Shoreline modelling on timescales of days to decades

Emily Hunt1, Mark Davidson1, Edward C. C. Steele2, Jessica D. Amies2, Timothy Scott1 and Paul Russell1

1Coastal Processes Research Group, University of Plymouth, Plymouth, PL4 8AA, UK and 2Met Office, FitzRoy Road, Exeter, EX1 3PB, UK

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 focused, 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 and 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 grain size, 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.

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 focused. 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.

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 (Scott et al., 2016; Castelle et al., 2018; Morim et al., 2018; Chowdhury et al., 2019; Morim et al., 2019; Meucci et al., 2020); rising sea levels (Nicholls et al., 2014; Fox-Kemper et al., 2021) and significant morphological changes and impacts to vulnerable coastlines (Enríquez et al., 2017; Wiggins et al., 2019; 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., 2018a). Morphodynamic change can result in
loss of land and infrastructure through erosion and can signifi-
cantly change the likelihood of wave overtopping and flooding.
Consequently, the development of methodological approaches
for predicting morphodynamic change over daily-to-decadal time-
scales 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 infor-
mation 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 indi-
cator (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 amongst 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 elabora-
tion. 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 dur-
ations surrounding longshore processes (weeks-to-years)
(Winter, 2012), although often overlap within the same cate-
gorised 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 consid-
eration of these processes in morpho-dynamic 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 dif-
erent 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.

A suggested classification of approaches to modelling coastal
evolution is presented in section ‘The modelling complexity
spectrum’, with special reference to equilibrium models in section
‘Equilibrium concepts’, which have emerged as particularly useful
means of generating stable, computationally-efficient, long-term
models of coastal processes. These sections (‘The modelling com-
plexity spectrum’ and ‘Equilibrium concepts’) present the frame-
work for a more general overview of shoreline modelling on
timescales of days-to-decades, presented in section ‘Modelling
approaches’, followed by a discussion and concluding remarks on

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 and referred to throughout the paper. SLR refers to sea level rise. Aspects of this figure have been modified from Fenster et al. (1993) and Winter (2012).
the future direction and challenges in shoreline modelling (section ‘Discussion and concluding remarks’).

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 (cf. De Vriend, 1997; Wolinsky, 2009; Reeve et al., 2016) is becoming increasingly challenging as models are developed and combined. Models are generally classified based upon spatial (metres/km), 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 (Dean, 1977; Bruun, 1988; 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 (Dastgheib et al., 2008; Van Der Wegen and Roelvink, 2008; O’Shea and Murphy, 2020), 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 et al., 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 (Kroon et al., 2008; Senechal et al., 2009; Turner et al., 2016; Ludka et al., 2019; Castelle et al., 2020) and improved technology, including coastal video monitoring systems (Holman et al., 1993; Davidson et al., 2007; Kroon et al., 2007; Siegle et al., 2007; Smit et al., 2007) and satellite data (e.g. Luijendijk et al., 2018; Vos et al., 2019a,b; Castelle et al., 2021). 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

![Figure 2. The morphodynamic modelling complexity spectrum (left), with corresponding simplified model examples on the right. Advantages/disadvantages are shown in green/red, respectively.](https://doi.org/10.1017/cft.2023.5 Published online by Cambridge University Press)
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:

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

(1)

where $\frac{d\psi}{dt}$ represents temporal change in some aspect of the beach morphology (e.g. shoreline position or beach volume), $\mu$ is a (tunable) response rate parameter, $F$ is a forcing term (usually related to incident waves), $\psi$ is a dependent parameter (typically the shoreline location, dimensionless fall velocity or wave energy) and $\psi_e$ is the long-term (or weighted) average of antecedent values of $\psi$. Note that in static equilibrium models, $\psi_e$ is constant in time, but in dynamic equilibrium systems it varies temporally. In simple equilibrium models $\chi = 1$, whilst in more complex models, $\chi$ is a spatially varying shape function. Davidson and Turner (2009), for example, used $\chi$ 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 tend asymptotically to the underlying equilibrium value with time under conditions of constant forcing ($F =$ constant, $\psi_e =$ 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.

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.

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 physics-based process models. We detail a wide range of models beyond the traditional shoreline models, for example, profile models, whereby a shoreline value may be extracted.
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. Luijendijk et al., 2018; Vos et al., 2019a; Castelle et al., 2021), 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) present 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.

### 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

### Table 1. Summary table of a selection of prominent models with (embedded) equilibrium components for a range of coastal processes

<table>
<thead>
<tr>
<th>References</th>
<th>$\zeta(t)$</th>
<th>$\mathcal{F}(t)$</th>
<th>$\psi(t)$</th>
<th>$\psi_e$</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wright et al., 1985</td>
<td>Beach state (1-5)</td>
<td>$\Omega = \frac{H}{aT}$</td>
<td>$\Omega = \sum_{k=0}^{\infty} \frac{H_{k}}{aT_{k}}$</td>
<td>$\phi$ is the number of days before the prediction time and represents the 'beach memory'</td>
<td></td>
</tr>
<tr>
<td>Larson and Kraus, 1989</td>
<td>Sediment transport</td>
<td>$c_l$ Sand transport rate coefficient</td>
<td>$D \cdot \frac{\partial \eta}{\partial x}$</td>
<td>$D_0$ Constant value specific to site/ beach profile</td>
<td>SBEACH profile model which contains four distinct transport zones. This disequilibrium term operates in the surfzone</td>
</tr>
<tr>
<td>Plant et al., 1999</td>
<td>Sandbar position</td>
<td>$c_l H^2$</td>
<td>$x_{bar}$</td>
<td>$c_j H$</td>
<td>Equilibrium bar position changes with $H$</td>
</tr>
<tr>
<td>Madsen and Plant, 2001</td>
<td>Beach gradient ($\beta$)</td>
<td>$c_l H^3$</td>
<td>$\beta$</td>
<td>$\beta_x = f(H, L, D)$</td>
<td>$p$ – variable exponent</td>
</tr>
<tr>
<td>Miller and Dean, 2004</td>
<td>Shoreline</td>
<td>$c = f(H or \Omega)$</td>
<td>$x$</td>
<td>$x_e = f(W, B, H, \eta)$</td>
<td>Cross-shore transport only</td>
</tr>
<tr>
<td>Davidson and Turner, 2009</td>
<td>Profile</td>
<td>$c_l \rho^{0.5} \zeta(x, t)$</td>
<td>$\Omega$</td>
<td>$\Omega$</td>
<td>Here $\zeta(x, t)$ is a dimensionless cross-shore varying shape function</td>
</tr>
<tr>
<td>Yates et al., 2009</td>
<td>Shoreline</td>
<td>$c_l \rho^{0.5} E$</td>
<td>$E$</td>
<td>$c_j x + c_2$</td>
<td>Cross-shore transport only</td>
</tr>
<tr>
<td>Davidson et al., 2013</td>
<td>Shoreline</td>
<td>$c_l \rho^{0.5}$</td>
<td>$\Omega$</td>
<td>$\Omega_{e} = \sum_{k=0}^{\infty} \frac{H_{k}}{aT_{k}}$</td>
<td>ShoreFor model, cross-shore transport only</td>
</tr>
<tr>
<td>Turki et al., 2013</td>
<td>Shoreline</td>
<td>$c_{ao}$</td>
<td>$R$</td>
<td>$R_h$</td>
<td>Longshore transport only. $R = x$-displacement at the embayment edge. $\omega$ is the rate of beach change $= f$ (wave parameters and embayment geometry)</td>
</tr>
<tr>
<td>Stokes et al., 2015</td>
<td>Sandbar rhythmicity</td>
<td>$c_l \rho^{0.5}$</td>
<td>$\Omega$</td>
<td>$\Omega_{e} = \sum_{k=0}^{\infty} \frac{H_{k}}{aT_{k}}$</td>
<td>ShoreFor-type model</td>
</tr>
<tr>
<td>Prodrer et al., 2016</td>
<td>Grain size/sorting</td>
<td>$c$</td>
<td>$S$</td>
<td>$S_e = \sum_{k=0}^{\infty} \frac{H_{k}}{aT_{k}}$</td>
<td>ShoreFor-type model based on wave steepness</td>
</tr>
<tr>
<td>Vitousek et al., 2017</td>
<td>Shoreline</td>
<td>One-line model with Yates et al. (2009) for cross-shore terms</td>
<td>Longshore and cross-shore processes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Burvingt et al., 2018</td>
<td>Beach volume</td>
<td>$c_l \rho^{0.5}$</td>
<td>$\Omega$</td>
<td>$\Omega_{e} = \sum_{k=0}^{\infty} \frac{H_{k}}{aT_{k}}$</td>
<td>ShoreFor model applied to beach volume</td>
</tr>
<tr>
<td>Robinet et al., 2018</td>
<td>Shoreline</td>
<td>One-line model with Davidson et al. (2013) for cross-shore terms</td>
<td>Cellular one-line model</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Davidson, 2021</td>
<td>Sediment transport</td>
<td>$c_l$</td>
<td>$D + \frac{\partial \eta}{\partial t}$</td>
<td>$D_i(x) + \frac{\partial \psi_e}{\partial t}$</td>
<td>ForCE model. Profile model like SBEACH</td>
</tr>
</tbody>
</table>

Note: $\zeta$, 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 and values vary for each table row); $\Omega$, dimensionless fall velocity; $S$, wave steepness; subscript $e$, represents equilibrium value. Other symbols are defined in the comments column.
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 (Wkle and Berliner, 2007), which are now a popular technique within coastal literature.

**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 simplicity models restrict 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 ‘Reduced-complexity models’.

A range of semi-empirical models is 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 (Miller and Dean, 2004; Yates et al., 2009; Davidson et al., 2013; Vitousek et al., 2017), 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 (Proctor et al., 2016) and sand bar location/behaviour (Plant et al., 1999). Equilibrium models (section ‘Equilibrium concepts’) 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 skillfully 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.

**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 involves 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.

**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 surzone boundaries were systematically attenuated at different rates through the other zones. Sediment transport in the surzone 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 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 predictions 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. McCarthy 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.
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) (Krueger et al., 1988; Young et al., 1995; Carley et al., 1999; Szymtkiewicz et al., 2000; Wamsley et al., 2003; Hanson and Kraus, 2011). 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 km 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, for example, ONELINE (Kamphuis, 1993), LITPACK (Kristensen et al., 2016), UNIBEST-CL+ (Deltas, 2011) and LONGMOOR (Tonnon et al., 2018). Although the GENESIS model and other similar counterparts (Deltas, 2011; Kristensen et al., 2016) 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.

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 ‘Semi-empirical models’), 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; Vitousek et al., 2017; Robinet et al., 2018). 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 Shields 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 ‘Equilibrium concepts’ (e.g. Davidson and Turner, 2009; Davidson et al., 2011, 2013).

Coupling of models is becoming a more common approach to enable the 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 (Brunn, 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. Antolín et al. (2019) developed a COupled GrOss-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 Palanale and Larson (2020), which also parametrised dune growth by aeolian transport as well as erosion.

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 the 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 (Warren and Bach, 1992; Lesser et al., 2004; Roelvink et al., 2009; Villaret et al., 2013). 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
target environment, and complexity, but it also renders long-term projections extremely
target prediction horizon of the required forecast and discussed
medium-to-long-term timescales have been discussed in conjunction, due to the
medium-to-long-term timescales, are reasonably straightforward for the less complex models, but remain
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
short-term timescales, 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.

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 ‘Equilibrium concepts’ 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, for example, Monte Carlo simulations, are commonly adopted to generate wave-forcing input parameters for coastal models (Davidson et al., 2010; Antolínez et al., 2016; Davidson et al., 2017; Antolínez et al., 2019; D’Anna et al., 2022), 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 the 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 (Howard et al., 2019; D’Anna et al., 2021; Davidson, 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., 2018b; 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.

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.

Open peer review. To view the open peer review materials for this article, please visit http://doi.org/10.1017/cft.2023.5.

Acknowledgements. E.H. would like to acknowledge the financial support from the School of Biological and Marine Sciences, University of Plymouth. The authors thank Teil Howard and Jonathan Tinker (Met Office) for their feedback on the final draft of the manuscript.

Competing interest. The authors declare none.

References


Anderson TR, Fletcher CH, Barbee MM, Romine BM, Lemmo S and Deleuvaux JMS (2018a) Modeling multiple sea level rise stresses reveals up to twice the land at risk compared to strictly passive flooding methods. Scientific Reports 8, 14484.

Anderson D, Ruggiero P, Antolínez JAA, Méndez FJ and Allan J (2018b) A climate index optimized for longshore sediment transport reveals


Howard T, Palmer MD and Bricheno LM (2019) Contributions to 21st century projections of extreme sea-level change around the UK. Environmental Research Communications 1, 095002.


