed Forward Neural Network (FFNN) (e.g. Rajasree et al. (2016), López et al. (2018), Hashemi et al. (2010), Goncalves et al. (2012)) is the most simple form of ANN, with input data travelling in only one direction and weightings remaining consistent. Goncalves et al. (2012) utilised a multi-layer FFNN to model short-term shoreline change and directly compared results with linear regression and robust parameter estimation models (whereby a normal distribution is assumed, and the effects of outliers are isolated and 'down-weighted'), while Rajasree et al. (2016) used a multi-layer FFNN to model long-term shoreline simulations, trained with past satellite images. López et al. (2018) and Hashemi et al. (2010) both utilised a 3-layer FFNN with backpropagation to model a cross-shore profile, demonstrating reasonable success.

A multi-layer perceptron ANN comprises a fully connected network. Weightings are learnt, modified and improved through iterative comparison between predicted outputs and the training dataset, and data propagation is bi-directional. Alizadeh et al. (2011) provided input wind and wave data into a multi-layer perceptron ANN to model shoreline position outputs and demonstrated good comparison with validation data. More recently, Simmons and Splinter (2022) demonstrated that a multi-layer perceptron ANN proved the most skilful under storm conditions when compared to process and reduced-complexity models.

Recurrent Neural Networks (RNNs) differ from the more basic ANNs due to the addition of a 'memory', which enables the incorporation of dependencies of data points upon previous data points. Zeinali et al. (2021) utilises a non-linear RNN to model short-term shoreline changes in Narrabeen, Australia, which performed well when compared to the training data. The study also explored a generalised regression, radial based function and time delay ANN. These methods proved to be simpler than the RNN algorithms, but not as skilful.

Recent blind tests of data-driven models applied to Tairua Beach, New Zealand (Montaño et al., 2020) have showed that data-driven models performed comparably to semi-empirical models. However, a specific challenge to the data-driven class of model is the lack of generality when predictions are extrapolated to encompass new sites or forcing conditions that were outside the parameter space of their training datasets. To some extent, generality can be improved by the addition of noise to input variables to avoid over tuning ANNs to specific data (Reed and Marks, 1999), for example, but the lack of generality remains a major limitation of this modelling type.

4.2 Semi-empirical models

Semi-empirical models link wave parameters (e.g., wave height, period and direction) directly to coastal response via equations that implicitly impose some system knowledge, without the intermediate steps of computing the details of complex wave shoaling and dissipation, the generation of nearshore currents or even sediment transport. These models are generally quite simple models, which whilst demanding some calibration data, are less data-dependent than their data-driven model counterparts. Frequently, the simplicity of these models restricts their widespread application, with some prominent models only being applicable to coastlines dominated by either longshore and/or cross-shore transport processes, for example. Generally, the computation of shoreline change due to gradients in longshore transport involves the intermediate steps of computing sediment flux and applying the conservation of volume principles; such models are discussed in section 4.3 (reduced-complexity models).

A range of semi-empirical models are presented in Table 1 for the prediction of the temporal evolution of a range of nearshore processes on cross-shore transport dominated coastlines, including: shoreline position (Yates et al., 2009, Davidson et al., 2013, Vitousek et al., 2017, Miller and Dean, 2004), beach volume (Burvingt et al., 2018), beach profile (Hsu et al., 1994, Tinker et al., 2009) , beach gradient (Madsen and Plant, 2001), sediment sorting and grain size (Prodger et al., 2016) and sand bar location/rhythmicity (Plant et al., 1999). Equilibrium models (Section 3) feature heavily amongst the semi-empirical class. When incident wave energy exceeds the antecedent average values, beaches tend to erode, shorelines recede landward, beach profiles flatten, sediments coarsen and become better sorted, and bars migrate offshore and straighten. The reverse is true when wave energy is less than the antecedent average value.

The empirical model of Wright et al. (1985) developed the foundation for subsequent profile models (Hsu et al., 1994, Davidson and Turner, 2009), while Miller and Dean (2004) were amongst one of the first to develop a semi-empirical model to forecast shoreline change, setting the path for similar models (Yates et al., 2009).

Shoreline rotation is a key process within some embayments that is perhaps lacking in previous equilibrium models. Turki et al. (2013) and Jaramillo et al. (2021) both present an equilibrium model for shoreline rotation, utilising the foundations provided by Miller and Dean (2004) and further developed by Yates et al. (2009).

In a simultaneous, but independent, development to Yates et al. (2009), Davidson and Turner (2009) proposed an equilibrium profile model with a forcing term proportional to the squared dimensionless fall velocity and a constant (static) equilibrium term, equal to the mean dimensionless fall velocity. The shoreline extracted from this profile evolution agreed well with observations and led to a further reduction into a shoreline model by Davidson et al. (2011), demonstrating its use in the projection of coastal change in the absence of measured waves using a Monte Carlo simulation forced by synthetic waves. This method of long-term projection was later extended (Davidson et al., 2017) where short-term predictions (≤7 days) forced by forecasted waves were complemented by projections using a statistical analysis of Monte Carlo simulations, forced by synthetic waves to produce a seamless assessment of beach evolution across multiple (short-to-long term) timescales (Davidson et al., 2019, Steele et al., 2019).

While the shoreline model of Davidson et al. (2011) demonstrated promising results at Gold Coast, Australia, it performed less well at other test sites, leading to the development of the ShoreFor model (Davidson et al., 2013), which included a dynamic equilibrium term that was functionally dependent on a weighted average of the antecedent dimensionless fall velocity (Table 1). Splinter et al. (2014) demonstrated that the resulting ShoreFor model skilfully predicted shoreline evolution at eight different global locations and that the model free parameters related systematically to site specific variables including wave and sediment parameters, promising more generic application of the model on cross-shore transport dominated coasts without the need for extensive calibration.

4.3 Reduced-complexity models

Reduced-complexity models include key processes, focussing only on specific aspects that are crucial to the representation of that process (van Maanen et al., 2016) at the target spatial and temporal scales (Figure 1). In a shoreline modelling context, this class of model covers a wide range of complexity space in Figure 2 (relative to data-driven models), and often involve increased dimensionality, more detailed treatment of wave shoaling and dissipation, explicit calculation of sediment transport and application of the principles of conservation of mass/volume. This type of model is generally better equipped to deal with more complex coastal environments, where simpler data-driven or semi-empirical models might struggle to replicate reality. Models are very diverse within this category, but some might include the effects of both significant longshore and cross-shore sediment transport components, natural headlands and coastal structures, for example.

4.3.1 Beach profile models

Beach profile models include a shoreline data-point and usefully extend the morphodynamic prediction in a cross-shore direction, in some cases facilitating the explicit modelling of the shoaling and dissipation of incident waves and changing sea level. Practically, profile models are very useful as they lend themselves to the prediction of coastal overtopping and flooding. The most versatile of these models in terms of daily to decadal projections are simplified further by depth-averaging. The further reduction of complexity in some of the models discussed here comes from the direct link between wave dissipation to sediment transport without explicit consideration of the intermediate process of generating surf zone currents.

The SBEACH model (Larson and Kraus, 1989) explicitly modelled wave shoaling, dissipation and setup across the beach profile. The model was designed to forecast storm induced beach change; however, the model formulation is both simple and sufficiently numerically efficient to facilitate projection to much longer time periods, providing the solutions remain skilful and stable. For the computation of sediment transport, the profile was divided into four morphodynamic zones. Sediment transport was computed in the surfzone and values at the surfzone boundaries were systematically attenuated at different rates through the other zones. Sediment transport in the surfzone was governed by an equilibrium equation (Table 1). This equilibrium term is a fixed, site-specific dissipation value (static equilibrium), with the profile evolution obtained by applying the principle of conservation of mass to the cross-shore distribution of sediment flux. The SBEACH model has been widely applied to a range of field and laboratory settings and demonstrates skilful predictions (Larson and Kraus, 1989, Rosati et al., 1993, Sommerfeld, 1996).

The Forecasting Coastal Evolution (ForCE) model (Davidson, 2021) fundamentally follows a similar method to that of SBEACH. Unlike SBEACH, ForCE has a single sediment transport equation (one zone, not four), which varies in magnitude in a cross-shore direction scaled by the spatial distribution in wave energy dissipation derived from a Battjes and Janssen (1978) wave model. The ForCE model is computationally simple and stable and allows for changing water levels due to tides, surge and longer-term sea-level rise (dynamic equilibrium).

Wolinsky and Murray (2009) developed a shoreline evolution model which predicts the evolution over long timescales of decades to millennia. This applied conservation principles through application of the shoreline Exner Equation for the conservation of sediment mass (Paola and Voller, 2005), and necessarily included not only the impacts of sea level rise, but also carefully accounted for the inland topography and substrate lithology. Results from the model suggested that shoreline retreat is highly dependent on the inland morphology and can potentially cause considerable deviation from simple Bruun (1962) law projections of shoreline recession due to sea level rise.

There have been many other profile translation models which can resolve coastal changes at short- to long- term timescales. Of these, the shoreline translation model of Cowell et al. (1995) affords a probabilistic estimate of profile change, allowing for open sediment budgets, storm variability, effects of mixed sediment sizes, and variable resistance in substrate material. Kinsela et al. (2017) introduced a mechanism for including short-term variability and Beuzen et al. (2018) used a shoreline translation mode to examine the impact of coastal structures. McCarroll et al. (2021) presented a rules-based solution based on the measured beach profile, which allowed for a variety of inland morphologies, including coastal structures.

Whilst many of the profile models discussed here include the capacity to include longshore gradients in sediment transport, this process is not modelled directly in most of the examples discussed above.

4.3.2 One-line models

Here, the term 'one-line model' represents the temporal evolution of the shoreline (rather than the beach profile). An early review of the evolution of one-line models can be found in Hanson (1989), which details the evolution of one-line models from their conception (Pelnard-Considère, 1957) to a more generalised application, including a variety of coastal structures and nature complexities (Hanson and Kraus, 1989). In an attempt to encapsulate cross-shore processes, subsequent early extension of one-line models to a multiple n-line format (e.g. Perlin and Dean, 1983) initially proved more difficult to validate and received much less practical engineering application (Hanson, 1989).

The initial restrictive "small wave angle" assumption imposed in the early analytical one-line models was partially relaxed with the advent of numerical 1D modelling approaches. The "small wave angle" assumption enables simplification of equations, based upon the foundation that the sine or tangent of the angle is approximately equal to the angle in question, providing the angle is "small" (Larson et al., 1987). Hanson and Kraus (1989) developed one of the best known and widely used one-line models, GENESIS (GENEralized model for SImulating Shoreline change) (Szmytkiewicz et al., 2000, Young et al., 1995, Wamsley et al., 2003, Carley et al., 1999, Hanson and Kraus, 2011, Krueger et al., 1988). The model considers sediment transport forced by oblique wave approach and longshore gradients in wave height and is one of the most ubiquitous models for the prediction of shoreline evolution on longshore transport dominated beaches over 1-100 months for coastlines 1-100km long. The ease of application and versatility of the GENESIS model in a variety of coastal settings led to an abundance of similar one-line modelling approaches, e.g. ONELINE (Kamphuis, 1993), LITPACK (Kristensen et al., 2016), UNIBEST-CL+ (Deltares, 2011) and LONGMOOR (Tonnon et al., 2018). Although the GENESIS model and other similar counterparts (Kristensen et al., 2016, Deltares, 2011) have been broadly applied worldwide, they have also been criticised in the literature (e.g. Young et al., 1995) for their simplifying assumptions and the reduced complexity philosophy.

4.3.3 Models combining cross-shore and longshore sediment transport processes.

A clear limitation of the early one-line models is the omission of cross-shore transport processes, which can be the dominant driver for shoreline change at some coastal localities. Models combining cross-shore and longshore transport processes promise much greater versatility in terms of their generic application.

The earlier attempts to extend one-line models to include cross-shore transport processes adopted by the n-line approach have been surpassed by the inclusion of semi-empirical models (Section 4.2), which are well suited to integration with one-line models. These models predict the impact of cross-shore sediment transport on shoreline evolution, whereby the cross-shore transport direction is dictated by a disequilibrium term (Hanson et al., 1997, Hanson and Larson, 1998, Robinet et al., 2018, Vitousek et al., 2017). Hanson et al. (1997) and Hanson and Larson (1998) presented one of the first examples of this approach, whereby the magnitude of the cross-shore transport term was functionally dependent on the product of the Shield's parameter, sediment fall velocity and the sediment grain size. The direction of transport, (onshore/offshore), was dictated by a comparison of the instantaneous fall velocity with a critical threshold value, not unlike the later equilibrium models, discussed in Section 3 (e.g. Davidson et al., 2011, 2013, Davidson and Turner, 2009).

Coupling of models is becoming a more common approach to enable inclusion of more processes, with Vitousek et al. (2017) presenting one of the first models to explicitly couple the one-line modelling format with an equilibrium shoreline model. CoSMoS-COAST is a hybrid one-line model which integrates the Yates et al. (2009) model for shoreline displacement due to cross-shore transport processes with a one-line model, and also includes terms that allow for a simple Brunn-law (Bruun, 1962) displacement of the shoreline due to sea level rise. The model was developed with the aim of predicting both medium- and long-term shoreline evolution, with a particular focus on responses to climate change. A key strength of CoSMoS-COAST was the use of an extended Kalman filter, enabling efficient calibration with limited data, assimilation of real-time data and the estimation of confidence intervals for model free parameters and predictions.

Robinet et al. (2018) developed a very similar model to Vitousek et al. (2017), integrating the Kamphuis (1993) longshore transport model with the ShoreFor model (Davidson et al., 2013) for the prediction of cross-shore terms. The resulting LX-Shore model included an accurate description of the nearshore wave field, derived from a spectral wave model and a cellular approach to shoreline modelling (as opposed to a one-line approach), which facilitated the modelling of complex morphologies, (e.g., sand spits).

Consideration of dune evolution is a key consideration when predicting shoreline change at some coastal locations. Antolínez et al. (2019) developed a COupled CrOss-shOre, loNg-shorE, and foreDune evolution model, COCOONED, that included the CERC longshore transport model in a one-line equation. Cross-shore transport was determined by the Miller and Dean (2004) equilibrium shoreline model. The model is applicable to similar time and space scales to CoSMoS-COAST, also including sediment source/sink and sea level terms, but additionally including the impacts of foredune erosion on shoreline change. A similar longshore/cross-shore transport one-line model was proposed by Palalane and Larson (2020), which also parametrised dune growth by aeolian transport as well as erosion.

4.4 Process models

Process, physics-based or bottom-up modelling approaches occupy the base of the complexity spectrum (Figure 2). This class exhibits a broad range of diversity, including depth-averaged models (1D/2D), depth-resolving models (2D/3D), coastal profile and area models. Sherwood et al. (2022) provide a more thorough overview of classification and application of process-based models. The application of detailed process-based models (e.g., Mike 21, Delft 3D, XBeach or Telemac) is an established modelling approach, including the detailed physics of wave propagation, dissipation, generation of nearshore currents, sediment transport and the resulting morphological change with multiple feedback loops (Lesser et al., 2004, Roelvink et al., 2009, Villaret et al., 2013, Warren and Bach, 1992). This class of model has proved very successful in predicting a range of nearshore phenomena including storm/dune erosion and wave overtopping.

Process models are computationally expensive, meaning medium-to-long term projections are often challenging. The upscaling of processes represented in the bottom-up approach can range from centimetres to several kilometres. Therefore, errors resulting from imperfect physics and empirical representation of model components can cause an aggregation of errors, which lead to instabilities and inaccuracies in long model runs. In principle, the inclusion of more detailed physics in process models means that this class of model is the most widely applicable, least dependent on data for calibration and best able to deal with coastal complexities (e.g., coastal structures, complex natural coastlines and estuaries). However, whilst process models have proved to be the most effective way of predicting waves, currents and sediment transport in the short-to-medium term (days-to-years), their application to longer term projections of morphological change still remain a significant challenge. The complexity and non-linearity of process models not only causes problems with long-term stability and computational complexity, but it also renders long-term projections extremely sensitive to very subtle changes in the initial conditions. Moreover, the Monte Carlo or ensemble models runs, which are required to establish the probability of given long-term projections, are reasonably straight forward for the less complex models, but remain significantly challenging for complex process models. For these reasons, discussion of these models here is relatively brief. Combining process models with data-driven approaches may offer the potential to maintain the complexity of process models with reduced computational demand. This is a novel method, requiring significant future development, however Itzkin et al. (2022) applied this approach to model dune and beach evolution with reasonable success over multi-year timescales.

5 Discussion and Concluding Remarks

This paper presents an overview of shoreline evolution models in terms of a modelling complexity spectrum (Figure 2). The appropriate choice of model complexity depends not only on the intended space-/time- scales to be modelled (Figure 1), and the target environment, it strongly pivots on the balance between current system knowledge and the availability of relevant data (Figure 3). At present, deficiencies in both system knowledge and the widespread availability of data, coupled with the diverse nature and complexity of coastal systems, has meant that the most promising approaches to modelling shoreline evolution on timescales of days-to-decades are reduced-complexity models, positioned in the centre of the complexity spectrum.

Providing only short-term predictions are required, the diverse and complex nature of coastal systems is best approached through process-based models at the base of the complexity spectrum. However, the complexity and hence computational cost of this class of model, coupled with a sensitivity to small variations in initial conditions, currently renders medium-to-long-term forecasts with these types of models very challenging, particularly at large space and timescales, and when Monte Carlo or ensemble simulations are required to generate probabilistic projections.

Conversely, data-driven models provide the required computational efficiency to generate multi-decadal projections of shoreline change with ease, but in the absence of extensive and widespread data, they lack the generality required to cope with system complexities like anthropogenic structures, hard rock geology, complex wave transformations, supra-tidal morphology (e.g. cliffs and dunes), mixed grain size beaches and potential additional sources/sinks of sediment (e.g. from estuaries or anthropogenic input). This means that these models have limited ability to extrapolate accurately beyond the parameter space of their training dataset. Therefore, the ability of these models to provide accurate morphological forecasts over the long term with changing wave climates and sea level is questionable. For these reasons, reduced-complexity models occupy the promising middle ground between process models and data-driven models.

The simplicity of reduced-complexity models means that it is relatively easy to embed data-assimilation methods (e.g., Kalman filters) within their algorithms. This has the advantage of efficiently calibrating models, making effective use of noisy data and assigning confidence limits to model free parameters and estimates, ultimately improving the accuracy of predictions (Long and Plant, 2012, Vitousek et al., 2017, Ibaceta et al., 2020, Alvarez-Cuesta et al., 2021, Ciritci and Turk, 2020).

Proceeding with the notion that reduced-complexity models offer the most realistic (immediate) vehicle for the prediction of coastal morphodynamic change on daily-to-decadal timescales (short-to-medium term) and beyond, what then are the future challenges that need to be addressed within this class of model before they become suitable effective and applied coastal management tools? The answers to this question are dependent on the target prediction horizon of the required forecast and discussed below accordingly, from short to long timescales. Medium and long term timescales have been discussed in conjunction, due to the shared challenges they face, particularly with regards to uncertainties surrounding model forcing.

5.1 Short term timescales

Over the short term (days-to-weeks), management objectives include the prediction of coastal evolution due to storms or storm sequences. The challenges within this timeframe include, optimising the complexity of the models so they can adequately cope with complex coastal environments and facilitate wide-spread regional application, whilst maintaining sufficient computational efficiency, skill and stability. Specifically, these complexities include coastal structures, mixed-beach sediments, sediment bypassing, dune-dynamics and limited sediment supply. Many of these challenges have already been partially solved in existing models, but bringing them together seamlessly in a single efficient model remains a significant challenge.

Short term (weather) data used as forcing are intrinsic to the shoreline modelling problem, directly impacting the skill of the shoreline models that they drive. The application of ensemble approaches (e.g. Saetra and Bidlot, 2004, Bunney and Saulter, 2015, Alves et al., 2013) is considered best practice in mitigating the initial condition uncertainty on short term timescales (Steele et al., 2017, Siddorn et al., 2016). A pioneering example application is described in the context of shoreline evolution by Steele et al. (2019).

5.2 Medium-to-long term timescales

Over the medium term (months-to-decades), models are required to resolve morphological changes over seasonal, interannual and longer-term climate change timescales. Here, models must consider slower and more poorly understood sediment transport processes, which become increasingly significant over longer timescales, including the erosion of cliff-backed coastlines of various lithology (Walkden and Dickson, 2008), natural and anthropogenic sediment source-sinks (e.g., river inputs and beach replenishment) and sediment transport between the surfzone on offshore regions beyond the depth of closure (Harley et al., 2022).

With the inclusion of more processes (complexity) required to achieve more widespread geographical application of models, care must be taken to maintain sufficient stability and computational efficiency, also required to model medium-to-long term coastal change. Here several methodologies can be invoked. Firstly, it has been demonstrated that the inherently stable equilibrium models discussed in

Section 3 are appropriate to a plethora of coastal processes and that embedding equilibrium processes in more complex models can significantly enhance stability. Secondly, complex processes can be accurately encapsulated by data learning methodologies, including Artificial Neural Networks (ANN). Thus, embedding ANNs within more complex models can also increase computational efficiency (Itzkin et al. (2022).

Medium-to-long term projections present even more challenges in terms of the provision of realistic (climate) forcing conditions for morphodynamic models. Wave forcing models required by morphological models must inherently account for much greater unknowns. These include the "internal variability", "model uncertainty" and "scenario uncertainty" (Hawkins and Sutton, 2009). Internal variability is associated with the natural fluctuations and chaotic nature of the climate system. Model uncertainty arises from the differences in the way individual models have been designed to replicate real-world processes. Scenario uncertainty is associated with future global economic and emissions trajectories. To account for these uncertainties and represent the possible future pathways, sets of emissions scenarios have been generated, with Representative Concentration Pathways (RCPs; Moss et al., 2010, Van Vuuren et al., 2011) or Shared Socioeconomic Pathways (SSPs; Riahi et al., 2017). Ensemble approaches, e.g. Monte Carlo simulations, are commonly adopted to generate wave forcing input parameters for coastal models (Davidson et al., 2010, Davidson et al., 2017, D'Anna et al., 2022, Antolínez et al., 2019, Antolínez et al., 2016), providing a probabilistic description of wave conditions and enabling uncertainty to be easily quantified. Vitousek et al. (2021) provide a literature review and detailed description of application of an ensemble approach using a Kalman filter, to simulate wave forcing for shoreline modelling. The use of ensemble forcing, where possible, is deemed necessary to account for intrinsic uncertainties (Vitousek et al., 2021).

Although sea level forcing can somewhat be considered of secondary importance in the context of shoreline modelling on short timescales, the impact of sea level rise cannot be neglected on medium-to-long timescales. Data suggests that while seasonal and interannual variability in wave conditions will continue to dominate the morphological response up until 2050, sea level rise is likely to be the main driver of coastal change beyond that (Davidson, 2021, Howard et al., 2019, D'Anna et al., 2021, D'Anna et al., 2022). There is currently no single model that can compute all the different contributions to both global and regional sea-level change directly – with the latest estimates compiled by determining the individual contributions to sea level separately and then combining these for different emissions scenarios (Fox-Kemper et al., 2021). To correctly inform local shoreline modelling, regional sea level projections are more appropriate than global means, (e.g. Chen et al., 2014, Hermans et al., 2020, Tinker et al., 2020). Relative sea level uncertainty varies greatly with geographical location – particularly in tectonically active areas and those where ocean dynamics may be subject to large changes – providing a further reminder of the care needed in the selection, treatment and interpretation of any forcing data (e.g. Vannitsem et al., 2021).

While differences exist between general circulation models (large-scale, numerical, climate models) in the detail of how wind fields are going to change in the future, there is generally better consensus in long-term trends of large-scale atmospheric patterns. Therefore, an alternative approach, potentially particularly well suited to seamless forecasts spanning short- to long- term (weather-to-climate) timescales, considers these *weather patterns* and *climate indices* that can be related directly to shoreline variability. Studies are starting to exploit this link to explain erosion/accretion events (Barnard et al., 2015, Castelle et al., 2017) and estimate shoreline evolution (e.g. Robinet et al., 2016, Anderson et al., 2018a, Wiggins et al., 2020, Montaño et al., 2021, Scott et al., 2021).

Extending reduced-complexity models to the long-term presents new challenges which are beyond the scope of detailed discussion here, but will likely include the use of rules-based modelling approaches

(Castelle and Masselink, 2023) and models with highly flexible grids and dynamic boundary conditions to cope with the high levels of coastal distortion (Roelvink et al., 2020), as well as a comprehensive consideration of eustatic and isostatic sea level variations.

5.3 Final remarks

Inevitably, the future direction of daily-to-decadal modelling of shoreline evolution will continue to be dynamic within complexity space (Figure 2). Progression towards the process-based end of the complexity spectrum will be facilitated by increasing computational capabilities and improved process knowledge. Conversely, the rapidly increasing availability of coastal data (e.g., satellite data) and data assimilation techniques promises increasing opportunity to migrate towards the data-driven end of the complexity spectrum. Therefore, occupying the promising middle ground, reduced-complexity models are well-positioned to benefit from the anticipated advances/drivers in both directions, building on their established potential for providing immediate practical, community-accessible capability for the seamless prediction/projection of shoreline change across timescales, through which further effective and efficient progress can be made.

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7 Conflict of interest statement

Conflicts of Interest: None.

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