Modelling mesoscale evolution of managed sandy shorelines with particular reference to Caribbean small islands

Volume one
Main text and references

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‘For millennia beyond computation, the sea’s waves have battered the coastlines of the world with erosive effect, here cutting back a cliff, there stripping away tons of sand from a beach, and yet again, in a reversal of their destructiveness, building up a bar or a small island. Unlike the slow geologic changes that bring about the flooding of half a continent, the work of the waves is attuned to the brief span of human life, and so the sculpturing of the continent’s edge is something each of us can see for ourselves.’

– Rachel Carson

Abstract

Modelling the mesoscale (10^1 to 10^2 years and 10^1 to 10^2 km) evolution of managed sandy shorelines is becoming increasingly necessary to guide the management of sandy coastal systems. Models that simulate mesoscale shoreline evolution assume an equilibrium active coastal profile. An equilibrium active coastal profile implies a fixed closure depth, defined as the seaward extent of the active coastal area, and shore-parallel depth contours, which present two limitations. *First*, an inability to account for sea-level rise, which will likely change the closure depth and be endogenous in coastal evolution over meso timescales. *Second*, an inability to account for complex planform morphologies where the closure depth varies longshore and depth contours are non-parallel. Such morphologies characterise sandy coastal systems in many vulnerable Caribbean islands where shoreline evolution models are most needed to guide coastal management. Hence, this thesis aims to create a method that accounts for sea-level rise and complex planform morphologies in mesoscale shoreline evolution predictions.

Using a managed sandy coastal system in New York, Puerto Rico, and Southern California as test sites, I first assess the sensitivity of two mesoscale shoreline evolution models, MIKE21 and the Bruun Rule, to identify the most essential boundary conditions influencing shoreline evolution predictions in different coastal morphologies. I use the results of this sensitivity study to inform the development and application of three shoreline evolution modelling approaches, which include introducing: (a) a time-varying closure depth in MIKE21 as a solution to incorporate sea-level rise effects in mesoscale shoreline evolution predictions; (b) a space-varying closure depth in MIKE21 as a solution to account for complex planform morphologies in shoreline evolution predictions; and (c) a time and space-varying closure depth in MIKE21 as a solution to incorporate the effects of both sea-level rise and complex planform morphologies in meso timescale shoreline evolution predictions.

Model sensitivity results show that nearshore discretisation, bathymetry, tides, friction and sediment properties are the key boundary conditions that influence shoreline evolution predictions regardless of the underlying morphology. I find that the optimal specifications of these boundary conditions match coastal system features, both morphology and processes. Specifying a time-varying closure depth in MIKE21 is found to provide a better alternative to the Bruun Rule for simulating mesoscale shoreline evolution under relative sea-level rise. However, I find that a time-varying closure depth causes MIKE21 to overpredict erosion over meso timescales, attributed to mean closure depth overestimation. Hence, there is a chance that a time-varying closure depth may improve mesoscale shoreline evolution predictions if closure depth time series estimations can be accurately prescribed. Enabling a space-varying closure depth in MIKE21 is found to replicate observed shoreline change in the Puerto Rico test site's complex planform morphology more realistically than existing modelling approaches. Lastly, allowing a time and space-varying closure depth in MIKE21 is found to provide *theoretically plausible* meso timescale shoreline evolution predictions under relative sea-level rise in the Puerto Rico test site's complex planform morphology compared to current modelling approaches.

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‘For you, a thousand times over…’

– Khaled Hosseini (The Kite Runner)

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Introduction and research questions

'Although human alterations obscure the effects of natural processes, they still provide the best clues to the future evolution of coastal systems where human influence is an endogenous factor.'

– Karl F. Nordstrom

1.1 Research rationale

Modelling mesoscale shoreline evolution (10^1 to 10^2 years; 10^1 to 10^2 km) is becoming increasingly necessary to guide the management of sandy coastal systems, which continually adjust to subtle changes in external forcings (Ranasinghe, 2016; Payo et al., 2017; Cooper et al., 2018). External forcings include sea-level rise and coastal engineering solutions (Table 1.1). Sandy coastal systems are subject to extensive human occupation globally and are the primary socioeconomic resource for many Caribbean and Pacific islands (Nurse et al., 2014; Luijendijk et al., 2018). These islands are among the most vulnerable locations likely to be severely challenged by sea-level rise this century (Nicholls and Cazenave, 2010; Nurse et al., 2014). Human occupation of sandy coastal systems and 20th-century sea-level rise have accelerated the retreat of sandy shorelines in many regions, resulting in the extensive use of coastal engineering solutions, such as hard defences and shore nourishment (Schlacher et al., 2008; Jackson and Nordstrom, 2020). The extensive use of hard defences threatens the continued existence of sandy coastal systems, limiting their ability to migrate under sea-level rise (Mentaschi et al., 2018; Cooper et al., 2020). Hard defences reduce erosion by deflecting wave energy, shifting the erosion problem downdrift (Barkwith et al., 2014a). Downdrift erosion from hard defences is a critical problem affecting sandy coastal systems in many Caribbean and Pacific islands (Nurse et al., 2014; Mycoo and Donovan, 2017). Sea-level rise will likely worsen the erosion of managed sandy shorelines by modifying wave climates, and the resulting interactions between wave-generated currents and hard defences (Kim and Suh, 2018). The combined effects of sea-level rise and coastal engineering solutions can influence the evolution of sandy coastal systems over decades to centuries across tens to hundreds of kilometres (Table 1.1) (Slott et al., 2010; Ells and Murray, 2012; Barkwith et al., 2014a). As a result, modelling mesoscale shoreline evolution in response to sea-level rise and coastal engineering is becoming increasingly necessary to support the management of sandy coastal systems, especially those in vulnerable small islands (Nurse et al., 2014). However, modelling mesoscale shoreline evolution is one of the most significant challenges facing coastal managers (Van Maanen et al., 2016; Leach et al., 2019; Payo et al., 2020).

Coastal managers often use shoreline evolution predictions from two-dimensional horizontal (2DH) or behaviour-oriented models to understand processes influencing coastal morphology in order to inform coastal management (De Vriend et al., 1993a; Hanson et al., 2003; Pontee, 2017). 2DH models simulate the physics of shoreline evolution over time and space, incorporating the effects of sea-level rise and coastal engineering solutions (Reeve et al., 2016). However, 2DH models are limited to micro timescale simulations (hours to years) because they cannot represent the vertical variation of undertow currents, causing the coastal profile to degenerate to an unrealistic shape in longer simulations (Kristensen et al., 2013; Franz et al., 2017). Undertow currents are the primary driving flux of cross-shore sediment transport (Ruessink et al., 1998; Albernaz et al., 2019). In contrast, behaviour-oriented models replicate known coastal behaviour rather than the physics from which the ‘known coastal behaviour’ emerges (French et al., 2016). Specifically, behaviour-oriented models assume an equilibrium active coastal profile based on the one-line theory or the Bruun Rule (Larson et al., 1987; Pontee, 2017). The active coastal profile extends from the beach berm to closure depth. The closure depth is the depth beyond which there is no significant sediment transport (Kraus and Harikai, 1983). The one-line theory assumes the active coastal profile moves shore-normal from littoral drift, whereas the Bruun Rule assumes the active coastal profile shifts upward and landward from sea-level rise (Pelnard-Considere, 1956; Bruun, 1962). The exclusion of the underlying physics in model calculations and the assumption of an equilibrium active coastal profile ensure a stable morphology update over meso timescales, but prevent behaviour-oriented models from simulating the combined effects of sea-level rise and coastal engineering solutions on shoreline evolution (Roelvink et al., 2016; Pontee, 2017). Also, an equilibrium active coastal profile implies shore-parallel depth contours and a constant closure depth, limiting the applicability of behaviour-oriented models in complex planform morphologies (Hurst et al., 2015). Complex planform morphologies are defined herein by non-parallel depth contours and longshore closure depth variations, characteristic of sandy coastal systems with coral reefs in many Caribbean and Pacific small islands (Nurse et al., 2014).

The limitations of 2DH and behaviour-oriented models have inspired the development of hybrid models for simulating mesoscale shoreline evolution (Ashton and Murray, 2006a; Karunarathna et al., 2008; Kaergaard and Fredsoe, 2013). Hybrid models maintain the physics-driven approach of 2DH models but use the one-line theory assumptions to update the morphology (Reeve et al., 2019). Specifically, hybrid models simulate coastal sediment transport physics, incorporating the effects of external forcings and complex planform morphologies, and uniformly redistribute the derived sediment transport gradients over the active coastal profile. The active coastal profile moves shore-normal from a change in sediment balance, resulting in a change in shoreline position (Kristensen et al., 2013; Franz et al., 2017). Using the one-line theory assumptions to update the morphology prevents the breakdown of coastal profiles, allowing hybrid models to simulate mesoscale shoreline evolution whilst maintaining the underlying physics (Kristensen et al., 2013). However, there are two limitations of the one-line theory morphology updating approach in hybrid models. *First*, an inability to account for sea-level rise in mesoscale shoreline evolution predictions as the one-line theory assumes an equilibrium coastal profile that moves shore-normal from littoral drift, implying a constant closure depth (Kaergaard and Fredsoe, 2013). Sea-level rise will likely change the closure depth and be endogenous in coastal evolution over meso timescales (Nicholls et al., 1996; Hallin et al., 2019). The *second* limitation is a failure to account for complex planform morphologies in shoreline evolution predictions, which also stems from the one-line theory equilibrium profile assumption (Kaergaard and Fredsoe, 2013; Hurst et al., 2015). An equilibrium coastal profile implies shore-parallel contours, which are not characteristic of complex planform morphologies. Hence, accounting for sea-level rise and complex planform morphologies in mesoscale shoreline evolution models are novel challenges.

The largest constraint in refining and applying shoreline evolution models over meso time and space scales is the availability of high-quality data to specify boundary conditions (Splinter et al., 2013; Williams and Esteves, 2017; Reeve et al., 2019). Boundary conditions include nearshore bathymetry, tides, waves and wind, each of which influences sediment transport and shoreline morphology (Gonenc and Wolfin, 2004; Williams and Esteves, 2017). There are no established guidelines on the appropriate resolution of boundary conditions data for modelling mesoscale shoreline evolution (Reeve et al., 2019). Instead, it is usually assumed that higher resolution data improve mesoscale shoreline evolution predictions (Le Cozannet et al., 2014; Burningham and French, 2017). However, this assumption is never typically tested due to a global lack of high-resolution bathymetry and coastal processes data (Le Cozannet et al., 2019). Related studies use data either available, surveyed or extrapolated from past data without quantifying the effects on model predictions (Slott et al., 2010; Reeve et al., 2016; Van Maanen et al., 2016; Álvarez et al., 2020). Using limited, coarse or extrapolated data to specify boundary conditions over meso time and space scales can generalise complex processes and adversely affect shoreline evolution predictions (Le Cozannet et al., 2019; Cooper et al., 2020). As it stands, the optimal boundary conditions data for simulating mesoscale shoreline evolution in managed sandy coastal systems are not yet defined (Pilkey et al., 2013; Nicholls et al., 2016; Reeve et al., 2019). In addition to shoreline evolution predictions, data scarcity also affects the design of appropriate coastal management schemes, especially in Caribbean and Pacific small islands (Simpson et al., 2012; Nurse et al., 2014; Mycoo and Donovan, 2017; Rölfer et al., 2020). Identifying the optimal data requirements for modelling mesoscale shoreline evolution is important for being able to refine the structure of shoreline evolution models to better support coastal management (Reeve et al., 2019; Montano et al., 2020). After all, the accuracy of shoreline evolution models is closely related to the quality of their input data (Roelvink et al., 2016; Vitousek et al., 2017).

This thesis seeks to improve our ability to model the mesoscale evolution of managed sandy shorelines in two ways. *First*, comprehensively assessing the sensitivity of shoreline evolution predictions to key model specifications (resolution, input data, and parameterisation) using test sites in different managed coastal morphologies with high-resolution bathymetry and coastal processes data. *Second*, establishing two novel methods that allow hybrid models to fully account for sea-level rise and complex planform morphologies in mesoscale shoreline evolution predictions. Anticipated outcomes will improve our knowledge of the main controls on mesoscale shoreline evolution in different managed coastal morphologies. Such knowledge can help refine mesoscale shoreline evolution models to better support coastal management in vulnerable small islands and elsewhere.

1.2 Aim and research questions

The overriding aim of this thesis is *to create a method for predicting the mesoscale evolution of managed sandy shorelines that accounts for sea-level rise and complex planform morphologies*. I develop four research questions to achieve this aim:

Research question one: What are the key boundary conditions needed to model the mesoscale evolution of managed sandy shorelines?

This research question arises from the uncertainty on the optimal boundary conditions needed to simulate shoreline evolution over meso time and space scales, which stems from a global lack of high-quality bathymetry and coastal processes data. To address this research question, I quantify the effects of coarsening bathymetry, tide, wave, and wind data on shoreline evolution predictions in data-rich managed sandy coastal systems following a step-wise calibration approach. I also quantify the impact of model discretisation and parameters describing additional coastal features (e.g. bed friction) on shoreline evolution predictions following a step-wise calibration approach. I use the results of these analyses to (a) identify the main controls on shoreline evolution in different morphologies and (b) specify the appropriate boundary conditions for addressing subsequent research questions.

Research question two: How can sea-level rise be incorporated in shoreline evolution models for mesoscale application in managed sandy coastal systems?

Sea-level rise will likely modify wave climates and the ensuing interactions between wave-generated currents and coastal engineering solutions, which can influence the evolution of managed sandy shorelines over meso time and space scales. Existing mesoscale shoreline evolution models assume an equilibrium active coastal profile, therefore cannot account for sea-level rise. An equilibrium active coastal profile implies a constant closure depth, which will likely change under sea-level rise. Thus, enabling a time-varying closure depth in mesoscale shoreline evolution models is potentially a novel solution to account for sea-level rise effects in these models. To test this assumption and answer research question two, I develop a method that allows the closure depth to vary annually in a hybrid model. I apply the hybrid model, with and without a time-varying closure depth, and a behaviour-oriented model to hindcast meso timescale shoreline evolution in a data-rich location. I quantify the success of the various modelling approaches to determine if a time-varying closure depth improves mesoscale shoreline evolution predictions. I use the outcomes to define the optimal modelling complexity and requirements for simulating the mesoscale evolution of managed sandy shorelines.

Research question three: How can complex planform morphologies be accounted for in shoreline evolution predictions?

The equilibrium coastal profile assumption of existing mesoscale shoreline evolution models also limits their ability to account for complex planform morphologies (e.g. coral reef systems), defined by non-parallel contours. An equilibrium coastal profile implies shore-parallel contours. Thus, allowing the closure depth to vary spatially in mesoscale shoreline evolution models is potentially a novel solution to account for complex planform morphologies in these models. I test this solution and address research question three by developing a method that enables a space-varying closure depth in a hybrid model. I apply the hybrid model, with a constant and space-varying closure depth, and a behaviour-oriented model to hindcast shoreline evolution in a managed coral reef system. I quantify each modelling approach accuracy to determine whether a space-varying closure depth improves shoreline evolution predictions in a complex planform morphology. I also use the outcomes to better understand the controls on shoreline evolution predictions in different coastal system morphologies.

Research question four: Can shoreline evolution models be developed to incorporate both sea-level rise and complex planform morphologies over meso timescales?

This research question applies the novel methods developed in this thesis to forecast meso timescale shoreline evolution in a managed sandy coastal system with a complex planform morphology. I compare the predictions with those from existing hybrid and behaviour-oriented models. This analysis also considers the accuracy of the various models quantified in research questions two and three. I use the outcomes to define the importance of accounting for sea-level rise and complex morphologies in shoreline evolution predictions concerning coastal management decision-making.

1.3 Thesis outline

Following Chapter 1, this thesis comprises seven chapters. Chapter 2 introduces the test sites and data used to address each research question. Chapter 3 reviews the methods available for modelling shoreline evolution across different time and space scales and presents the methods selected and developed to answer each research question. Chapter 4 evaluates the sensitivity of shoreline evolution predictions to boundary conditions, addressing research question one. Chapter 5 assesses whether a time-varying closure depth improves mesoscale shoreline evolution predictions under relative sea-level rise, addressing research question two. Chapter 6 concerns research question three, evaluating whether a space-varying closure depth improves shoreline evolution predictions in a complex planform morphology. Chapter 7 uses the methods developed in this thesis to forecast meso timescale shoreline evolution in a managed sandy coastal system with a complex planform morphology, addressing research question four. Chapter 8 synthesises the primary findings of Chapters 4 to 7 relative to the overriding aim of this thesis and makes suggestions for future research.

02
Test sites and data

'Fundamental studies of the evolution of natural coasts are of considerable scientific interest, but managerial interests require baseline information to assess the numerous physical, chemical and environmental problems along our shorelines, and it would be a mistake to neglect areas that have already been developed.'

– Karl F. Nordstrom

2.1 Introduction

This chapter introduces the test sites and data used to address the overriding aim and four research questions outlined in Chapter 1. Section 2.2 provides an overview of the sandy coastal system in each test site selected and discusses their suitability for modelling applications in this thesis. Section 2.3 presents the datasets available and obtained for each test site to answer each research question.

2.2 Test sites

Three test sites are selected in locations with a distinct coastal morphology and high-resolution bathymetry and coastal processes (tide, wind and wave) data. These include a managed sandy coastal system in New York (Fig. 2.1), Puerto Rico (Fig. 2.2), and Southern California (Fig. 2.3), each described in subsequent paragraphs. Fig. 2.4 compares each test site coastal profile morphology.

The New York test site includes most of Long Beach Barrier Island, located along the United States East Coast (Fig. 2.1a), and has a 12.5 km sandy shoreline managed by 43 groynes (Fig. 2.1b). Here and elsewhere, the shoreline is the Mean High Water (MHW) line. The shoreline in Fig. 2.1b indicates the longshore dimension of the New York test site. The shoreline is concave in the east and west and generally straight elsewhere, except for deformations from accretion (erosion) updrift (downdrift) of groynes (Fig. 2.1b). The New York test site has a mean tide range of 1.43 m and a simple planform morphology, defined by parallel depth contours (Fig. 2.1c). The average coastal profile gently slopes and decreases monotonically cross-shore, mirroring the envelope of coastal profiles sampled every 15 m longshore (Fig. 2.4a). Apart from groynes, coastal management in Long Beach Barrier Island previously included shore nourishment in Lido Beach in 1962 (152 911 m^3), and Point Lookout in 1990 (269 888 m^3), 1994 (428 151 m^3), 1995 (350 931 m^3), 2008 (490 844 m^3), and 2014 (519 897 m^3) (Valverde et al., 1999; Catania, 2015; USACE and NYSDEC, 2015). Lido Beach is in the New York test site, whereas Point Lookout is on the eastern tip of Long Beach Barrier Island (Fig. 2.1b). The blue and yellow polylines in Fig. 2.1b indicate areas previously nourished in Lido Beach and Point Lookout, respectively. Shore nourishment in Point Lookout indirectly supplies sand to beaches in the New York test site as littoral drift moves east to west along the Atlantic coast of Long Beach Barrier Island (Catania, 2015). Therefore, sediment transport boundary conditions used to simulate shoreline evolution in the New York test site must reflect the periodic sand supply from Point Lookout. Shore nourishment is now a key aspect of coastal management in Long Beach Barrier Island, with plans implemented in 2018 to nourish the island's Atlantic coast every five years for 50 years (USACE and NYSDEC, 2015). It is important to note that I use pre-2017 data to simulate shoreline evolution in the New York test site (see details in section 2.3), which means that model applications in this thesis are not fully representative of ongoing shore nourishment cycles in Long Beach Barrier Island.

The Puerto Rico test site is located along the island's Atlantic coast in San Juan (Fig. 2.2a) and has a ~5 km sandy shoreline. Although this test site longshore dimension is smaller than meso space scales (10^1 to 10^2 km), sandy shorelines in small islands are usually less than 10 km (Mycoo and Donovan, 2017). Meso timescales are more relevant than meso space scales for modelling shoreline evolution to guide coastal management in vulnerable small islands (Nurse et al., 2014). The shoreline in the Puerto Rico test site has a cuspate-cape shape. It is managed by breakwaters, seawalls and groynes, and buffered by fringing coral reefs (Fig. 2.2b; 2.2c). Hard defences are the only form of coastal management in the Puerto Rico test site because soft engineering solutions, such as shore nourishment, can damage coral reef ecosystems (Bush et al., 1995; Garcia-Sais et al., 2008). The reefs provide a steady sand supply to beaches in the Puerto Rico test site (Bird, 2010). Therefore, the sediment transport boundary conditions used to simulate shoreline evolution in this test site will need to reflect the steady supply of sand from reefs. The Puerto Rico test site has a mean tide range of 0.34 m and a complex planform morphology, defined by non-parallel depth contours, because of irregular reef substrate distribution (Fig. 2.2c). The average coastal profile is characterised by a steep upper beach and a gentle lower beach (Fig. 2.4b). On the contrary, the envelope of coastal profiles sampled every 15 m longshore show considerable cross-shore variability in bathymetry (Fig. 2.4b).

The Southern California test site is in Santa Monica, located along the United States West Coast (Fig. 2.3a), and has an 11 km sandy shoreline managed by eight groynes and two jetties (Fig. 2.3b). This test site has a mean tide range of 1.14 m and a simple planform morphology, characterised by parallel depth contours (Fig. 2.3c). The average coastal profile is steep and decreases monotonically seaward in slight contrast to the envelope of coastal profiles sampled every 15 m longshore (Fig. 2.4c). The shoreline is mostly straight, with deformations mainly around groynes (Fig. 2.3b). Coastal management in the Southern California test site also includes temporary sand berms built yearly for protection against winter storms (Gallien et al., 2015). The blue polylines in Fig. 2.3b indicate the locations where the berms are created. The temporary sand berms change the shape of the active coastal profile annually in the Southern California test site (Gallien et al., 2015). As a result, I cannot objectively test the accuracy of shoreline evolution predictions in the Southern California test site against related observations because existing mesoscale shoreline evolution models assume an equilibrium coastal profile (Roelvink et al., 2016; Pontee, 2017). An equilibrium coastal profile implies a constant time-averaged form (Larson et al., 1987; Hurst et al., 2015). However, using shoreline evolution observations as a baseline to evaluate the effects of changing model inputs on model predictions can provide useful insights into shoreline evolution drivers. Therefore, I only use the Southern California test site alongside the New York and Puerto Rico test sites to identify the key controls on shoreline evolution predictions in different managed coastal morphologies. The Southern California test site has a steep sloping coastal profile compared to the New York and Puerto Rico test sites. While an alternative test site devoid of temporary berms may have been ideal, a global lack of high-resolution data constrains the number of suitable test sites available for use in this thesis.

The contrasting morphology of each test site selected is ideal for addressing the overriding aim and four research questions of this thesis. The New York and Southern California test sites have a simple planform morphology compared to the Puerto Rico test site. However, the Southern California test site has a steep sloping coastal profile compared to the New York test site. These variations in coastal morphology across the three test sites are essential for addressing research question one, which evaluates the sensitivity of shoreline evolution models to boundary conditions. The New York test site's simple planform morphology aligns with the one-line theory assumption of parallel depth contours that underlie the morphology update in hybrid shoreline evolution models. As a result, the New York test site is suitable for addressing research question two, which creates a novel method to account for sea-level rise in hybrid models. In contrast, the Puerto Rico test site's morphology presents a novel challenge for hybrid models. The irregular reef substrate distribution in the Puerto

Rico test site means that this test site's closure depth varies alongshore. However, the morphology update in hybrid models assumes a constant closure depth based on the one-line theory, limiting their applicability in complex planform morphologies, characteristic of the Puerto Rico test site. Therefore, the Puerto Rico test site is ideal for handling research questions three and four. Research question three creates a novel approach that enables hybrid shoreline evolution models to account for complex planform morphologies. Research question four establishes a method that accounts for both sea-level rise and complex planform morphologies in mesoscale shoreline evolution predictions.

2.3 Data source and description

This section presents the datasets obtained to answer each research question outlined in Chapter 1. Section 2.3.1 introduces the high-quality bathymetry and coastal processes data obtained for testing model sensitivity in each test site to address research question one. Section 2.3.2 describes the mesoscale New York test site datasets obtained to address research question two. Section 2.3.3 introduces the Puerto Rico test site datasets obtained to address research questions three and four.

2.3.1 High-resolution data for model sensitivity testing

Based on the high-resolution bathymetry and coastal processes data available, I carry out model sensitivity testing from 01-Jan-2014 to 01-Feb-2016 in the New York test site, 01-Oct-2014 to 31-Mar-2016 in the Puerto Rico test site, and 01-Jan-2009 to 02-Aug-2011 in the Southern California test site. These periods allow for identifying the parameters and variables that cause the largest errors in shoreline evolution predictions to better understand the intrinsic behaviour of shoreline evolution models (Roelvink et al., 2016; Williams and Esteves, 2017). Such knowledge is needed to ensure the appropriate specification of model inputs for improving robustness and predictions (Pianosi et al., 2016). The sensitivity testing periods defined include seasonal wave climate conditions and the Atlantic Hurricane season, thus provide a good basis for gauging shoreline response to changes in external forcings in different morphologies. The Atlantic Hurricane season affects the New York and Puerto Rico test sites. Following paragraphs introduce the high-quality data obtained for assessing model sensitivity in each test site, with their details summarised in Table 2.1.

I obtain two bathymetry datasets for each test site, initial and observed. Fig. 2.5 shows each test site's initial bathymetry data. All bathymetry data are vertically referenced to MHW (m) and horizontally referenced to WGS84 (m). The initial bathymetry comprises hydrographic data surveyed at the start of the model sensitivity testing period, whereas the observed bathymetry comprises data surveyed at the end of the model sensitivity testing period. I use the initial bathymetry to simulate shoreline evolution and the observed bathymetry to quantify model sensitivity and performance. I use the Southern California test site's observed bathymetry to evaluate model sensitivity only, not performance. I cannot objectively assess model performance in the Southern California test site because of the annual creation of temporary sand berms. The shoreline position in each bathymetry is the zero-depth contour (MHW line). The initial shoreline is the baseline for mapping changes in shoreline position, and the observed shoreline is the baseline for gauging shoreline prediction error.

Figs. 2.6 to 2.8 illustrate each test site's coastal processes time series data obtained for model sensitivity testing. All tide data are vertically referenced to MHW (m). All wind data include wind speed and direction, and all wave climate data include wave height, period, and direction. There is a 3-week period (~ 4%) of missing wave climate data for the Puerto Rico test site, and ten days (~ 1%) of missing wind data for the Southern California test site. I interpolate all missing time series values using linear interpolation, which is appropriate for filling in small gaps (~15%) in coastal processes time series datasets (Pizarro et al., 2001; Emery and Thomson, 2004; English, 2005; Percival, 2008).

To represent hard defences in shoreline evolution simulations, I use geo-referenced satellite imagery to define the location and geometry of active defences. These include a 0.5 m resolution GeoEye-1 image of the New York test site (Fig. 2.1b), a 0.1 m resolution orthophoto of the Puerto Rico test site (Fig. 2.2b), and a 1 m resolution KOMPSAT-2 image of the Southern California test site (Fig. 2.3b). I use each test site's initial bathymetry data (Fig. 2.5) to derive the elevation of their hard defences.

The above data have a high temporal and spatial resolution compared to data usually available for vulnerable small islands. Global terrain models, such as the General Bathymetric Chart of the Oceans (~ 450 m resolution), often form the primary source of bathymetry for vulnerable small islands, whereas coastal processes time series data are rarely available because of sporadic coastal monitoring (Nurse et al., 2014; Mycoo and Donovan, 2017). Globally, it is also rare to find high-resolution bathymetry and coastal processes data for the same time period (Turner et al., 2016; Le Cozannet et al., 2019). Therefore, the above test sites and data are ideal for a comprehensive model sensitivity study to answer research question one, which will help define the optimal requirements for simulating mesoscale shoreline evolution in different coastal morphologies. Such knowledge can help refine coastal monitoring programmes, especially in resource-poor vulnerable islands, to better facilitate mesoscale shoreline evolution models as coastal management tools (Nicholls et al., 2016).

2.3.2 Data for addressing research question two

Research question two uses the New York test site to establish an approach that allows a time-varying closure depth in hybrid models in order to account for sea-level rise in mesoscale shoreline evolution predictions. Developing and testing such an approach require meso timescale hindcast simulations of shoreline evolution. The following paragraphs describe the data obtained to hindcast meso timescale shoreline evolution in the New York test site for addressing research question two.

Based on historical bathymetry and tide data available, I use the period 01-Jan-1966 to 01-Feb-2016 to hindcast meso timescale shoreline evolution in the New York test site. The initial bathymetry for these simulations is a 1966 coastal relief model with a spatial resolution of 10 m (Fig. 2.9a). The source of this relief model is a 1966 topobathymetric map from the United States Geological Survey (USGS) (Fig. 2.9b). The initial bathymetry is vertically referenced to MHW (m) and horizontally referenced to WGS84 (m). The tide time series data for the meso timescale hindcast simulations are presented in Fig. 2.9c. The tide time series data are in hourly intervals, vertically referenced to MHW (m), and inherently include the relative sea-level rise trend over the meso timescale hindcast period.

The New York test site's wind, wave and hard defences data obtained for assessing model sensitivity are also used to carry out the meso timescale hindcast simulations. Wind and wave data for the New York test site are only available for the 21st century, sporadically over the 2000s and more frequent from the mid-2010s. Therefore, I repeat the wind and wave climate data obtained for model sensitivity testing (Fig. 2.6) in the meso timescale hindcast simulations. Repeating the wind and wave data in these simulations facilitates the primary objective of testing whether a time-varying closure depth improves meso timescale shoreline evolution predictions. The New York test site's hard defences data obtained for model sensitivity testing are also appropriate for the meso timescale hindcast simulations because the same structures have been present in the site since 1966 (Catania, 2015).

I use the New York test site's observed bathymetry obtained for model sensitivity testing (Table 2.1) to quantify the accuracy of the meso timescale hindcasts of shoreline evolution. The periods defined for evaluating model sensitivity and hindcasting meso timescale shoreline evolution in the New York test site both end on 01-Feb-2016. Thus, the observed bathymetry obtained for model sensitivity testing is appropriate for assessing the accuracy of the meso timescale shoreline evolution hindcasts.

2.3.3 Data for addressing research questions three and four

Research question three defines an approach to account for complex planform morphologies in shoreline evolution predictions, and research question four applies the methods developed in this thesis to forecast mesoscale shoreline evolution in a complex planform morphology. I use the Puerto Rico test site and datasets described in the paragraphs below to address both research questions.

To answer research question three, I develop an approach that enables a space-varying closure depth in hybrid models as a solution to account for complex planform morphologies. Establishing such an approach does not require mesoscale hindcast simulations. Therefore, I use the Puerto Rico test site's data obtained for testing model sensitivity (Table 2.1) to answer research question three.

To address research question four, I use the Puerto Rico test site's 2014 bathymetry (Fig. 2.5) to forecast meso timescale (2014 to 2064) shoreline evolution using a time and space-varying closure depth. The tide time series data for these simulations are a 50-year (1969 to 2018) historical record of tide levels observed in the Puerto Rico test site (Fig. 2.10) superimposed with a 0.28 m sea-level rise. 0.28 m is the Intergovernmental Panel on Climate Change global median sea-level rise projection for 2046 to 2065 (Church et al., 2013). The tide data are in hourly intervals and vertically referenced to MHW (m). The Puerto Rico test site's wind, wave, and hard defences data obtained for assessing model sensitivity (Table 2.1) are also used to facilitate the meso timescale forecasts of shoreline evolution. Research question four does not forecast likely meso timescale shoreline evolution in the Puerto Rico test site. Instead, the objective of research question four is to compare meso timescale shoreline evolution predictions from models that can and cannot account for sea-level rise and complex morphologies with respect to implications for coastal management decisions. Therefore, all data selected to facilitate the meso timescale forecast simulations of shoreline evolution in the Puerto Rico test site are appropriate for addressing research question four objective.

2.4 Summary

The above test sites and data are selected to address the aim and research questions of this thesis. Each test site's contrasting morphology and high-resolution bathymetry and coastal processes data allow for a comprehensive sensitivity study of shoreline evolution models to address research question one. The New York test site’s simple planform morphology, historical bathymetry data, and multidecadal tidal records allow for addressing research question two, which develops an approach to account for sea-level rise in hybrid models. The Puerto Rico test site’s non-parallel depth contours provide an ideal basis for establishing an approach that accounts for complex planform morphologies in shoreline evolution predictions to address research question three. The Puerto Rico test site’s morphology is also appropriate for handling research question four, which applies the methods introduced in this thesis to forecast meso timescale shoreline evolution under sea-level rise in a complex planform morphology. Chapter 3 uses the above test sites and data to develop the experimental design for addressing the overriding aim and research questions outlined in Chapter 1.

03
Model selection and approach

'…truth...is much too complicated to allow anything but approximations…'

– John von Neumann

3.1 Introduction

This chapter introduces the methods used to address the aim and research questions of this thesis. It starts by reviewing existing shoreline evolution models in section 3.2 concerning their ability to simulate mesoscale shoreline evolution in managed sandy coastal systems, identifying the most suitable models for use in this thesis. Subsequent sections outline the computational framework of the selected models (section 3.3), present the methods used for model application (sections 3.4 and 3.5), and discuss the approaches used for model sensitivity testing, calibration, and quantifying model outputs and performance (sections 3.6 and 3.7). The latter part of this chapter (sections 3.8 to 3.10) discusses the steps taken to develop, evaluate, and apply novel methods that account for sea-level rise and complex planform morphologies in meso timescale shoreline evolution predictions.

3.2 Model review and selection

Coastal managers often use shoreline evolution predictions from two-dimensional horizontal (2DH), behaviour-oriented, and hybrid models as a baseline for informing coastal management (De Vriend et al., 1993a; Hanson et al., 2003; Pontee, 2017; Reeve et al., 2019). Subsequent sections review these models ability to simulate mesoscale shoreline evolution in managed sandy coastal systems.

3.2.1 2DH models

2DH models use a modular approach to simulate the physics of coastal sediment transport and shoreline evolution in response to the combined interactions of various external forcings (Table 1.1) (Hanson et al., 2003; Payo et al., 2017; Pontee, 2017). These models typically comprise four modules, including spectral wave, flow, sediment transport, and morphology (Fig. 3.1a) (De Vriend et al., 1993b; Roelvink et al., 2016). The spectral wave module simulates wave propagation, shoaling, breaking, and dissipation based on some form of the wave action conservation equation. The spectral wave module generates the wave radiation stresses that drive the current in the flow module and influence littoral drift in the sediment transport module. The flow module solves the depth-averaged non-linear shallow water equations, providing the time and space variations in water levels and currents that drive wave propagation in the spectral wave module and influence littoral drift in the sediment transport module. The sediment transport module combines bedload transport and suspended load transport from wave-current interactions to simulate littoral drift. The morphology module updates the shoreface morphology in response to littoral drift gradients generally based on Exner (1925) sediment continuity equation. Examples of 2DH models are Delft3D (Deltares, 2016), MIKE 21/3 Coupled Model FM (Kaergaard and Fredsoe, 2013), and TELEMAC-2D (Hervouet, 2007).

A mesh provides the spatial discretisation in 2DH models, dividing the model space into quadrilateral or triangular computational units called elements. A finite difference, element or volume approach is used to discretise and solve the governing equations inside each element. Interpolating the mesh with boundary conditions (e.g. bathymetry, hard defences, and tidal levels) allows 2DH models to simulate the combined effects of multiple external forcings on sediment transport gradients and shoreline evolution (De Vriend et al., 1993b). The ability to include tidal levels enables 2DH models to account for sea-level rise in shoreline evolution predictions. Sea-level rise is singled out here as it will likely be an endogenous driving factor in mesoscale coastal evolution (Stive et al., 2002; Slott et al., 2010). However, an increase in model space, number of elements, or simulation period increases the computational cost of 2DH models as governing equations are discretised and solved inside individual elements. Consequently, 2DH models are generally restricted to simulations over micro time and space scales (Table 1.1) (De Vriend et al., 1993a; Roelvink et al., 2012; Reeve et al., 2016).

In principle, 2DH models are robust tools for simulating shoreline evolution in managed sandy coastal systems (Hanson et al., 2003; Reeve et al., 2016). As a result, there is keen scientific interest in applying 2DH models over meso time and space scales to guide coastal management in many regions. However, two uncertainties limit the mesoscale application of all process-driven models for informing coastal management. The *first* uncertainty is on the relationship between model spatial discretisation and solutions. The *second* uncertainty concerns the appropriate specifications (boundary conditions and parameterisation) for simulating mesoscale shoreline evolution (De Vriend et al., 1993b; Yeu et al., 2018; Reeve et al., 2019). These two uncertainties stem from limited studies on the sensitivity of shoreline evolution models primarily because of a global lack of high-quality bathymetry and coastal processes data (Blanco et al., 2019). Both uncertainties make it difficult to define the optimal model and data requirements for simulating mesoscale shoreline evolution in managed sandy coastal systems (Pilkey et al., 2013; Le Cozannet et al., 2014; Burningham and French, 2017). Comprehensive model sensitivity testing in data-rich locations may help identify the primary controls on shoreline evolution predictions in different coastal morphologies and address the uncertainties abovementioned. Such knowledge has the potential of refining and improving mesoscale shoreline evolution models to better support coastal management (Nicholls et al., 2016).

2DH models simulate the physics of shoreline evolution on a horizontal plane, therefore cannot account for the vertical variations of undertow currents that strongly influence surf zone morphodynamics (Franz et al., 2017; Albernaz et al., 2019). Undertow currents are seaward currents that move beneath the surface of waves approaching the shore. These currents form the main driving flux of cross-shore sediment transport, and their interactions with waves influence coastal profile evolution (Mariño-Tapia et al., 2007; Zhang et al., 2012; Franz et al., 2017). An inability to simulate the vertical variations of undertow currents means that 2DH models fail to describe the delicate balance of the cross-shore sediment transport that evolves the coastal profile (Kristensen et al., 2013). As a result, a fundamental limitation of 2DH models is that the coastal profile gradually degenerates to an unrealistic shape (Kaergaard and Fredsoe, 2013). The gradual breakdown of coastal profiles introduces small errors at each time step in a simulation, causing shoreline evolution predictions to become unreliable in simulations longer than micro timescales (hours to years) (Johnson and Zyserman, 2002; Callaghan et al., 2006; Kristensen et al., 2013; Albernaz et al., 2019). These limitations of 2DH models have encouraged the application of behaviour-oriented models for simulating mesoscale shoreline evolution (Hurst et al., 2015; Reeve et al., 2016; Payo et al., 2017).

3.2.2 Behaviour-oriented models

Behaviour-oriented models are simple mathematical formulations that simulate known coastal behaviours rather than the physics underlying the known coastal behaviours (Capobianco et al., 1999; Hanson et al., 2003; Masselink and Gehrels, 2014; French et al., 2016). These models use a rule-based approach and a diffusion type formulation that force the evolution of coastal profiles towards equilibrium (Roelvink et al., 2012; Kristensen, 2013). Behaviour-oriented models focus on processes that drive shoreline evolution over decades to centuries and consider processes operating at smaller timescales as noise (De Vriend et al., 1993a; Stive et al., 1995). The one-line theory and the Bruun Rule often form the basis of behaviour-oriented models (Larson et al., 1987; Pontee, 2017).

The one-line theory assumes the active coastal profile, defined as the area extending from the beach berm (D_b) to closure depth (D_c), keeps its shape and moves shore-normal in response to time and space variations in longshore sediment transport gradients (Q) (Fig. 3.2) (Pelnard-Considere, 1956):

$$\frac{\Delta y}{\Delta t} = -\frac{1}{h_a}\frac{\Delta Q}{\Delta x} \quad \text{(Eqn. 3.1)}$$

where y is the cross-shore shoreline position, x is the longshore distance, and h_a is the active height of the coastal profile ($D_b + D_c$). The one-line theory makes two further assumptions: (a) a change in Q causes a uniform redistribution of sediment over the active coastal profile, and (b) there is unlimited sand available for transport (Thomas and Frey, 2013; Valentine, 2016; DHI, 2017a). As per the one-line theory, the active coastal profile moves landward (seaward) from sediment gain (loss), implying that D_b and D_c are constant and depth contours are shore-parallel (Fig. 3.3a) (Hurst et al., 2015). The one-line theory thus has four limitations. *First*, an inability to account for sea-level rise as D_c is assumed constant (Leach et al., 2019). Sea-level rise will likely change D_c and influence meso timescale shoreline evolution (Nicholls et al., 1996). The *second* limitation is an inability to predict shoreline evolution in complex planform morphologies as depth contours are considered shore-parallel. The *third* limitation is restricted applicability in areas where repeated shore nourishment changes D_b, which is considered fixed in time (Karasu et al., 2008). The *fourth* limitation is an inability to simulate longshore growth of spits and deformations from hard defences since the active coastal profile is assumed to move shore-normal (Fig. 3.3b) (Kaergaard and Fredsoe, 2013). The one-line theory, however, is usually valid for sandy coasts with a simple planform morphology and a steady sand supply from littoral drift, thereby forming the basis of several behaviour-oriented models, including COVE (Hurst et al., 2015), GENESIS (Hanson, 1989), and UnaLinea (Sutherland et al., 2015). The one-line theory formulation can also partly account for the effects of sea-level rise, hard defences, and complex planform morphologies by using Q estimations from process-driven models.

The Bruun Rule assumes the active coastal profile maintains an equilibrium shape and shifts upward and landward (shore-normal) from sea-level rise while preserving mass (see Fig. 3.4) (Bruun, 1962):

$$R = SLR\left(\frac{L}{D_b + D_c}\right) \quad \text{(Eqn. 3.2)}$$

where R is shoreline retreat, SLR is relative sea-level rise, and L is the distance between D_b and D_c. The Bruun Rule makes three assumptions. *First*, the upper beach erodes due to the landward translation of the active coastal profile. *Second*, the material eroded from the upper beach is deposited offshore, such that the volume eroded equals the volume deposited. *Third*, the rise in the nearshore bottom from deposition is equivalent to SLR, maintaining a constant water depth offshore

(Bruun, 1962; Bruun, 1983; Bruun, 1988). These Bruun Rule assumptions have three limitations, one distinct and two shared with one-line models. The distinct limitation is an inability to account for littoral drift as sediments eroded onshore are assumed to be deposited offshore. Littoral drift is the main driving flux of longshore shoreline evolution in managed sandy coastal systems (Ranasinghe et al., 2007). The Bruun Rule shares two limitations with one-line models are: (a) limited applicability in complex morphologies due to its equilibrium profile assumption; and (b) an inability to predict longshore evolution of spits and deformations from hard defences as the active coastal profile is assumed to retreat shore-normal from SLR (Roelvink et al., 2016). Notwithstanding these limitations, the Bruun Rule is the only known model that directly links shoreline evolution to sea-level rise (Sharaan and Udo, 2020). Therefore, the Bruun Rule forms the basis of several behaviour-oriented models that are developed for predicting meso timescale shoreline evolution (Le Cozannet et al., 2016), including the Shoreface Translation Model (Cowell et al., 1992) and SimCLIM (Warrick, 2009).

One-line and Bruun Rule models also have three shared similarities and advantages. *First*, their equilibrium profile assumption prevents the degeneration of coastal profiles, allowing mesoscale applications and addressing the key limitation of 2DH models (Kristensen, 2013). *Second*, one-line and Bruun Rule models are based on a simple diffusion type formulation applied to individual cross-shore profiles (Pontee, 2017). Using individual cross-shore profiles allow both models to consider spatial variations in D_b and D_c for predicting longshore shoreline evolution. A minimal data requirement is the *third* similarity and advantage of one-line and Bruun Rule models, which enables their application in data-poor regions. One-line and Bruun Rule models mainly require initial bathymetry data because most of their variables describe the coastal profile (Payo et al., 2017). Existing knowledge or outputs from process-driven models can inform their forcing terms, Q and SLR.

There are two primary differences between one-line and Bruun Rule models. *First*, the active coastal profile moves shore-normal in response to longshore sediment transport in one-line models and sea-level rise in Bruun Rule models. *Second*, one-line models incorporate a time-stepping scheme (Δt) in their formulation, allowing time-dependent (unsteady) shoreline evolution predictions in contrast to Bruun Rule models (Kaergaard and Fredsoe, 2013). Bruun Rule models only generate an overall estimate of shoreline change (Bruun, 1962). Therefore, one-line models can help facilitate some understanding of the temporal variations in shoreline evolution in comparison to Bruun Rule models.

3.2.3 Hybrid models

The limitations and usefulness of 2DH and behaviour-oriented models have inspired the creation of hybrid models for simulating mesoscale shoreline evolution (Reeve et al., 2016). Hybrid models combine elements of 2DH and behaviour-oriented models, as discussed in the paragraph below. The creation of hybrid models is fuelled by the need for process-driven models (e.g. 2DH models) that simulate mesoscale shoreline evolution to better support coastal management (Payo et al., 2020). The primary limitation of process-driven models is an inability to represent the delicate balance of cross-shore sediment transport, which degenerates the coastal profile to an unrealistic shape in simulations longer than micro timescales (Franz et al., 2017; Albernaz et al., 2019). However, these models help us understand the complex processes influencing the sediment transport gradients that influence shoreline evolution (Roelvink et al., 2016; Pontee, 2017). As a result, considerable scientific efforts have been directed towards developing mesoscale process-driven models in recent decades (Reeve et al., 2016). These efforts resulted in the widespread use of a behaviour-oriented approach for the morphology update in 2DH models to eliminate the cross-shore effect that breaks down the coastal profile (Hanson et al., 2003; Karunarathna and Reeve, 2013; Kristensen et al., 2013). Using a behaviour-oriented approach for the morphology update in 2DH models ensures the coastal profile keeps an equilibrium form in processes simulations over meso time and space scales (Reeve et al., 2019). Exploratory hybrid modelling reveals that such an approach allows for a good description of the spatial effects of wave-current interactions on sediment transport and associated shoreline change over meso time and space scales (Ashton and Murray, 2006b; Slott et al., 2010; Karunarathna and Reeve, 2013). This finding has directed additional scientific efforts to advance hybrid models for simulating mesoscale shoreline evolution (Antolínez et al., 2019; Payo et al., 2020).

Hybrid models simulate sediment transport from combined wave-current action on a mesh and use the resulting gradients to update the shoreline morphology according to the one-line theory (Kristensen et al., 2013). These models essentially have the same modular structure as 2DH models, except the morphology update is rule-based (constrained) to prevent coastal profile degeneration, as illustrated in Fig. 3.1b (Kaergaard and Fredsoe, 2013). As a result, hybrid models maintain the underlying physics of coastal sediment transport, simulating the combined effects of the various external forcings affecting coastal systems (e.g. wave climate, sea-level rise, and hard defences) on sediment transport gradients (Slott et al., 2006). The morphology update in hybrid models is based on the one-line theory rather than the Bruun Rule because of the Q (littoral drift gradients) and t (time) terms in the one-line theory equation (Eqn. 3.1). Q updates the shoreline morphology in response to littoral drift gradients, the driving flux of the time and space variations in shoreline evolution, and t allows time-dependent (unsteady) shoreline evolution predictions (Kaergaard and Fredsoe, 2013). Available hybrid models include the Coastal Evolution Model (CEM) (Ashton and Murray, 2006a; 2006b), CoastalME (Payo et al., 2017), MIKE21 FM Shoreline Model (MIKE21) (DHI, 2017b), and Karunarathna and Reeve (2013) exploratory model. These models are all open-source except the industry-standard MIKE21 model (Pye et al., 2017). Hereafter, CEM, CoastalME and Karunarathna and Reeve (2013) exploratory model are referred to as the open-source hybrid models.

Three key differences set MIKE21 apart from the open-source hybrid models. *First*, MIKE21 facilitates wave transformation over parallel and non-parallel contours by discretising a spectral wave module on a finite volume mesh, whereas waves are transformed based on the assumption of shore-parallel contours in the open-source hybrid models (Ashton and Murray, 2006a; Kaergaard and Fredsoe, 2013; Karunarathna and Reeve, 2013; Payo et al., 2017). As a result, MIKE21 can facilitate processes simulations over simple and complex planform morphologies, whereas the open-source hybrid models are restricted to gentle sloping bathymetries and low planform curvature (Payo et al., 2017; Pye et al., 2017). The *second* difference is that wave transformation is based on non-linear wave theory in MIKE21 (e.g. Stokes 1st, 3rd and 5th order wave theory) and linear wave theory in the open-source hybrid models (Ashton and Murray, 2006a; Karunarathna and Reeve, 2013; DHI, 2016c; Payo et al., 2017). In contrast to linear wave theory, non-linear wave theory accounts for bottom friction effects on wave propagation (Holthuijsen, 2007). The open-source hybrid models thus cannot account for wave refraction or wave energy loss due to bottom friction compared to MIKE21

(Ashton and Murray, 2006a; DHI, 2017b; Payo et al., 2017; Pye et al., 2017). The effects of bottom friction on wave propagation significantly affect shoreline evolution in coral reef environments. In such environments, the bottom friction acting over the reef flat dissipates as much wave energy as wave breaking (Lowe et al., 2007; De Lalouvière et al., 2020). Consequently, the open-source hybrid models are not appropriate for wave-current simulations in the Puerto Rico test site and the many small island coastal systems with reefs in the Caribbean and Pacific. The *third* difference between MIKE21 and the open-source hybrid models is that MIKE21 uses local s, N coordinates to formulate the one-line theory equation whereas the open-source hybrid models use fixed x, y coordinates (Ashton and Murray, 2006a; Kaergaard and Fredsoe, 2013; Karunarathna and Reeve, 2013). s is the shore-parallel coordinate, and N is the shore-perpendicular coordinate. The use of local coordinates forces each point along a shoreline to evolve perpendicular to its orientation, allowing MIKE21 to handle complex shoreline geometries and simulate shoreline deformations from hard defences (Drønen et al., 2011; Kristensen et al., 2013). In contrast, the open-source hybrid models are restricted to straight shorelines primarily because formulating the one-line theory equation with fixed x, y coordinates causes errors in shoreline continuity solutions along curved areas where multiple y coordinates share an x coordinate (see Fig. 3.3b). Considering these differences, MIKE21:

1. potentially offers a better approach than the open-source hybrid models for simulating mesoscale shoreline evolution across a broad range of managed sandy coastal system morphologies; and
2. better represents the underlying physics of coastal systems than the open-source hybrid models, which apply more simplifying assumptions (e.g. wave propagation based on linear wave theory).

It is important to note that hybrid models, including MIKE21, are not yet verified over meso timescales due to a global lack of decadal bathymetry and coastal processes data. Also, the advancement of hybrid models is still an active area of scientific research (Antolínez et al., 2019; Payo et al., 2020).

Hybrid shoreline evolution modelling is not limited to the self-contained software packages provided by MIKE21 and the open-source hybrid models abovementioned. The mesoscale hybrid modelling concept discussed above can be facilitated by coupling existing one-line theory behaviour-oriented models (e.g. COVE and GENESIS) with 2DH wave and flow models (e.g. SWAN and FVCOM), as outlined in Hurst et al. (2015), Franz et al. (2017), Limber et al. (2017), and Payo et al. (2017). For example, coupling FVCOM (Finite Volume Community Ocean Model) with SWAN (Simulating WAves Nearshore) can facilitate 2DH wave-current simulations over parallel and non-parallel contours (Chen et al., 2018; Yang et al., 2020). The wave-current outputs from coupling FVCOM and SWAN can drive the sediment transport and shoreline morphology update in COVE (Hurst et al., 2015). And the morphology outputs from COVE can update the bathymetry in FVCOM and SWAN (Franz et al., 2017). COVE is presently the only one-line theory behaviour-oriented model that handles complex shoreline geometries as it uses local coordinates for the shoreline morphology update (Payo et al., 2017). In this regard, coupling FVCOM, SWAN, and COVE offer an advanced shoreline evolution modelling approach relative to the open-source hybrid models available. The open-source hybrid models available are limited to straight shorelines, as discussed in the preceding paragraph. However, coupling COVE with any 2DH wave and flow models does not provide a better alternative to MIKE21 concerning the handling of complex morphologies. While coupled 2DH wave and flow models account for complex morphologies, their wave climate outputs, for example, will be transformed based on the assumptions of linear wave theory and shore-parallel contours in COVE (Hurst et al., 2015). Consequently, coupling 2DH wave and flow models with COVE is not appropriate for wave-current simulations in the Puerto Rico test site's complex morphology compared to MIKE21.

Despite the advances MIKE21 offers for simulating mesoscale shoreline evolution, its use of the one-line theory for the morphology update has some limitations. The one-line theory assumes the active coastal profile moves shore-normal from a change in littoral drift gradients. This assumption means that the berm height and closure depth are constant, and depth contours are considered shore-parallel in MIKE21 shoreline morphology update (Kaergaard and Fredsoe, 2013; Kristensen et al., 2013; DHI, 2017b). These simplified shoreline morphology updating assumptions prevent MIKE21 from fully accounting for sea-level rise and complex planform morphologies in mesoscale shoreline evolution predictions. Sea-level rise will likely change the closure depth and affect shoreline change over meso timescales (Nicholls et al., 1996; Stive et al., 2002). Complex planform morphologies are defined herein by non-parallel contours and longshore closure depth variations, both features of coastal systems in many Caribbean and Pacific small islands (Nurse et al., 2014). Shoreline evolution models are arguably most needed for guiding coastal management in these locations (Simpson et al., 2009). Hence, including sea-level rise and complex planform morphology effects in mesoscale shoreline evolution models are novel challenges affecting coastal management in vulnerable small islands. Enabling a time and space-varying closure depth in MIKE21 may address these challenges.

3.2.4 Model selection

Preceding sections show that MIKE21 offers the best approach for mesoscale shoreline evolution simulations across a broad range of coastal system morphologies. This finding is also clear in Table 3.1, which compares the abilities of existing shoreline evolution models. MIKE21 combined use of a finite volume discretisation for coupled processes simulations (wave, flow and sediment transport) and local coordinates for the shoreline morphology update sets it apart from other mesoscale shoreline evolution models. As discussed below, these characteristics of MIKE21 is essential for answering each research question outlined in Chapter 1 and handling each test site's morphology.

MIKE21 is currently the only model that enables coupled 2DH mesoscale wave, flow, and sediment transport simulations on a finite volume mesh (Table 3.1). MIKE21 can facilitate such simulations because it applies the one-line theory to constrain the shoreline morphology update and prevent the degeneration of coastal profiles that restricts traditional 2DH models to micro timescales. A finite volume discretisation enables MIKE21 to simulate the combined effects of external forcings (e.g. wave climate, tides, sea-level rise, and hard defences) on sediment transport gradients over **both** parallel and non-parallel contours. Sediment transport gradients are the main driving flux of time and space variations in shoreline change (Barkwith et al., 2014b; Garel et al., 2019). As a result, MIKE21:

1. allows for identifying the most important boundary conditions for simulating mesoscale shoreline evolution in different coastal morphologies to address research question one comprehensively.
2. provides a good basis for developing an approach that accounts for sea-level rise in mesoscale shoreline evolution predictions to answer research question two. MIKE21 is suitable for creating

such a method because it already accounts for sea-level rise in coastal processes simulations.

3. is most appropriate for addressing research questions three and four because it incorporates non-parallel contours in mesoscale coastal processes simulations relative to alternative models (Table 3.1). Research question three develops an approach that accounts for complex planform morphologies in shoreline evolution predictions. Research question four applies the methods created in this thesis to predict mesoscale shoreline evolution in a complex planform morphology.
4. is most suitable to handle each test site's morphology (Fig. 2.4) as it is the only model the allows mesoscale coastal processes simulations over parallel and non-parallel contours (Table 3.1).

MIKE21 use of local coordinates for the shoreline morphology update is essential for simulating shoreline evolution in each test site. Each test site has shoreline undulations and deformations that have been formed in response to hard defences (Figs. 2.1 to 2.3). Local coordinates allow each shoreline point to evolve perpendicular to its orientation in contrast to fixed x, y coordinates, enabling simulations of longshore shoreline undulations and deformations. Using fixed x, y coordinates to simulate shoreline change in areas with undulations and deformations tend to cause errors in shoreline continuity solutions as multiple y coordinates share an x coordinate (see Fig. 3.3b). The ability to handle complex shoreline geometries and non-parallel contours in coupled mesoscale coastal processes simulations gives MIKE21 the edge over other models available for simulating mesoscale shoreline evolution in managed sandy coastal systems. Alternative mesoscale shoreline evolution models can either handle complex shorelines or non-parallel contours, not both (Table 3.1).

MIKE21 morphology update assumes an equilibrium active coastal profile that moves shore-normal from a change in sediment balance based on the one-line theory, which corresponds closely to the Bruun Rule. The difference between the morphology update in hybrid models and the Bruun Rule is the sediment transport forcing that shifts the active coastal profile. The active coastal profile moves from process-driven littoral drift gradients in MIKE21 and sea-level rise in the Bruun Rule. Sea-level rise will likely be an endogenous driving factor in mesoscale coastal evolution and is, therefore, an essential forcing component to include in mesoscale shoreline evolution simulations. In contrast to MIKE21 and related hybrid models, the Bruun Rule directly links shoreline evolution to sea-level rise (Woodworth et al., 2005; Le Cozannet et al., 2019). Despite many criticisms (Cooper and Pilkey, 2004), the Bruun Rule is not yet unvalidated over meso time scales because of a global lack of decadal coastal data to assess its assumptions (Le Cozannet et al., 2019). Also, MIKE21 and related models are not are yet validated over mesoscale applications as these models have only been applied experimentally over meso time and space scales for illustrating their proof of concept (Slott et al., 2010; Barkwith et al., 2014b; Van Maanen et al., 2016; Payo et al., 2020). Hence, the optimal complexity for simulating the mesoscale evolution of managed sandy shorelines is not yet identified.

A noteworthy distinction between MIKE21 and the Bruun Rule concerns their representation of a coastal system's underlying physics. MIKE21 couples a 2DH approach for wave, flow and sediment transport simulations with a one-line theory approach for the shoreline morphology update. MIKE21 thus resolves the underlying physics of coastal sediment transport but forces the coastal profile to keep an equilibrium form in response to littoral drift gradients. On the other hand, the Bruun Rule is no more than an equilibrium coastal profile that maintains its position relative to sea-level by moving upwards and landwards from a rise in sea-level. Profile movement in the Bruun Rule ceases when a mass balance is achieved cross-shore. The Bruun Rule, therefore, assumes that the coastal profile is a closed material balance system. Altogether, MIKE21 considers the key processes underpinning shoreline change, whereas the Bruun Rule simply linearises the relation between sea-level rise and shoreline change. Cooper et al. (2020) argue that shorelines *will* and *must* retreat as sea-level rises. Hence, the Bruun Rule simplified representation of the relation between sea-level rise and shoreline evolution may provide an equivalent basis as MIKE21 for studying mesoscale shoreline behaviour.

Acknowledging the critical role shoreline evolution models play in guiding coastal management decisions, I select MIKE21 and the Bruun Rule for application in this thesis. Applying both models will help develop two essential understandings. *First*, using both models to address research question one, which evaluates model sensitivity to boundary conditions, will improve our knowledge of the key controls on shoreline evolution predictions in different coastal systems. *Second*, comparing shoreline evolution predictions from the novel methods introduced in this thesis with those from MIKE21 current approach and the Bruun Rule will help define the optimal complexity for simulating mesoscale shoreline evolution in different coastal system morphologies. Such understandings are necessary for refining mesoscale shoreline evolution models to better support coastal management.

3.3 Computational structure of MIKE21 and the Bruun Rule

This section outlines the structure of MIKE21 in section 3.3.1 and the Bruun Rule in section 3.3.2.

3.3.1 MIKE21

MIKE21 combines a 2D description of waves, hydrodynamics (flow and current), and sediment transport with a one-line description of the shoreline position. MIKE21 couples four modules, as illustrated in Fig. 3.5. These include MIKE 21 Spectral Wave (MIKE21 SW), MIKE 21 Hydrodynamic (MIKE21 HD), MIKE 21 Sand Transport (MIKE21 ST), and MIKE 21 Shoreline Morphology (MIKE21 SM). A detailed description of all MIKE21 modules are provided in DHI (2016b), DHI (2016c), and DHI (2017b). Therefore, subsequent paragraphs only describe the essential features of each module.

MIKE21 SW simulates the wave field by discretising the wave action conservation equation on an unstructured mesh, made of triangular elements, using a cell-centred finite volume approach. MIKE21 SW facilitates two types of formulations: *fully spectral* and *directional decoupled parametric*. The *fully spectral formulation* is based on Komen et al. (1994) wave action conservation equation, which uses the directional-frequency wave action spectrum as the dependent variable. The *directional decoupled parametric* formulation uses Holthuijsen et al. (1989) parameterisation of the wave action conservation equation, made in the frequency domain by introducing the zeroth and the first moment of the wave action spectrum as dependent variables. I use the directional decoupled parametric formulation in this thesis because it is appropriate for simulating nearshore wave propagation and wave transformation over cross-shore distances up to 50 km (Ti et al., 2018). MIKE21 SW accounts for the effects of depth and current-induced wave refraction and shoaling, wind-wave generation, bed friction, wave breaking based on Battjes and Janssen (1978) formulation, and wave diffraction based on Holthuijsen et al. (2003) phase-decoupled refraction-diffraction approximation. MIKE21 SW generates the radiation stresses that drive the mean flow in MIKE21 HD.

MIKE21 HD simulates the flow and current by discretising the non-linear shallow-water equations on the same computational mesh as MIKE21 SW using a finite volume approach. These equations include continuity and momentum equations formulated in Cartesian coordinates. MIKE21 HD generates the time and space variations in water levels required for simulating wave condition changes under tide level variations in MIKE21 SW. MIKE21 HD also generates the time and space variations in current velocity and direction that determine wave action propagation in MIKE21 SW.

MIKE21 ST simulates sediment transport from combined wave-current action. This module provides a quasi-3D description of the force balance and hydrodynamics through the water column and a detailed description of the instantaneous turbulent boundary stresses from wave-current interactions. Fredsøe's (1984) integrated momentum approach calculates the time and vertical variations in bed shear stress, turbulence, flow velocity, and sediment concentration. MIKE21 ST determines total sediment transport by calculating bed load and suspended load transport separately. The bed load transport is derived from the instantaneous Shields parameter using Engelund and Fredsøe (1976) model, and the suspended load transport is the product of the instantaneous flow velocities and sediment concentration. Vertical variations in suspended sediment concentration are derived from Fredsoe et al. (1985) vertical diffusion equation for suspended sediment. During a simulation, MIKE21 ST calculates sediment transport rates by linear interpolation in a precomputed sediment transport table based on the wave, current, and water level conditions in MIKE21 SW and MIKE21 HD. The sediment transport table must consider the range of wave, current, and sediment conditions likely to occur in the simulation. The littoral drift gradients calculated from MIKE21 ST update the shoreface morphology and shoreline position according to MIKE21 SM shoreline continuity equation.

MIKE21 SM divides the shoreface into shore-perpendicular strips and integrates the change in sediment volume (vol) on each shoreface strip. vol is determined from littoral drift gradients in MIKE21 ST. MIKE21 SM combines vol with a predefined active coastal profile to calculate the change in shoreline position at each time step (Δt), using a modified version of the one-line equation:

$$\frac{\Delta N}{\Delta t} = \frac{vol}{dA_z} \quad \text{(Eqn. 3.3)}$$

where ΔN is the distance the shoreline moves perpendicular to its orientation and dA_z is the vertical area of the active coastal profile in each shoreface strip over which MIKE21 SM uniformly distributes vol. During a simulation, the bathymetry outside of shoreface strips remains constant. An iterative procedure focusing on the change in shoreline position ensures the conservation of sediment mass. After each iteration, there is a comparison between vol in each shoreface strip and the sediment volume available for deposition or erosion (determined from littoral drift gradients). This comparison determines the error of vol in each shoreface strip and correct the shoreline position according to:

$$\Delta N_{i+1} = \Delta N_i + 0.5 \cdot \frac{vol_{error}}{dA_z} \quad \text{(Eqn. 3.4)}$$

where vol_{error} is the error in sediment volume change and i is the iteration number in the simulation.

3.3.2 Bruun Rule

The original Bruun Rule assumes shoreline retreat is equal to sea-level change divided by the upper shoreface slope (Eqn. 3.2) (Bruun, 1962). It is based on the premise that sandy coastal systems have homogenous sediment properties and shore-parallel contours (Bruun, 1983; Shand et al., 2013). Modified versions of the Bruun Rule also assume linearity between sea-level rise and shoreline retreat but contain additional parameters on heterogeneous coastal material, coastal profiles, and cliff elevation specific to either cliffed coastal systems or atoll islands (Malcolm and Janet, 1997; Cowell and Kench, 2001; Young et al., 2014). Sandy coastal systems differ from cliffed coastal systems and atoll islands in sediment sorting, profile shape, and planform evolution (Pontee et al., 2004; Karunarathna et al., 2016). Therefore, I use the original Bruun Rule in this thesis since modified versions are specific to coastal morphologies different from those of each test site selected.

All test sites selected are sandy coastal systems, each with contrasting morphology. The New York and Southern California test sites have simple planform morphologies with shore-parallel contours compared to the Puerto Rico test site (Fig. 2.4). The simple planform morphology of the New York and Southern California test sites conforms to the morphology assumptions of the original Bruun Rule. The Puerto Rico test site non-parallel depth contours do not conform to the shore-parallel assumption underlying all Bruun Rule versions. However, the original Bruun Rule morphology assumptions better align with the Puerto Rico test site low-lying sandy coastal system. Therefore, the original Bruun Rule formulation is most appropriate for application across each test site selected.

3.4 Applying MIKE21

This section describes the *general* setup of MIKE21 for application in each test site. It has four subsections: section 3.4.1 presents the methods used for generating the mesh to simulate the coupled 2D wave, flow, and sediment transport field; section 3.4.2 details the specifications and parameterisation of MIKE21 SW, MIKE21 HD and MIKE21 ST; section 3.4.3 describes the representation of hard defences in MIKE21 process-driven modules; and section 3.4.4 outlines the setup of MIKE21 SM for updating the shoreface morphology and shoreline position. Later in this chapter, sections 3.8 and 3.9 discuss the steps taken to develop a novel approach that accounts for sea-level rise and complex planform morphologies in MIKE21 SM morphology update, respectively.

3.4.1 Mesh generation

I use high-resolution bathymetry, tide, and wave height data (Figs. 2.5 to 2.8) to define the spatial domain for generating MIKE21 finite volume mesh for coastal processes simulations in each test site. Each domain is projected in UTM coordinates with the following dimensions and specifications:

> *New York test site (Fig. 2.1):* This test site's spatial domain is 12.5 km longshore and 2 km cross-shore, incorporating all land area and extending to a depth of ~13 m below Mean High Water (MHW). Analysing the New York test site's wave climate time series obtained (Fig. 2.6) reveals a mean wave height of 1.2 m with a standard deviation of 0.69. Therefore, a 13 m depth boundary will not affect wave approach to the shoreline because waves generally break at a depth equal to 1.2 times their height (Turner et al., 1997; Basterretxea-Iribar et al., 2019). Throughout this thesis, the shoreline is the MHW line (the zero-depth contour in the bathymetry).

Puerto Rico test site (Fig. 2.2): This test site's spatial domain is 4 km longshore and 3 km cross-shore. The domain extends from 5 m above MHW (400 m landward of the shoreline) to 50 m below MHW, covering the coral reef network's full extent. The sea boundary is deep to allow wave propagation over the coral reefs and wave approach to the shoreline. The highest tide level ever recorded in San Juan is less than 1 m above MHW (NOAA, 2017c). Therefore, the land boundary is notably high, which will prevent the entire domain from getting wet (flooding) during simulations to avoid spurious predictions of sediment transport and shoreline evolution.

Southern California test site (Fig. 2.3): This test site's spatial domain is 10.2 km longshore and 1.05 km cross-shore. The domain extends from 30 m above MHW (300 m landward of the shoreline) to 13 m below MHW. The Southern California test site's wave climate time series obtained have a mean wave height of 1.02 m with a standard deviation of 0.39 (Fig. 2.8). Therefore, a 13 m depth boundary will not affect wave approach to the shoreline. The land boundary is also notably high to ensure that the entire domain does not flood during simulations.

I divide each spatial domain into two zones: nearshore and offshore. In the New York and Southern California test sites, the nearshore is the area landward of the closure depth and the offshore is the area seaward of the closure depth. I define the closure depth in the New York and Southern California test sites as the most seaward contour with shoreline undulations, following Kaergaard (2011). The coral reef network's sea boundary separates the nearshore and offshore in the Puerto Rico test site.

I specify a maximum element area of 625 m^2 (25 m resolution) nearshore and 4 900 m^2 (70 m resolution) offshore to generate the mesh in each spatial domain for initial simulations. I use Shewchuk (1996) Delaunay refinement method for mesh generation. A maximum resolution of 25 m nearshore and 70 m offshore create the finest mesh discretisation that is computationally feasible to apply MIKE21 in the New York test site domain, the largest domain defined. I use the same resolution for mesh generation in each test site to objectively quantify spatial discretisation effects on shoreline evolution predictions in different coastal morphologies. The nearshore and offshore resolutions defined correspond to process length scales of primary shoreline evolution drivers (e.g. seasonal wave climate and tides) (Table 1.1) (Stive et al., 2002; Reeve et al., 2019). The resulting meshes are finite volume discretisations with triangular elements (Fig. 3.6). There are 42 154 elements in the New York test site's mesh, 20 878 in the Puerto Rico test site's mesh, and 13 032 in the Southern California test site's mesh. Each mesh has a land, sea and two connecting boundaries (see Fig. 3.6).

3.4.2 Spectral wave, hydrodynamic, and sediment transport modules

MIKE21 process-driven modules require an initial bathymetry, boundary conditions, and specification of parameters describing coastal system features not easily measured in the field. The following paragraphs describe how the initial bathymetry and boundary conditions are specified in MIKE21 SW, MIKE21 HD and MIKE21 ST, and then discuss how each of these modules is parameterised.

The bathymetry is the main initial condition in MIKE21 process-driven modules because it provides the basis for simulating wave-current interactions in the presence of hard defences and the ensuing sediment transport gradients that drive shoreline change. I specify the bathymetry for MIKE21 application in each test site by interpolating their initial bathymetry (Fig. 2.5) onto their mesh using the natural neighbour approach. I convert the initial bathymetry into x, y, z data points to facilitate mesh interpolation. The natural neighbour approach creates a triangulated irregular network from the x, y, z data points and assigns a weighted value to each data point surrounding each mesh node based on the distance from the data point to the node. The depth in the centre of a triangular mesh element is the average of the depth values interpolated at each of the element nodes. The natural neighbour approach is suitable for mesh interpolation as it preserves the original bathymetry data and produces a continues bed surface, with smoothly changing gradients, between neighbouring mesh elements (Takagi, 1998; Mitas and Mitasova, 2005). Fig. 3.7 shows the interpolated mesh nodes in 3D, and Fig. 3.8 shows the 2D planimetric view of the interpolated mesh for each test site.

Various boundary conditions provide the forcings in MIKE21 to drive the wave and flow simulations. In each test site, high-resolution tide and wave climate data (Figs. 2.6 to 2.8) provide the primary forcings in MIKE21 HD and MIKE21 SW. I force tides and waves at the sea boundary and keep the connecting boundaries open to facilitate littoral drift. I specify the connecting boundaries as lateral wave boundaries in MIKE21 SW and Flather boundaries in MIKE21 HD. Lateral wave boundaries neglect the effects of waves propagating outside the boundary and use incoming wave information from the sea boundary instead (Fairley et al., 2009; Qiao et al., 2020). Lateral wave boundaries are specific to boundaries where contours are perpendicular to the boundary line (DHI, 2016c), characteristic of each mesh connecting boundaries (Fig. 3.8). On the other hand, Flather boundaries are based on the Flather (1976) condition, a radiation boundary condition that minimises spurious reflections from flow moving out of the domain (Divett et al., 2013). The Flather condition is the most efficient open boundary condition for process-driven coastal models (Ye et al., 2011; Jakacki et al., 2017). Flather boundaries require specifications of expected free surface elevations and current velocities in x, y directions. Enabling the Flather condition forces the difference between the expected and calculated free surface elevation out of the domain at the long wave phase speed, preventing spurious reflections. I run an initial simulation in each test site using their interpolated mesh and Table 3.2 specifications to generate the data for the Flather condition. I also include the effects of wind on the flow and wave fields in each test site using high-resolution wind data (Figs. 2.6 to 2.8). Wind is forced over the entire model domain rather than at a boundary. All forcings are entered using a dampened interval of 2 hours to prevent shock waves from generating inside the model domain.

In MIKE21 ST, I specify a zero-sediment flux gradient at all mesh boundaries (Fig. 3.8) except the land boundary. A zero-sediment flux gradient is an open boundary condition allowing the same sand volume in and out of the domain as demanded by the changing hydrodynamics in the model space. Doing so avoids a glass wall effect by preventing the sudden deposition or erosion of sediment at the open boundaries (Coco, 2003; Preston et al., 2018). As a result, zero sediment flux boundaries ensure the conservation of sediment mass and prevent instabilities from generating at the boundaries and propagating inside the model domain (Li et al., 2008; Kristensen, 2013; Luo et al., 2013; Sherwood et al., 2018). However, zero sediment flux boundaries are generally specific to coastal systems receiving an adequate sand supply because these boundaries assume an unlimited sand supply is available for transport (Preston et al., 2018). Therefore, these boundaries are appropriate for modelling shoreline evolution in all three test sites as each site receives an adequate sand supply from external sources, including updrift shore nourishment (New York and Southern California test sites) and fringing coral reefs (Puerto Rico test site) (Bird, 2010; Catania, 2015; Gallien et al., 2015).

I parameterise each process-driven module in MIKE21 to include key coastal system features that are not represented by boundary conditions and difficult to measure in the field. Specifically, I setup MIKE21 SW to account for wave breaking, bottom friction, water level variations, and current variations. The water level and current variations are derived from MIKE21 HD and ensure wave action conservation in MIKE21 SW. I use the wave radiation stresses from MIKE21 SW to drive the mean flow in MIKE21 HD. The radiation stresses are the flux of momentum carried by waves that enter the water column upon wave breaking, from where they generate the nearshore currents that drive sediment transport. Also, I setup MIKE21 HD to consider eddy viscosity based on Smagorinsky (1963) zero equation turbulence model, bed friction based on Manning's n reciprocal, Coriolis forcing, and wind friction. Lastly, I parameterise MIKE21 ST to account for the effects of sand grain size, sand porosity, and sediment grading coefficient in sediment transport gradients. The sediment grading coefficient describes the sediment sorting in the coastal system. Table 3.2 lists the default specification of each parameter included in MIKE21 for pre-calibration simulations in each test site.

MIKE21 ST calculates littoral drift rates by linear interpolation in a precomputed sediment transport table based on flow and wave conditions in the model domain. The precomputed sediment transport table specifies the range of current speed, wave height, wave period, wave height to water depth ratio, the angle between current and waves, median grain size, sediment grading, and bed slope that may appear in the simulation. Errors accumulate in MIKE21 ST calculations if simulation conditions are not within their defined range in the precomputed sediment transport table, causing MIKE21 SM shoreline evolution predictions to become unreliable. I run multiple initial simulations using different sediment transport tables in each test site to identify conditions best describing their coastal system. All precomputed sediment transport tables account for relative sand density, Shields parameter, ripples, bed slope, suspended sediment concentration, undertow, and wave-induced near-bed velocities. Table 3.3 outlines the precomputed sediment transport table calibrated for each test site.

3.4.3 Representing hard defences

As hard defences are usually smaller than the size of mesh elements, MIKE21 simulates their effect on wave, flow, and sediment transport conditions using a sub-grid approach (Fig. 3.9). MIKE21 treats hard defences, such as groynes, as polyline features. Each node forming a polyline representing a hard defence has x, y coordinates and an elevation (z) value relative to MHW. The x, y coordinates specify the location and horizontal dimension, and z describes the elevation features. The polyline length defines the hard defence width perpendicular to the flow direction. The hard defences in the New York and Southern California test sites are cross-shore structures ranging from 1 to 2 m above MHW to ~1 m below MHW. There are five cross-shore structures in the Puerto Rico test site, similar to those in the New York and Southern California test sites. The Puerto Rico test site also has ten longshore structures, all above MHW, for protecting private beach properties. I use georeferenced satellite imagery (Figs. 2.1 to 2.3) to digitise each hard defence polyline using a 1 m node spacing. A 1 m node spacing best captures the elevation features of the hard defences in each test site. The satellite imagery provides the x, y coordinates of each polyline node, and the initial bathymetry (Fig.

2.5) provides the z values. Fig. 3.9 shows all digitised hard defence polylines and their spatial distribution in each test site's mesh. During a simulation, MIKE21 redefines each hard defence polyline as a selection of mesh element faces, as illustrated in Fig. 3.9d. A selection of mesh element faces representing a hard defence can either interrupt or block a sediment flux during a simulation.

MIKE21 HD uses either a standard weir expression or overtopping discharge data to calculate flow discharge over hard defences during a simulation. I use the standard weir expression to simulate discharge over each test site's cross-shore structures as overtopping discharge data are not available. The standard weir expression calculates discharge (Q) over a section of a structure corresponding to an element face with the length (width) (W) according to Villemonte (1947) formula:

$$Q = WC_w(H_{us} - H_w)^k \left[1 - \left(\frac{H_{ds} - H_w}{H_{us} - H_w}\right)\right]^{0.385} \quad \text{(Eqn. 3.5)}$$

where C_w is the weir coefficient, k is the weir exponential coefficient, H_{us} is the upstream water level, H_{ds} is the downstream water level, and H_w is the weir level relative to MHW. MIKE21 HD derives H_{us}, H_{ds}, and H_w from water level variations in MIKE21 HD during a simulation. k remains fixed at 1.5, and the default value of C_w is 1.838 $m^{1/2}/s$. The weir coefficient (C_w) is a function of the gravitational constant and the discharge coefficient and geometric properties of a hard defence structure. I use the default value of C_w in all initial and pre-calibration simulations in each test site.

I use an overtopping discharge of 0 $m^3/s/m$ to describe flow interactions with the Puerto Rico test site longshore defences, preventing flow movement onshore of these structures for two reasons. *First*, the Puerto Rico test site's longshore defences are 2 to 3 m above MHW, much higher than the tide levels and wave heights recorded there (Fig. 2.7). *Second*, the Puerto Rico test site's longshore defences are designed to block onshore flow movement for private property protection (Fig. 2.2b).

MIKE21 SW solves the energy balance equation to describe wave interactions with hard defences:

$$K_t^2 + K_r^2 + K_l^2 = 1 \quad \text{(Eqn. 3.6)}$$

where K_t represents the transmission coefficient, K_r is the reflection coefficient, and K_l is the loss (wave attenuation) coefficient. K_t describes the intensity of a transmitted wave height relative to an incident wave height, whereas K_r describes the intensity of a reflected wave height relative to an incident wave height. K_t is estimated according to Goda et al. (1967) formulation in MIKE21 SW:

$$K_t = K_{t,max} \qquad \frac{f}{H_i} < \left(\frac{f}{H_i}\right)_{min}$$

$$K_t = \frac{1}{2}\left(1 - sin\left(\frac{\pi}{2}\frac{\frac{f}{H_i} + \beta}{\alpha}\right)\right) \qquad \left(\frac{f}{H_1}\right)_{min} \leq \frac{f}{H_i} \leq \left(\frac{f}{H_i}\right)_{max}$$

$$K_t = K_{t,min} \qquad \frac{f}{H_i} > \left(\frac{f}{H_i}\right)_{max} \qquad \text{(Eqn. 3.7)}$$

where α and β are two fitting coefficients, $K_{t,min}$ is the minimum transmission coefficient, and $K_{t,max}$ is the maximum transmission coefficient. H_i represents the incoming wave height and f is the freeboard, defined as the crest level of the structure minus the surface elevation. α is 2.2 and β is 0.4, as recommended by Goda et al. (1967) and Goda (1969). K_r ranges from 0 (waves absorbed) to 1 (waves reflected). Cross-shore structures in each test site do not fully reflect nor fully absorb waves as they range in elevation above and below MHW. Therefore, I use a K_r of 0.5 (partial wave reflection) to describe wave interactions with each test site's cross-shore structures. In contrast, I use a K_r of 1 to describe wave interactions with the Puerto Rico test site's longshore structures because these structures have been designed to protect private properties by fully reflecting waves.

3.4.4 Shoreline morphology module

MIKE21 SM uses four inputs to update the shoreface morphology and shoreline position during a simulation, including a baseline, an initial shoreline, an edge map, and predefined coastal profiles. The baseline and edge map define the spatial domain for MIKE21 SM calculations. The initial shoreline and predefined coastal profiles specify the bathymetry inside MIKE21 SM domain. Fig. 3.10 shows the general configuration of MIKE21 SM domain. I use the same principles to setup MIKE21 SM in each test site using the MIKE Zero Mesh Generator (DHI, 2017c), as described below.

The baseline orientation sets the direction for shoreline movement during a simulation, and the initial shoreline defines the initial shoreline position subject to accretion and erosion. I specify the baseline landward of the beach berm. The beach berm forms the onshore extent of the active coastal profile. Table 3.2 specifies each test site's beach berm elevation. The zero-contour in the initial bathymetry used for mesh interpolation (Fig. 2.5) is the initial shoreline. Both baseline and initial shoreline are polylines made up of nodes, each containing x, y coordinates. The spacing between baseline nodes determines the initial shoreline resolution. The baseline and initial shoreline nodes are staggered, such that there is one shoreline node between two baseline nodes (Fig. 3.10). The initial shoreline has two nodes outside of MIKE21 SM domain for boundary condition purposes (Fig. 3.10). The boundary condition is zero gradient in littoral drift to ensure sediment mass conservation and prevent numerical instabilities at MIKE21 SM boundaries (DHI, 2017b). Each node in the initial shoreline defines one shoreline edge that moves shore-normal during a simulation. I use a 15 m resolution to specify the baseline and initial shoreline in each test site. A 15 m resolution is fine compared to the spatial scale of shoreline undulations and deformations in each test site, which is greater than 50 m.

The edge map defines the mesh elements that determine a shoreline edge movement during a simulation (Fig. 3.10). The edge map assigns mesh elements to a shoreline edge by dividing the shoreface into strips perpendicular to the baseline. If mesh elements overlap strips, MIKE21 SM uses piecewise constant interpolation to map sediment transport gradients from MIKE21 ST onto strips. The baseline is the onshore boundary of the edge map, and the baseline resolution defines the longshore width of each strip. Two baseline nodes generate one strip. Each strip has one shoreline node (shoreline edge) between baseline nodes, as illustrated in Fig. 3.10. The offshore boundary of the edge map is the depth contour seaward of the closure depth. Using the depth contour seaward of the closure depth as the offshore boundary ensures the edge map includes the active coastal profile full extent. The closure depth in the New York and Southern California test sites is the most seaward contour with shoreline undulations in the initial bathymetry (Fig. 2.5). In contrast, the Puerto Rico test site's closure depth varies longshore based on reef substrate distribution. As MIKE21 does not consider closure depth variations, the closure depth for pre-calibration simulations in the Puerto Rico test site is the deepest general shore-parallel contour landward of reefs in the initial bathymetry (Fig. 2.5b). Table 3.2 gives the closure depth values for pre-calibration simulations in each test site.

The coastal profile defines a representative cross-shore profile that moves shore-normal with a shoreline edge during a simulation. I define one coastal profile in each shoreface strip as a polyline feature running through the initial shoreline node in the strip, perpendicular to the baseline (Fig. 3.10). Each coastal profile polyline extends beyond the beach berm and closure depth and comprises nodes with x, y coordinates and an elevation (z) value relative to MHW. MIKE Zero Mesh Generator obtains z from the interpolated mesh bathymetry. Each coastal profile polyline has a node spacing (resolution) of 1 m. During a simulation, sediment volume change within the active limits of the coastal profile in a shoreface strip determines the shore-normal movement of the shoreline edge in the strip based on Eqn. 3.3. MIKE21 SM calculates the sediment volume change in a shoreface strip by adding the sediment volume change in each mesh element within the strip. Essentially, MIKE21 SM collapses the sediment transport gradients from MIKE21 ST onto the edge map, where it becomes integrated with the predefined active coastal profiles (Kaergaard, 2011). In each shoreface strip, the active coastal profile moves seaward (landward) from sediment gain (loss), as illustrated in Fig. 3.3.

3.5 Applying the Bruun Rule

This section outlines the *general* configuration of the Bruun Rule for application in each test site. The Bruun Rule is a simple 2D formulation (Eqn. 3.2) relating shoreline retreat (R) to relative sea-level rise (SLR) by the ratio of the active coastal profile horizontal (L) and vertical dimensions, berm height (D_b) and closure depth (D_c). The following paragraphs describe the procedures taken to apply the Bruun Rule in each test site and also outline how D_b, D_c, L, and SLR are estimated in each test site.

I apply the Bruun Rule equation (Eqn. 3.2) in cross-shore transects every 5 m longshore to estimate shoreline change in the New York and Southern California test sites. All transects are generated along the D_b and D_c contours in the initial bathymetry (Fig. 2.5), as illustrated in Fig. 3.11a. 2 449 transects are created in the New York test site and 1 941 in the Southern California test site. I use the relevant D_b and D_c values in Table 3.2 for initial Bruun Rule formulations in both test sites. The distance between D_b and D_c in each transect is L. Thus, L varies in each transect while D_b and D_c are constant. The SLR value for each Bruun Rule formulation in the New York and Southern California test sites is derived from their sea-level rise rate. The sea-level rise rate is 0.004 m yr^{-1} in the New York test site, based on mean sea-level data from 1932 to 2019 (NOAA, 2017d), and 0.002 m yr^{-1} in the Southern California test site, based on mean sea-level data from 1933 to 2019 (NOAA, 2017e).

I use the same principles above to apply the Bruun Rule in the Puerto Rico test site, except I vary D_c and L in each transect based on reef substrate distribution in the initial bathymetry (Fig. 2.5b), as illustrated in Fig. 3.11b. 702 transects are used to formulate the Bruun Rule in the Puerto Rico test site. In reefs transects, D_c is the depth nearest the shoreline where hard substrate first appears in line with the closure depth definition for coral reef systems (Eversole and Fletcher, 2003). In non-reef transects, D_c is the most seaward depth contour in the initial bathymetry reflecting shoreline undulations. I use the relevant D_b value in Table 3.2 for the Bruun Rule formulation in each transect. The SLR specification in these formulations is derived from the Puerto Rico test site's relative sea-level rise rate, which is 0.002 m yr^{-1} based on mean sea-level data from 1962 to 2019 (NOAA, 2017c).

3.6 Model sensitivity testing and calibration

This section presents the methods used to address research question one: *What are the key boundary conditions needed to model the mesoscale evolution of managed sandy shorelines?* To address this question, I assess model sensitivity to ten boundary conditions, including nearshore discretisation, bathymetry, tides, wind, waves, bed friction, sediment grain size, sediment grading, sediment porosity, and the weir coefficient of hard defences. The importance of testing model sensitivity to these conditions is discussed below. I assess MIKE21 sensitivity to all ten boundary conditions and the Bruun Rule sensitivity to bathymetry and tides only. Bathymetry and tides are the only boundary conditions that affect the Bruun Rule. I use the model sensitivity results to identify and specify the appropriate values (calibrate) of key model inputs for later shoreline evolution simulations.

Based on high-quality bathymetry and coastal processes data available, I assess MIKE21 and the Bruun Rule sensitivity from 01-Jan-2014 to 01-Feb-2016 in the New York test site, 01-Oct-2014 to 31-Mar-2016 in the Puerto Rico test site, and 01-Jan-2009 to 02-Aug-2011 in the Southern California test site. These periods allow for identifying the specifications causing the largest errors in shoreline evolution predictions (Roelvink et al., 2016; Williams and Esteves, 2017). As discussed in Chapter 2, this knowledge is crucial for adjusting model inputs to improve robustness and results. Data used for model sensitivity testing in each test site are listed in Table 2.1 and presented in Figs. 2.6 to 2.8.

Sections 3.6.1 to 3.6.4 introduce the methods used to evaluate model sensitivity in each test site. Section 3.6.1 outlines the approach used to assess MIKE21 sensitivity to nearshore spatial discretisation. Section 3.6.2 details the steps taken to evaluate MIKE21 and the Bruun Rule sensitivity to bathymetry data spatial resolution. Section 3.6.3 discusses the procedures used to investigate MIKE21 and the Bruun Rule sensitivity to coastal processes data temporal resolution. Lastly, section 3.6.4 describes the methods used to evaluate MIKE21 sensitivity to free parameters.

3.6.1 Nearshore spatial discretisation

Mesh discretisation in the nearshore is a critical specification in shoreline evolution models because it affects the representation of nearshore bathymetry, which influences the wave-current interactions that drive sediment transport (Kerr et al., 2013; Belibassakis and Karathanasi, 2017; Yeu et al., 2018). To appropriately guide coastal management, shoreline evolution predictions should be independent of the mesh discretisation (Fringer et al., 2019; Sasikumar et al., 2020). The independent mesh discretisation is defined as the mesh with the coarsest nearshore resolution that does not significantly affect model solutions even if the nearshore resolution gets finer. An independent mesh discretisation ensures that model solutions are due to the underlying physics and not the mesh resolution used. However, specifying an independent mesh discretisation is unbounded, nor are there any objective rules to guide mesh construction (Hardy et al., 1999; Williams and Esteves, 2017). Related studies use the finest mesh discretisation computationally feasible or process length scales to define a mesh resolution without gauging the effects on model solutions (Bloemendaal et al., 2018; Bilskie et al., 2020). Therefore, the importance of the nearshore discretisation in shoreline evolution models is not yet defined, nor are the optimal (minimal) requirements established for specifying the nearshore bathymetry in these models. The following paragraphs outline the method used to identify the independent mesh discretisation in each test site.

I successively coarsen the nearshore resolution in each mesh (Fig. 3.6) from a maximum of 25 m to 65 m at 5 m intervals to assess MIKE21 sensitivity to nearshore spatial discretisation. Therefore, eight additional meshes are generated for each test site. The range of resolution used for the nearshore spatial discretisation (25 m to 65 m) corresponds to process length scales of primary shoreline evolution drivers (Table 1.1). In each additional mesh, the maximum offshore resolution is 70 m. As aforementioned, a maximum resolution of 25 m nearshore and 70 m offshore create the finest mesh discretisation that is computationally feasible to apply MIKE21 in the New York test site. Using the same mesh resolution range to apply MIKE21 in each test site allows for a better understanding of nearshore spatial discretisation effects on shoreline evolution predictions in different coastal morphologies. Table 3.4 provides details of the meshes used for assessing MIKE21 sensitivity to nearshore discretisation in each test site. Figs. 3.12, 3.13, and 3.14 present the finest, median and coarsest mesh generated for the New York, Puerto Rico, and Southern California test site, respectively. All additional meshes are interpolated following the procedures in section 3.4.2.

I assess MIKE21 sensitivity to nearshore discretisation in each test site by running one simulation using each of their meshes and the relevant specifications in Tables 3.2 and 3.3. To be specific, the nearshore spatial discretisation is the only input varied in these simulations. I quantify the effects of different nearshore spatial discretisations on MIKE21 accuracy and predictions of net littoral drift and net shoreline change using the statistical methods in section 3.7. These statistical methods include tests that assess for significant differences in net littoral drift and net shoreline change predictions in response to variations in nearshore discretisation. I use the results of these tests to identify the independent mesh discretisation for further simulations in each test site. Net littoral drift is the difference between the total sediment volume transported to the right and left of a shoreline edge at the end of a simulation. Net littoral drift is included in all model sensitivity evaluations for two reasons. *First*, net littoral drift is the volume of sand transport of concern in shoreline evolution studies as it indicates the main direction of longshore sediment transport (Davidson-Arnott, 2010). *Second*, net littoral drift is the primary forcing variable in MIKE21 SM shoreline continuity equation (see Eqn. 3.3).

3.6.2 Spatial resolution of bathymetry data

The bathymetry data define the bed surface elevation that influences wave-current interactions and sediment transport simulations in MIKE21 and the value of L in the Bruun Rule model. L is the distance between beach berm and closure depth. Overly coarse bathymetry data may exclude intricate sea-floor features and affect MIKE21 net littoral drift and net shoreline change predictions. Bathymetry data resolution also influences the location and cross-shore spacings between depth contours, which affect L and associated Bruun Rule predictions. However, there are no defined guidelines concerning bathymetry data resolution for simulating shoreline evolution, as discussed in section 3.2. The following paragraphs describe the approach used to assess MIKE21 and the Bruun Rule sensitivity to bathymetry data resolution in each test site. I use the results to define the optimal bathymetry data spatial resolution for modelling shoreline evolution in different coastal morphologies.

I resample the New York and Puerto Rico test sites initial bathymetry from 3 m to 9, 27, 81, 90, 100, and 500 m, and the Southern California test site's initial bathymetry from 10 m to 27, 81, 90, 100, and 500 m, to assess model sensitivity to bathymetry data resolution. In all cases, I use the nearest neighbour resampling method described below. Fig. 2.5 shows each test site's initial bathymetry. All resampling resolutions are within the bathymetry data resolution range available for vulnerable small islands. Global terrain models, such as the Shuttle Radar Topography Mission (90 m resolution), General Bathymetric Chart of the Oceans (~450 m resolution), and ETOPO1 Global Relief Model (1.8 km resolution), are often the only source of bathymetry for vulnerable small islands (Giardino et al., 2018; Parodi et al., 2020). Thus, the above resampling resolutions allow for testing the usefulness of open-source bathymetry for modelling shoreline evolution. Such knowledge can help refine coastal monitoring to better facilitate mesoscale shoreline evolution models as coastal management tools.

Nearest neighbour resampling assigns the value from a cell centre in the original raster to the closest cell in the output raster, retaining the same values from the original raster. Nearest neighbour resampling is commonly used to generate bed surfaces because it preserves original values (Li and Wong, 2010; Saksena and Merwade, 2015). However, it is possible that nearest neighbour resampling can generate blocky bed surfaces and exaggerate the slope between cells in the output raster as it simply creates greater distances between the original raster data points. Possible slope artefacts in resampled bed surfaces do not present a problem for MIKE21 processes simulations. MIKE21 interpolates the raw data points from the resampled bed surfaces onto the mesh using the natural neighbour method to generate the model bathymetry (see section 3.4.1). Thus, there are two steps for coarsening the bathymetry to test MIKE21 sensitivity. *First*, resampling the high-resolution initial bathymetry using the nearest neighbour method. *Second*, interpolating the data points from the resampled bathymetry onto the mesh using the natural neighbour method. In contrast, the Bruun Rule sensitivity to bathymetry resolution is tested using L estimates from the resampled bed surfaces. Therefore, possible slope artefacts in resampled bed surfaces can affect the Bruun Rule predictions.

To ensure that the Bruun Rule predictions are due to bathymetry resolution and not the resampling method used, I degrade the initial bathymetry in each test site to the abovementioned resolutions using bilinear interpolation and compare the results with those from nearest neighbour resampling. Bilinear interpolation assigns values to cells in the output raster based on a weighted average of the four nearest cell centres in the original raster, creating a continuous bed surface devoid of slope artefacts. The primary limitation of bilinear interpolation is the non-retention of original values. I use a two-sample Kolmogorov-Smirnov test to compare the slope and elevation in bed surfaces of the same resolution generated from nearest neighbour resampling and bilinear interpolation. A two-sample Kolmogorov-Smirnov test is a distribution-free test that compares whether the empirical distributions of two samples are significantly different (Smirnov, 1939). If the resulting p value is lower than the 5% significance level (0.05), the empirical distributions between two samples are significantly different. Tables 3.4 to 3.6 compare the difference between bed surfaces generated from nearest neighbour resampling and bilinear interpolation. In all cases, the p value of a two-sample Kolmogorov-Smirnov test is greater than the 5% significance level, indicating that bed surfaces generated from nearest neighbour resampling and bilinear interpolation are not significantly different.

I assess MIKE21 sensitivity to bathymetry data resolution in each test site by running successive simulations using their independent mesh discretisation interpolated with coarsening (resampled) bathymetry data and Tables 3.2 and 3.3 specifications. Therefore, the only input changed in these simulations is the bathymetry data resolution used for mesh interpolation. I quantify the effects of coarsening bathymetry data on MIKE21 performance and net littoral drift and net shoreline change predictions using the statistical methods in section 3.7. I use the outcomes to define the optimal bathymetry data resolution for modelling shoreline change in different coastal system morphologies.

I assess the Bruun Rule sensitivity to bathymetry data in each test site by applying its equation to cross-shore transects every 5 m longshore and successively changing L based on the beach berm (D_b) and closure depth (D_c) contours in coarsening (resampled) bathymetry data. I keep all other Bruun Rule variables (D_b, D_c, and SLR) constant. I quantify the effects of varying L on the Bruun Rule accuracy and predictions using the methods in section 3.7 and compare the results with those from MIKE21 sensitivity testing to bathymetry resolution. I use the outcomes to better understand the influence of bathymetry data resolution on shoreline change predictions in different coastal systems.

3.6.3 Temporal resolution of tide, wind, and wave climate data

Tide, wind and wave climate data provide the primary boundary conditions that drive the coupled wave, flow and sediment transport field in MIKE21, whereas sea-level rise is the only forcing in the Bruun Rule. As sea-level rise rates are typically derived from tide records, tide data may indirectly influence the Bruun Rule. At present, there is considerable uncertainty on the optimal data requirements for representing tides, wind and wave climate in shoreline evolution models, which stem from limited sensitivity studies on these models (Blanco et al., 2019). The following paragraphs first outline the methods used to assess MIKE21 sensitivity to tide, wind and wave climate data, and then describe the approach used to evaluate the Bruun Rule sensitivity to tide data. I use the outcomes of these sensitivity tests to understand the impact of tide, wind, and wave climate data on shoreline evolution predictions in different coastal systems. Such knowledge allows for identifying the essential boundary conditions for simulating shoreline evolution in different coastal morphologies.

I resample each test site's high-resolution tide, wind and wave climate datasets (Figs. 2.6 to 2.8) using linear interpolation to evaluate MIKE21 sensitivity to each coastal process boundary condition. Linear interpolation defines a new value by connecting two known adjacent values with a straight line. If the known values are x_1, y_1 and x_2, y_2, the y value for a point x between the known values is:

$$y = y_1 + (x - x_1)\frac{y_2 - y_1}{x_2 - x_1} \quad \text{Eqn. 3.8}$$

I resample each test site's tide and wind data from 6 min to 10, 20, 30, 40, 50, and 60 min. I resample the New York and Puerto Rico test sites wave climate data from 60 min to 10, 20, 30, 40, and 50min, and the Southern California test site's wave climate data from 30 min to 10, 20, 40, 50 and 60 min. These time series resampling resolutions are within the range of tide data resolutions available in vulnerable small islands (Caldwell et al., 2015; Giardino et al., 2018). Figs. 3.15, 3.16, and 3.17 show a sample of each test site's original and resampled tide, wind speed, and wave height data. The linear interpolation method used to resample each test site's coastal processes data facilitates the main objective of testing model sensitivity to these data temporal resolution. MIKE21 also applies linear interpolation to fill gaps in coastal processes time series datasets used for boundary conditions.

I first assess MIKE21 sensitivity to tides, followed by wind and waves. I use a step-wise calibration approach because a standard rule for calibrating and evaluating the sensitivity of coastal evolution models is tuning each input one at a time to identify the key parameters (variables) affecting model solutions (Gonenc and Wolfin, 2004). In each test site, I run one simulation using the original tide, wind and wave data followed by multiple simulations that substitute the original data for either of these variables with a resampled dataset. I also use daily high/low tide data and tide predictions (Fig. 3.15) as substitutes for the original tide data to evaluate MIKE21 sensitivity to tides comprehensively. The daily high/low tide data and tide predictions for each test site are from NOAA (NOAA, 2017c; NOAA, 2017d; NOAA, 2017e). The daily high/low tide data have an irregular frequency, and the tide predictions have a 6 min resolution. Table 3.8 lists all simulations carried out to test MIKE21 sensitivity to coastal processes time series resolution. Each simulation is based on the independent mesh discretisation and specifications in Tables 3.2 and 3.3. The independent mesh discretisation is interpolated with the relevant bathymetry in Fig. 2.5. I quantify the effects of varying tide, wind, and wave climate data resolution on MIKE21 accuracy and net littoral drift and net shoreline change predictions using the methods in section 3.7. I use the outcomes to understand the relative influence of tides, wind, and wave climate on shoreline evolution predictions in different coastal morphologies.

Assessing the Bruun Rule sensitivity to tide data entails changing the sea-level rise (SLR) value in its equation and quantifying the effects on resulting predictions. NOAA seasonally adjusts tide data from 1932 to 2019 to estimate the New York test site's sea-level rise rate (0.004 m yr^{-1}); 1962 to 2019 to calculate Puerto Rico test site's sea-level rise rate (0.002 m yr^{-1}); and 1933 to 2019 to derive Southern California test site's sea-level rise rate (0.002 m yr^{-1}) (NOAA, 2017c; NOAA, 2017d; NOAA, 2017e). I obtain each test site's raw tide data and tide predictions for the period underlying their relative sea-level rise rate from NOAA. I use the raw tide data to calculate an *unadjusted* relative sea-level rise rate and define an *unadjusted* SLR value, and tide predictions to calculate a *predicted* relative sea-level rise rate and define a *predicted* SLR value for the associated sensitivity testing period (Table 3.2). I assess the Bruun Rule sensitivity to tide data in each test site by applying its equation to cross-shore transects every 5 m longshore using their unadjusted and predicted SLR values. I keep all other variables (D_b, D_c, and L) constant, specifying each as discussed in section 3.5. I quantify the effects of varying SLR on the Bruun Rule accuracy and net shoreline change predictions using the methods in section 3.7. I compare the results with those from MIKE21 sensitivity testing to tide data to better understand tidal effects on shoreline evolution predictions in different coastal morphologies.

3.6.4 Free parameters

Compared to the Bruun Rule, MIKE21 incorporates several parameters describing coastal system features that influence sediment transport simulations, called free parameters. Free parameters are constants in a simulation whose values are difficult to define *a priori* (e.g. friction). Free parameters can significantly affect model solutions, and their specification in shoreline evolution models require calibration bounded by physically realistic values (Mole et al., 2012; Splinter et al., 2013). The following paragraphs outline the calibration of MIKE21 free parameters in each test site. I use the results to define the necessary inputs for simulating shoreline evolution in different coastal system morphologies. I apply this knowledge to setup MIKE21 for addressing research questions two to four.

I calibrate five free parameters in MIKE21 for each test site, including bed resistance, sand grain diameter, sand porosity, sediment grading coefficient, and the weir coefficient of hard defences. All five parameters describe essential coastal system features that can potentially influence MIKE21 sediment transport simulations and associated shoreline evolution predictions, as described below:

> *Bed resistance* describes the friction acting on the flow as it moves over the bathymetry. In MIKE21, Manning's n reciprocal ($m^{1/3}/s$) defines the degree of bed resistance in the model space. Bed resistance affects the flow rate and wave dissipation, influencing sediment transport and redistribution over the mesh bathymetry (Putnam and Johson, 1949; Masselink et al., 2014).
>
> *Sand porosity* specifies the water retention capacity of sand sediments in the coastal system. The porosity of sand sediments affects the shoreface morphology by influencing the concentration of suspended sediments (Verstraeten and Poesen, 2001; Frings et al., 2011).
>
> *Sand grain diameter* (mm) defines the mean grain size of sand in the coastal system. The size of sand grains directly influences their mobility rate and the sand volume that can become entrained in the flow. As sand grain size increases, the littoral drift decreases. Littoral drift gradients affect the shoreface morphology and shoreline position (Van Rijn, 1998; King, 2005).
>
> *Sediment grading coefficient* describes the sorting of sediments in the coastal system, influencing longshore sediment transport. Well-sorted sediments have smaller grains and are less resistant to flow than poorly sorted sediments with mixed grain sizes (Folk and Ward, 1957).
>
> *Weir coefficient* ($m^{1/2}/s$) is a function of the gravitational constant and the discharge coefficient and geometry of hard defences. The weir coefficient controls the overtopping discharge at hard defences, affecting sediment redistribution and flow around structures (Ali and Uijttewaal, 2014).

I use a stepwise calibration approach to run simulations with varying values of each free parameter above to calibrate MIKE21 for further applications in each test site. I first calibrate bed resistance to identify an appropriate Manning's n reciprocal for later simulations and then do the same for sand porosity, sand grain diameter, sediment grading coefficient, and weir coefficient. In these simulations, I use the defined range of values for sand grain diameter from Wentworth (1922), sand porosity from Nimmo (2013), and sediment grading coefficient from Folk and Ward (1957). I use the reciprocal of Chow (1959) Manning's n values for sand material to define a suitable range of Manning's n reciprocal, and Horton (1906) weir coefficient tables to identify an appropriate range of weir coefficient values. Table 3.9 details the range of values used to calibrate each free parameter. Bounded by the physically realistic values established, I run four calibration simulations for sand porosity and sediment grading coefficient, five for sand grain diameter, six for Manning's n reciprocal, and nine for weir coefficient in each test site. All calibration simulations are based on the independent mesh discretisation and specifications in Tables 3.2 and 3.3. As before, the independent mesh discretisation is interpolated with the relevant bathymetry in Fig. 2.5. I quantify the effects of varying the values of each free parameter on MIKE21 performance and net littoral drift and net shoreline change predictions using the statistical methods in section 3.7. I use the results to define the relative influence of each free parameter on shoreline evolution predictions in different coastal morphologies.

3.7 Quantifying model sensitivity and performance

This section introduces the variables, data, and statistical methods used to quantify model sensitivity and performance. The key variables used to quantify MIKE21 sensitivity are net littoral drift and net shoreline change. Net littoral drift is the primary variable derived from coupling MIKE21 SW, MIKE21 HD and MIKE21 ST, and the only forcing term in the shoreline continuity equation in MIKE21 SM. I use net shoreline change as the primary variable to assess MIKE21 performance because there is no observed sediment transport data to verify its net littoral drift predictions. The Bruun Rule only calculates shoreline change in response to relative sea-level rise compared to MIKE21. Thus, net shoreline change is the primary variable used to quantify the Bruun Rule sensitivity and performance.

MIKE21 provides the updated shoreline position and accumulated net littoral drift in each shoreface strip as points at the end of a simulation. The shoreline points are in x, y Cartesian coordinates, forming a polyline of the predicted shoreline. The net littoral drift points are also in x, y format, where x is the shoreface strip and y is net littoral drift over x, creating a line graph of the predicted net littoral drift in the model space. The predicted net shoreline change is the difference between the initial and predicted shorelines. The initial shoreline is the observed MHW line at the start of a simulation (zero-depth contour in the initial bathymetry). In each test site, I calculate the predicted net shoreline change in each cross-shore transect generated for the Bruun Rule application using AMBUR (Analyzing Moving Boundaries Using R) (Jackson et al., 2012). Thus, I obtain the same number of net shoreline change points to quantify MIKE21 and the Bruun Rule sensitivity and performance. Net shoreline change points from transects in groyne locations, however, are excluded from model sensitivity and accuracy assessments due to the assumptions of MIKE21 and the Bruun Rule morphology update. MIKE21 and the Bruun Rule assume the active coastal profile moves from a change in sediment balance, ignoring the underlying bed features (e.g. elevation, slope, and hard defences) over which the profile migrates (Roelvink et al., 2012; Cooper et al., 2020). As a result, groynes within a migrating profile will also move with the profile, giving an erroneous change in shoreline position (Kristensen, 2013; Roelvink et al., 2016). Under 5% of transects generated in each test site are located in groyne locations. Excluding such transects, the total number of transects used for obtaining net shoreline change points to quantify model sensitivity and performance is 2 330 in the New York test site, 695 in the Puerto Rico test site, and 1 894 in the Southern California test site.

There are two steps involved in quantifying model sensitivity. The *first* step concerns a normality test to determine whether model predictions of key variables follow a normal distribution. The *second* step involves selecting and applying a suitable statistical test, which best fits the distribution of the key variables predicted, to assess for significant differences between outputs of the same variable in response to a change in model input. I use the Jarque-Bera (JB) test for normality testing. If output X from each simulation with varying Y values follows a normal distribution, I use a parametric test to assess for significant differences between different outputs (samples) of X from a change in Y. I use a non-parametric test if samples are not normally distributed. The JB test matches the skewness and kurtosis of each sample data to determine if it follows a normal distribution (Jarque and Bera, 1980):

$$JB = n\left[\frac{skew^2}{6} + \frac{(kurt-3)^2}{24}\right] \qquad \text{Eqn. 3.9}$$

where n is the sample size, $skew$ is the sample skewness coefficient, and $kurt$ is the sample kurtosis coefficient. A normal distribution has a $skew$ of 0 and a $kurt$ of 3. The JB test returns a p value between 0 to 1. If p is less than the 5% significance level (0.05), the sample data is not normally distributed. All JB test p values obtained are ~ 0, implying that all outputs from applying MIKE21 and the Bruun Rule are not normally distributed. Thus, I use the non-parametric Kruskal-Wallis (KW) test to assess for significant differences between outputs of key variables from a change(s) in input(s).

The KW non-parametric statistical test ranks each value in a sample and uses the median of the ranks to decide whether two or more samples are significantly different (Kruskal and Wallis, 1952):

$$KW = \left[\frac{12}{N(N+1)}\sum_{i=1}^{c}\frac{R_i^2}{n_i}\right] - 3\,(N+1) \qquad \text{Eqn. 3.10}$$

where n_i is the size of sample i, N is the sum of the n_i's, c is the total number of samples, and R_i is the sum of ranks in the i^{th} sample. The KW statistical test also returns a p value between 0 to 1. A p value lower than the 5% significance level implies that at least one sample stochastically dominates another but does not identify which sample(s) is (are) different from the others. Therefore, after each Kruskal-Wallis test, I run Dunn's multiple pairwise comparison test. Dunn's test compares the difference in the sum of ranks between two samples with the expected average difference based on the number of samples and their size (Dunn, 1964). Dunn's test statistic returns a matrix of p values showing where differences between different pairs of samples occur. Both KW and Dunn's test statistics are used in related model sensitivity analysis studies (cf. Burningham and French, 2017).

I calculate the Mean Absolute Error (MAE) in shoreline change predictions to assess model accuracy:

$$MAE = \frac{1}{n}\sum abs\left|\Delta Shc_{obs} - \Delta Shc_{pred}\right| \qquad \text{Eqn. 3.11}$$

where ΔShc_{obs} is the observed net shoreline change per transect, ΔShc_{pred} is the predicted net shoreline change per transect, n is the total number of absolute errors (equivalent to the total number of transects), and abs is the absolute difference. The observed net shoreline change is the difference between the initial and observed shoreline position (x, y), calculated using AMBUR (Jackson et al., 2012). The initial shoreline is the observed MHW line at the start of a simulation, and the observed shoreline is the observed MHW line at the end of a simulation. I select MAE over alternative measures of accuracy, such as the Mean Square Error (MSE) and Root Mean Square Error (RMSE), because MAE is the most natural and unambiguous measure of average error magnitude (Sutherland et al., 2004; Willmott and Matsuura, 2005). Statistics such as MSE and RMSE do not describe average error alone because they are functions of the distribution of error magnitudes, square root of the number of errors, and MAE (Sutherland et al., 2004). Also, any measure of average error based on the sum of squared errors will get increasingly larger than the MAE as the distribution of error magnitudes becomes more variable (Willmott and Matsuura, 2005). However, there are two limitations of using MAE. *First*, it is difficult to determine whether a MAE value indicates acceptable or poor model performance, especially in the absence of defined standards for model accuracy. *Second*, MAE does not show model over or under-prediction since all MAE values are positive and ignore direction of errors. In this regard, the MAE cannot objectively describe model performance. Therefore, I only use MAE to gauge how a change in model input affects the error in model outputs.

I use the Brier Skill Score (BSS) to describe model performance objectively. The BSS is a non-dimensional measure of the accuracy of a prediction relative to a baseline (Brier, 1950), recommended for verifying the performance of coastal morphology models (Sutherland et al., 2004). The BSS considers direction and indicates how far a model prediction deviates from a baseline (e.g. the observed shoreline). To calculate the BSS of net shoreline change predictions, I use the formula:

$$BSS = 1 - \frac{\sum\left(Sh_{obs} - Sh_{pred}\right)^2}{\sum(Sh_{obs} - Sh_{init})^2} \qquad \text{Eqn. 3.12}$$

where Sh_{int} is the initial shoreline position per transect, Sh_{pred} is the predicted shoreline position per transect, and Sh_{obs} is the observed shoreline (baseline) position per transect. BSS ranges from -∞ to 1. A BSS of 1 indicates perfect agreement between Sh_{obs} and Sh_{pred}, 0 indicates that Sh_{pred} is closer to Sh_{init}, and a negative BSS indicates that Sh_{pred} is further away from Sh_{obs}. Unlike MIKE21, the Bruun Rule does not generate a predicted shoreline position in x, y coordinates but instead predicts the magnitude of net shoreline retreat (m), which can be negative or positive. Negative retreat means accretion, and positive retreat means erosion. To estimate the BSS of the Bruun Rule predictions, I use the calculated net shoreline retreat value to update Sh_{int} and find Sh_{pred} in each transect. Sutherland et al. (2004) classify a BSS of 1 to 0.5 as excellent, 0.5 to 0.2 as good, 0.2 to 0.1 as reasonable, 0.1 to 0 as poor, and ≤ 0 as bad. I use the same classification to interpret BSS values. Sutherland et al. (2004) BSS classification scheme is also commonly used to verify model performance in related studies (cf. Ruessink et al., 2003; Scott and Mason, 2007; Dodet et al., 2019).

In addition to MAE and BSS, I use basic descriptive statistics (e.g. mean and standard deviation), kernel density plots, scatter plots, time series plots, and line graphs to quantify and visualise the distribution of net shoreline change residuals in the model domain. The net shoreline change residuals are the difference (actual error) between shoreline change observed and predicted. The aforementioned statistics and graphs allow for identifying areas in the model domain where there is (a) a good or bad fit between predicted and observed data and (b) model over or under prediction. I use the information from these statistics and graphs to better interpret all MAE and BSS estimations.

3.8 A novel approach to account for sea-level rise effects in hybrid models

This section outlines the workflow used to address research question two: *How can sea-level rise be incorporated in shoreline evolution models for mesoscale application in managed sandy coastal systems?* Sea-level rise will inevitably modify the wave setup and undertow currents (the primary driving flux of the cross-shore mass balance that evolves the coastal profile) by forcing deeper waters closer to the shoreline (Aagaard and Sørensen, 2012; Franz et al., 2017; Idier et al., 2019). Water depth increases will cause wave breaking closer to the shoreline, potentially increasing the undertow mobilisation and offshore transport capacity of near-bed sediments (Guannel, 2010; Aagaard and Sørensen, 2012). Sea-level rise can consequently alter the active coastal profile shape, particularly the offshore part, by influencing cross-shore sediment mass balance through its effects on the wave setup and associated undertow (Aagaard and Sørensen, 2012; Idier et al., 2019). A gross simplification in advanced mesoscale shoreline evolution models is that the coastal profile keeps an equilibrium form during the shoreline morphology update. As discussed in section 3.2.1, this simplification is needed to prevent coastal profile degeneration and associated unreliable shoreline evolution predictions as current mesoscale shoreline evolution models cannot account for the 3D variation of undertow currents that drive coastal profile evolution. A consequence of the equilibrium profile assumption is that current mesoscale shoreline evolution models cannot account for sea-level rise in their shoreline morphology update. Sea-level rise, however, will likely be an endogenous driving factor in mesoscale coastal change (Stive et al., 2002). An equilibrium coastal profile implies the active coastal profile has a fixed berm height and closure depth (Hurst et al., 2015). Acknowledging the rationale for the equilibrium profile assumption of mesoscale shoreline evolution models, I slightly modify this assumption in MIKE21 to include closure depth time variations as a simple solution to mirror the effects of sea-level rise on the offshore part of the profile. Doing so may offer an interim novel solution to account for sea-level rise in the morphology update in mesoscale shoreline evolution models until we can represent undertow currents in these models. The closure depth is a useful index of sea-level variations as it indicates the seaward extent of morphodynamics.

Section 3.8.1 describes the steps taken to allow a time-varying closure depth in MIKE21. Section 3.8.2 outlines a model comparison study carried out to test if a time-varying closure depth improves meso timescale shoreline evolution predictions. Section 3.8.3 outlines a further model comparison study completed to compare meso timescale shoreline evolution predictions for a theoretical future sea-level environment from the method created in section 3.8.1 and existing modelling approaches.

3.8.1 Enabling a time-varying closure depth

The workflow developed to include a time-varying closure depth in meso timescale shoreline evolution simulations runs MIKE21 annually with a different closure depth and uses the morphology and hydrodynamic (wave, flow, and sediment transport) outputs from each annual simulation to hot-start subsequent annual simulations. This approach does not modify the algorithms used within MIKE21 code. Instead, it forces MIKE21 to simulate meso timescale shoreline evolution iteratively over one-year periods that incorporate a change in the offshore limit of the active coastal profile. Albeit manually forced, this iterative procedure allows the offshore part of the coastal profile to vary vertically over time based on the changing hydrodynamics in the model space. A time-varying closure depth therefore enables us to better account for sea-level and wave climate variations, both of which influence coastal morphodynamics and profile evolution (Slott et al., 2010; Aagaard and Sørensen, 2012). A time-varying closure depth can thus lessen the gross simplifications of MIKE21 shoreline morphology update, which force the coastal profile to maintain fixed vertical limits contrary to the physics underlying cross-shore sediment transport and coastal profile evolution (Tinker et al., 2006).

To apply and test the above approach, I run five meso timescale hindcast simulations of shoreline evolution (01-Jan-1966 to 01-Feb-2016) in the New York test site (RQ2 hindcasts), as below. RQ2 hindcast one generates boundary conditions for RQ2 hindcasts two to five, and RQ2 hindcast four generates additional boundary conditions for RQ2 hindcast five. RQ2 hindcasts two and three apply MIKE21 current principles as controls to test if a time-varying closure depth improves meso timescale shoreline evolution predictions. RQ2 hindcast five is the iterative simulation that includes the time-varying closure depth. Each RQ2 hindcast is described below, with their workflow shown in Fig. 3.19.

RQ2 hindcast one: generating data for the Flather (1976) condition

RQ2 hindcast one generates the current velocities and free surface elevation to facilitate the Flather (1976) condition at the open boundaries (Fig. 3.6a) in subsequent hindcasts. This hindcast is carried out using the New York test site's independent mesh discretisation interpolated with its 1966 bathymetry (Fig. 2.9). I specify a 4.2 m closure depth and develop MIKE21 SM domain accordingly. 4.2 m is the most seaward depth contour with shoreline undulations in the 1966 bathymetry. Other specifications include the calibrated Manning's n reciprocal, grain diameter, sand porosity, grading coefficient, and weir coefficient determined from section 3.6.4. All other parameters are specified according to Tables 3.2 and 3.3. I force tides and waves at the sea boundary and keep the connecting boundaries open in MIKE21 SW as lateral wave boundaries, open in MIKE21 ST as zero sediment flux boundaries, and closed in MIKE21 HD because of no Flather condition data. The New York test site's 1966 to 2016 tide time series (Fig. 2.9c) drive the flow in MIKE21 HD. The tide time series include the sea-level rise trend over the 50-year hindcast period. I repeat the New York test site's 2014 to 2016 wind and wave climate time series (Fig. 2.6) over the 50-year hindcast due to limited data on these variables. Repeating these time series data facilitates the RQ2 hindcasts objective of determining if a time-varying closure depth improves meso timescale shoreline evolution predictions.

RQ2 hindcast two: constant closure depth

RQ2 hindcast two maintains MIKE21 principles, assuming a fixed closure depth. It has the same setup as RQ2 hindcast one, except I apply the Flather (1976) condition at the open boundaries in MIKE21 HD using the current velocities and free surface elevation generated from RQ2 hindcast one. RQ2 hindcast two net shoreline change predictions provide a baseline for evaluating whether a time-varying closure depth significantly improves meso timescale shoreline evolution predictions.

RQ2 hindcast three: applying the one-line theory

RQ2 hindcast three enforces the one-line theory assumptions and has the same setup as RQ2 hindcast two, except mesh bathymetry, closure depth, and MIKE21 SM domain. This hindcast is carried out using the New York test site's independent mesh discretisation interpolated with a modified bathymetry dataset. The modified bathymetry is created by interpolating the New York test site's 1966 bathymetry data points (Fig. 2.9) with the depth (z) values from its 2014 bathymetry (Fig. 2.5a). Based on the one-line theory, this interpolation will shift the 2014 coastal profiles back to their 1966 position. The one-line theory assumes the coastal profile keeps a constant shape while moving shore-normal from a change in sediment balance. The New York test site's 1966 and 2014 average coastal profiles are notably different (Fig. 3.18). MIKE21 and related hybrid models do not simulate coastal profile evolution. Instead, these models work on the premise that the active coastal profile keeps a fixed shape in line with the one-line theory. Therefore, using the 1966 bathymetry to hindcast shoreline evolution through to 2016 may compromise MIKE21 accuracy and shoreline evolution predictions. Shifting the 2014 coastal profiles back to their 1966 position will ensure the initial (1966) and predicted (2016) profiles have a similar shape to uphold the one-line theory principles of MIKE21 morphology update. The New York test site's 2014 and 2016 average coastal profiles have negligible differences (Fig. 3.18). Thus, using the 2014 coastal profile shape is appropriate for upholding the one-line theory principles of MIKE21 morphology update. I use a 6 m closure depth in RQ2 hindcast three, the most seaward contour with shoreline undulations in the modified bathymetry, and revise MIKE21 SM domain. RQ2 hindcast three net shoreline change predictions provide another baseline to evaluate if a time-varying closure depth improves meso timescale shoreline evolution predictions.

RQ2 hindcast four: generating annually updated mesh bathymetry from 1966 to 2016

This hindcast generates annually updated mesh bathymetry data to facilitate RQ2 hindcast five iterative shoreline evolution simulations. MIKE21 provides the updated mesh bathymetry at each output time-step as an interpolated mesh file that can form the numerical basis of further simulations. However, MIKE21 only updates the bathymetry between the beach berm and closure depth. RQ2 hindcast four has the same setup as RQ2 hindcast three, except I specify the most seaward contour in the initial mesh bathymetry as the closure depth and update MIKE21 SM domain accordingly. Doing so ensures that MIKE21 provides a fully updated mesh bathymetry at each output time-step.

RQ2 hindcast five: annual updates of mesh bathymetry and closure depth

This simulation is an iterative process comprising 50 annual hindcast simulations of shoreline evolution from 1966 to 2016, each with an updated closure depth. Annual hindcast simulation one (1966 to 1967) has the same setup as RQ2 hindcast three. Annual hindcast simulations two (1967 to 1968) to 50 (2015 to 2016) have the setup as annual hindcast simulation one, except I use: (a) the relevant mesh bathymetry output from RQ2 hindcast four as the computational basis, (b) a revised closure depth, and (c) an updated MIKE21 SM domain based on the new closure depth. The closure depth in annual hindcast simulations two to 50 is calculated using nearshore significant wave heights data from the preceding yearly hindcast simulation, according to Birkemeier (1985) formula:

$$D_c = 1.57H_e \qquad \text{Eqn. 3.13}$$

where H_e is the effective wave height defined as:

$$H_e = \overline{H}_s + 5.6\sigma_s \quad \text{Eqn. 3.14}$$

where $\overline{H}_s$ is the annual mean significant wave height, and σ_s is the associated standard deviation. I use significant wave heights generated in the nearshore to calculate closure depths as this is where refraction and shoaling modify the wave characteristics that affect shoreline evolution (Sabatier et al., 2004). I use Birkemeier (1985) formula as the original Hallermeier (1978) closure depth formula over-predicts the closure depth by around 25% (Nicholls et al., 1998; Valiente et al., 2019). In annual hindcast simulations two to 50, I use the calculated shoreline position and hydrodynamic fields (wave, current, and sediment transport) from the preceding yearly hindcast as hot starts. The mesh bathymetry, closure depth and MIKE21 SM domain are the only inputs revised in RQ2 hindcast five.

To determine whether a time-varying closure depth improves meso timescale shoreline evolution predictions, I quantify and compare the accuracy of RQ2 hindcasts two, three and five net shoreline change predictions using the methods in section 3.7. I use the results to address research question two and define the suitability of using the one-line theory to simulate mesoscale shoreline evolution.

3.8.2 Comparison with the Bruun Rule

I apply the Bruun Rule to hindcast shoreline evolution in the New York test site from 01-Jan-1966 to 01-Jan-2016 (RQ2 hindcast six) as below, and compare the results with those from RQ2 hindcasts two, three and five. This comparison allows for determining if a time-varying closure depth improves meso timescale shoreline evolution predictions to comprehensively address research question two.

To facilitate the above model comparison study, I formulate the Bruun Rule in cross-shore transects every 5 m longshore in the New York test site. These Bruun Rule formulations are based on the New York test site's: (a) 1966 berm height (1.14 m) and closure depth (4.2 m); and (b) observed SLR from 1966 to 2016 (0.2 m), estimated from its relative SLR rate (0.004 m yr^{-1}) (NOAA, 2017d). The horizontal extent of the active coastal profile varies in each transect based on the distance between the beach berm and closure depth. I quantify and compare the error of the Bruun Rule formulation discussed here with those of RQ2 hindcasts two, three, and five using the methods in section 3.7.

3.8.3 Mesoscale forecast simulations

I run four exploratory meso timescale forecast simulations of shoreline evolution (01-Jan-2014 to 01-Jan-2064) in the New York test site, as below (RQ2 forecasts). The first three are carried out with and without a time-varying closure depth in MIKE21, and the fourth using the Bruun Rule. The objective of these forecasts is to compare shoreline evolution predictions for a theoretical future sea-level environment from three different models with respect to implications for coastal management.

RQ2 forecast one: constant closure depth

RQ2 forecast one maintains the one-line theory principles of MIKE21 morphology update, assuming a constant closure depth. It has the same setup as RQ2 hindcasts two to five (see section 3.8.1), except mesh bathymetry, closure depth, MIKE21 SM domain and tide time series. RQ2 forecast one is based on the New York test site's independent mesh discretisation interpolated with its 2014 bathymetry (Fig. 2.5a). I use a 5.8 m closure depth and develop MIKE21 SM domain accordingly. 5.8 m is the most seaward depth contour with shoreline undulations in the 2014 bathymetry. I superimpose the New York test site's 1966 to 2016 tide data (Fig. 2.9a) with a 0.28 m sea-level rise to drive MIKE21 HD. 0.28 m is the Intergovernmental Panel on Climate Change (IPCC) global median sea-level rise projection for 2046 to 2065 (Church et al., 2013). Superimposing the 1966 to 2016 tide data with a 0.28 m sea-level rise facilitates the objective of the RQ2 forecasts previously mentioned.

RQ2 forecast two: generating annually updated mesh bathymetry from 2014 to 2064

This simulation updates the mesh bathymetry annually from 2014 to 2064 to enable RQ2 forecast three. Therefore, RQ2 forecast two shoreline evolution predictions are excluded from model comparisons. RQ2 forecast two has the same setup as RQ2 forecast one, except I use the most seaward contour in the initial mesh bathymetry as the closure depth and update MIKE21 SM domain.

RQ2 forecast three: annual updates of mesh bathymetry and closure depth

This simulation is an iterative process comprising 50 annual forecast simulations of shoreline evolution, each carried out in MIKE21 with an updated closure depth. Annual forecast one (2014 to 2015) has the same setup as RQ2 forecast one. Annual forecasts two (2015 to 2016) to 50 (2063 to 2064) have the same inputs as annual forecast one, except mesh bathymetry, closure depth, and MIKE21 SM domain. In annual forecasts two to 50, I use the relevant mesh bathymetry output from RQ2 forecast two as the numerical basis, update the closure depth using nearshore wave data from the preceding forecast as before, and revise MIKE21 SM domain based on the new closure depth. I hot-start annual forecasts two to 50 using the calculated shoreline position and hydrodynamic fields (wave climate, current, and sediment transport) from the preceding yearly hindcast. The mesh bathymetry, closure depth and MIKE21 SM domain are the only inputs revised in RQ2 forecast three.

RQ2 forecast four: applying the Bruun rule

This simulation applies the Bruun Rule in cross-shore transects every 5 m longshore in the New York test site. These formulations are based on the New York test site's 2014 berm height (1.14 m) and closure depth (5.8 m), and a SLR of 0.28 m. 0.28 m is the IPCC global median sea-level rise projection for 2046 to 2065 (Church et al., 2013). As before, the horizontal dimension of the active coastal profile fluctuates in each transect based on the distance between the beach berm and closure depth.

I quantify and compare RQ2 forecasts one, three and four shoreline evolution predictions using the methods in section 3.7. This analysis considers the accuracy of the various modelling approaches evaluated in sections 3.8.1 and 3.8.2. I use the outcomes to define the importance of accounting for sea-level rise in meso timescale shoreline change predictions to address research question two fully.

3.9 A novel approach for handling complex planform morphologies in hybrid models

This section outlines the process used to account for complex planform morphologies in shoreline evolution predictions to address research question three: *How can complex planform morphologies be accounted for in shoreline evolution predictions?* Complex planform morphologies are defined herein by non-parallel contours, characteristic of coral reef systems in many Caribbean and Pacific small islands where shoreline evolution models are needed as coastal management tools. Wave transformation over non-parallel contours generates spatial variations in wave heights approaching the shoreline, resulting in some areas having a shallower closure depth than others (Bender and Dean, 2003; Sabatier et al., 2004; Keshtpoor et al., 2015). In coral reef environments, wave transformation and energy dissipation over non-parallel depth contours play a crucial role in influencing shoreline evolution, as discussed in section 3.2.2. However, the equilibrium profile assumption constraining the morphology update in advanced mesoscale shoreline evolution models does not allow these models to account for closure depth spatial variations. Consequently, these models cannot realistically simulate longshore shoreline evolution in complex morphologies. This inability stems from the closure depth's influence on the cross-shore extent of morphodynamics in shoreline evolution models. Acknowledging the need to constrain the morphology update in mesoscale shoreline evolution models (i.e. to prevent coastal profile degeneration), I slightly modify MIKE21 equilibrium coastal profile assumption to include closure depth spatial variations as a simple solution to mirror the effects of wave transformation over non-parallel contours on the offshore limit of active coastal profiles longshore. Doing so may offer an interim novel solution to account for complex morphologies in the morphology update in mesoscale shoreline evolution models until we can represent undertow currents, which govern coastal profile evolution, in these models. Section 3.9.1 describes the steps taken to incorporate a space-varying closure depth in MIKE21. Section 3.9.2 outlines a model comparison study carried out for testing whether a space-varying closure depth can significantly improve net shoreline change predictions in a complex planform morphology.

3.9.1 Enabling a space-varying closure depth

The workflow developed to allow a space-varying closure depth in shoreline evolution simulations applies MIKE21 coupled process-driven modules over the same mesh bathymetry while applying its shoreline morphology module on smaller coastal segments with the same general closure depth. This process does not modify MIKE21 code. Instead, it forces MIKE21 to update the shoreline morphology iteratively over irregular spatial intervals, with each interval having a different specification for the offshore limit of the active coastal profile based on their underlying morphology and wave climate. Although manually forced, this iterative procedure allows the offshore part of the coastal profile to vary vertically over space to better account for the effects of wave transformation over non-parallel contours on shoreline dynamics. Hence, a space-varying closure depth can further reduce the gross simplifications of MIKE21 shoreline morphology update, which force the coastal profile to have the same vertical limits longshore regardless of the bed surface and the wave climate.

To apply and test the above iterative procedure, I run two micro timescale hindcast simulations of shoreline evolution (01-Oct-2014 to 31-Mar-2016) in the Puerto Rico test site (RQ3 hindcasts) as outlined below. The duration of these hindcasts facilitates their primary objective of evaluating whether a space-varying closure depth better predicts the longshore trends (i.e. accretion and erosion) of shoreline evolution in a complex planform morphology to answer research question three.

RQ3 hindcast one: constant closure depth

RQ3 hindcast one maintains MIKE21 one-line theory principles, assuming a constant closure depth.

This hindcast is carried out as an experimental control to test whether a space-varying closure depth improves shoreline evolution predictions in a complex planform morphology. I run RQ3 hindcast one using the Puerto Rico test site's independent mesh discretisation interpolated with its 2014 bathymetry (Fig. 2.5b). I use the 5.5 m contour in the 2014 bathymetry as the closure depth and develop MIKE21 SM domain accordingly. 5.5 m is the deepest general shore-parallel contour landward of reefs in the 2014 bathymetry. Other inputs include the calibrated Manning's n reciprocal, grain diameter, porosity, grading coefficient, and weir coefficient determined from section 3.6.4. All other parameters are specified according to Tables 3.2 and 3.3. I force tides and waves at the sea boundary and keep the connecting boundaries open as before. The Puerto Rico test site's 2014 to 2016 tide, wind and wave climate time series (Fig. 2.7) drive the hydrodynamics in the model space.

RQ3 hindcast two: longshore variations in closure depth

RQ3 hindcast two iteratively simulates shoreline evolution over irregular spatial intervals to account for closure depth longshore variations. Each iterative simulation has the same setup as RQ3 hindcast one, except closure depth and MIKE21 SM domain. MIKE21 SM domain in each iterative simulation is developed to constrain the morphology update in a continuous coastal stretch with the same general closure depth (see Fig. 3.20). Reef substrate distribution determines the longshore variability of the Puerto Rico test site's closure depth. The closure depth in reef areas is the depth nearest the shoreline where hard substrate first appears, whereas the closure depth in non-reef regions is the most seaward contour with shoreline undulations. Altogether, seven iterative shoreline evolution simulations comprise RQ3 hindcast two (see Fig. 3.20). To be specific, I only revise MIKE21 SM domain and the closure depth in RQ3 hindcast two iterative simulations. All other inputs are the same, including the mesh. Only the general longshore variability of the Puerto Rico test site's closure depth is considered in RQ3 hindcast two as the associated objective is to evaluate whether a space-varying closure depth improves net shoreline change predictions in a complex planform morphology.

I quantify and compare RQ3 hindcasts one and two net shoreline change prediction accuracy using the statistical methods in section 3.7. I use the results to address research question three and define the optimal complexity required for simulating shoreline evolution in a complex planform morphology.

3.9.2 Comparison with the Bruun Rule II

I apply the Bruun Rule to hindcast shoreline evolution in the Puerto Rico test site from 01-Oct-2014 to 31-Mar-2016 (RQ3 hindcast three) using a space-varying closure depth as described below, and compare the results with those from RQ3 hindcasts one and two. This comparison enables a comprehensive study to determine if a space-varying closure depth in MIKE21 significantly improves net shoreline change predictions in complex morphologies to address research question three fully.

To facilitate the above comparison, I apply the Bruun Rule in cross-shore transects every 5 m longshore in the Puerto Rico test site. These formulations are based on the Puerto Rico test site's: (a) 2014 berm height (1.5 m) and closure depth, and (b) observed SLR from 2014 to 2016 (~ 0.004 m) (NOAA, 2017c). The berm height and SLR values are the same in each transect. The closure depth varies based on reef substrate distribution (Fig. 3.11b). The horizontal dimension (L) of the active coastal profile is the distance between the beach berm and closure depth. Hence, L also varies in each transect. I quantify and compare the prediction accuracy of the Bruun Rule formulations discussed here with those of RQ3 hindcasts one and two using the statistical methods in section 3.7.

3.10 Incorporating sea-level rise and complex planform morphologies in hybrid models

This section outlines the workflow created to address research question four: *Can shoreline evolution models be developed to incorporate both sea-level rise and complex planform morphologies over meso timescales?* Section 3.8 discusses that a time-varying closure depth offers a potential solution to mirror sea-level rise effects on the offshore part of the coastal profile. Section 3.9 subsequently discusses that a space-varying closure depth will likely provide a solution to account for the effects of wave transformation over non-parallel contours on the offshore active limit of active coastal profiles longshore, which largely govern shoreline evolution in complex planform morphologies. Based on these discussions, it is plausible to assume that a time and space-varying closure depth may allow us to better account for sea-level rise **and** complex morphologies in meso timescale shoreline evolution predictions. Section 3.10.1 outlines the steps taken to test this assumption using MIKE21.

3.10.1 Enabling a time and space-varying closure depth

The workflow defined to allow a time and space-varying closure depth in meso timescale shoreline evolution simulations *annually* runs MIKE21 coupled process-driven modules on the same mesh while applying its shoreline morphology module to smaller coastal segments with the same closure depth. In each annual simulation, the closure depth in each coastal segment is updated based on their wave climate in the preceding annual simulation. This iterative process does not modify MIKE21 code. Instead, it forces MIKE21 to update the shoreline morphology annually over irregular spatial intervals based on the changing hydrodynamics in the model domain. Despite manually forced, this iterative process allows the offshore limit of the active coastal profile to vary vertically over time and space to better account for the effects of (a) sea-level rise and (b) wave climate variations over non-parallel contours on shoreline morphodynamics. If successfully incorporated, a time and space-varying closure depth in MIKE21 will allow a more realistic description of the coastal profile evolution relative to the one-line theory simplifications that presently underlie its shoreline morphology update.

To trial the above approach, I run five meso timescale shoreline evolution forecasts in the Puerto Rico test site (10-Oct-2014 to 10-Oct-2064), as below. RQ4 forecasts one to three show how the novel modelling concepts introduced in preceding sections can be used to simulate meso timescale shoreline evolution in a complex morphology. RQ4 forecast four uses MIKE21 current approach, and RQ4 forecast five applies the Bruun Rule. The objective of these forecasts is to compare shoreline evolution predictions for a theoretical future sea-level environment in a complex morphology from different modelling methods with respect to implications for coastal management decision-making.

RQ4 forecast one: generating data for the Flather (1976) condition

Apart from the Flather condition and tide forcing, RQ4 forecast one has the same specifications as RQ3 hindcast one. This forecast generates the free surface elevation and current velocities data needed to facilitate the Flather condition at the open boundaries in RQ4 forecasts two to four. Therefore, RQ4 forecast one net shoreline change predictions are excluded from model comparisons. I superimpose the Puerto Rico test site's 1969 to 2018 tide time series (Fig. 2.10) with a 0.28 m sea-level rise to drive the flow field. 0.28 m is the IPCC global median sea-level rise projection for 2046 to 2065 (Church et al., 2013). I repeat the Puerto Rico test site's 2014 to 2016 wind and wave climate time series (Fig. 2.7) over the 50-year forecast period. Repeating these coastal processes time series datasets facilitates the objective of the RQ4 forecasts aforementioned.

RQ4 forecast two: generating annually updated mesh bathymetry from 2014 to 2064

RQ4 forecast two updates the mesh bathymetry yearly from 2014 to 2064 to enable RQ4 forecast three. Thus, RQ4 forecast two shoreline evolution predictions are also excluded from model comparisons. This forecast has the same specifications as RQ4 forecast one, except I use the most seaward contour in the initial mesh bathymetry as the closure depth and revise MIKE21 SM domain.

RQ4 forecast three: annual and longshore variations in closure depth

RQ4 forecast three is an iterative process comprising 50 annual simulations from 2014 to 2064 to include time and space variations in the closure depth. These annual simulations combine the principles of RQ2 hindcast five (outlined in section 3.8.1) and RQ3 hindcast two (outlined in section 3.9.1). Each annual simulation has the same specifications as RQ3 hindcast two, comprising seven iterations, as illustrated in Fig. 3.20. The experimental framework of RQ4 forecast three is as follows:

1. Annual simulation one (2014 to 2015) has seven iterations (outlined in Fig. 3.20). Each iteration has the same interpolated mesh and specifications as RQ4 forecast two, except closure depth and MIKE21 SM domain. Each iteration forces MIKE21 SM to update the shoreline morphology in one continuous coastal stretch with the same general closure depth. The closure depth and MIKE21 SM domain in each iteration are defined in Fig. 3.20. To be specific, annual simulation one comprises one computational mesh, seven closure depths, and seven MIKE21 SM domains.
2. Annual simulation two (2015 to 2016) has the same setup as the first annual simulation, except mesh bathymetry and closure depth. RQ4 forecast two 2015 mesh bathymetry output provides the numerical basis. I use Birkemeier (1985) formula to update the closure depth in each MIKE21 SM domain based on their nearshore significant wave heights in the preceding annual simulation.
3. Annual simulations three (2016 to 2017) to 50 (2063 to 2064) adopt the same principles and have the same numerical setup as annual simulation two. The only inputs updated in these annual simulations are the closure depth in each MIKE21 SM domain and the mesh bathymetry.

RQ4 forecast four: constant closure depth

RQ4 forecast four maintains MIKE21 principles, assuming a constant closure depth. It has the same setup as RQ4 forecast two, except closure depth and MIKE21 SM domain. I specify a 5.5 m closure depth (the deepest general shore-parallel contour landward of reefs in the Puerto Rico test site's 2014 bathymetry – see Fig. 2.5b) in RQ4 forecast four and update MIKE21 SM domain accordingly.

RQ4 forecast five: applying the Bruun Rule

RQ4 forecast five formulates the Bruun Rule equation in cross-shore transects every 5 m longshore in the Puerto Rico test site. These Bruun Rule formulations are based on (a) the Puerto Rico test site's 2014 berm height (1.5 m) and closure depth, and (b) a 0.28 m relative SLR. 0.28 m is the IPCC global median sea-level rise projection for 2046 to 2065 (Church et al., 2013). The berm height and

SLR values are the same in each transect whereas the closure depth and the horizontal dimension of the active coastal profile (beach berm to closure depth) vary based on reef substrate distribution.

I quantify and compare RQ4 forecasts three, four, and five shoreline evolution predictions using the methods in section 3.7. This analysis considers the accuracy of the various modelling approaches quantified in the preceding sections. I use the outcomes to define the importance of incorporating sea-level rise and complex planform morphology effects in meso timescale shoreline evolution predictions with respect to coastal management decision-making, to address research question four.

3.11 Summary

This chapter outlines the methods used throughout this thesis. Following paragraphs summarise the modelling approaches used to address each research question outlined in Chapter 1, reiterating the reasons for their selection. Tables 3.10 and 3.11 summarise each simulation carried out in this thesis.

MIKE21 and the Bruun Rule are selected to address each research question of this thesis. MIKE21 offers the best approach for simulating mesoscale shoreline evolution over a broad range of managed sandy coastal morphologies as it uses a 2DH finite volume discretisation for processes simulations and local coordinates for the shoreline morphology update. Such an approach allows for:

1. addressing research question one, which identifies the most essential boundary conditions (e.g. tides and friction) for simulating mesoscale shoreline evolution in different coastal morphologies.
2. developing a novel approach that accounts for sea-level rise in mesoscale shoreline evolution predictions to answer research question two. MIKE21 is suitable for handling research question two because it simulates the effects of sea-level rise on littoral drift gradients (the primary driving flux of the time and space variations in shoreline evolution in managed sandy coastal systems).
3. addressing research questions three and four that deal with complex planform morphologies, defined herein by non-parallel depth contours. Research question three establishes a novel approach that accounts for complex planform morphology effects in shoreline evolution predictions. On the other hand, research question four applies the novel approaches introduced in this thesis to forecast meso timescale shoreline evolution in a complex planform morphology.
4. simulating shoreline deformations in response to hard defences, characteristic of each test site.

However, MIKE21 shoreline morphology update assumes the active coastal profile moves shore-normal from a change in sediment balance in line with the one-line theory, which corresponds closely to the Bruun Rule. The key difference between both models is that the active coastal profile moves from littoral drift gradients in MIKE21 and sea-level rise in the Bruun Rule. Therefore, applying both models in this thesis will help develop two essential understandings. *First*, using both models to address research question one will allow us to better understand the primary controls on shoreline evolution in different managed coastal system morphologies. *Second*, comparing mesoscale shoreline evolution predictions from MIKE21, the Bruun Rule, and the methods created in this thesis will help define the optimal complexity for modelling shoreline evolution in managed sandy coastal systems over meso time and space scales. These understandings are important for refining the mesoscale application of shoreline evolution models to better support coastal management planning.

Following chapters present results from: (a) model sensitivity tests (Chapter 4); (b) applying MIKE21 with a time-varying closure depth to simulate mesoscale shoreline evolution in the New York test site (Chapter 5); (c) applying MIKE21 with a space-varying closure depth to hindcast shoreline evolution in the Puerto Rico test site (Chapter 6); and (d) applying MIKE21 with a time and space-varying closure depth to forecast meso timescale shoreline evolution in the Puerto Rico test site (Chapter 7).

04
Sensitivity to boundary conditions

'Like a novel, a model may be convincing – it may "ring true" if it is consistent with our experience of the natural world. But just as we may wonder how much the characters in a novel are drawn from real life and how much is artifice, we might ask the same of a model: How much is based on observation and measurement of accessible phenomena, how much is based on informed judgment, and how much is convenience?'

– Oreskes et al. (1994)

4.1 Introduction

This chapter presents the results from model sensitivity testing and calibration in each test site. I use these results to answer research question one: *What are the key boundary conditions needed to model the mesoscale evolution of managed sandy shorelines?* Section 4.2 outlines the effects of nearshore discretisation, bathymetry spatial resolution, coastal processes temporal resolution, and free parameters (Manning's n, grain diameter, porosity, grading coefficient, and weir coefficient) on shoreline evolution predictions in each test site. I test MIKE21 sensitivity to each of these boundary conditions and the Bruun Rule sensitivity to bathymetry and tidal resolution only. Bathymetry and tides are the only boundary conditions implicitly included in the Bruun Rule. I use the model sensitivity test results to define (calibrate) the model inputs used in Chapters 5 to 7 simulations. Section 4.3 presents and compares MIKE21 and the Bruun Rule calibrated shoreline evolution predictions in each test site, defining the optimal model for application in different managed coastal morphologies.

4.2 Effects of boundary conditions on net shoreline change predictions

This section quantifies the effects of boundary conditions on shoreline evolution predictions in each test site using the Brier Skill Score (BSS), Mean Net Change (MNC), Mean Absolute Change (MAC), and Mean Absolute Error (MAE) statistics. I also use Kruskal-Wallis and Dunn's statistics to test for significant differences in shoreline evolution predictions from boundary condition variations. Section 3.7 outlines the functional form of each statistic used to quantify model sensitivity. Greater emphasis, however, is placed on the BSS in model sensitivity evaluations since it is a directional measure of accuracy that describes how well a model replicates observed data (Brier, 1950). Sections 4.2.1 to 4.2.3 describe the sensitivity of shoreline evolution predictions to boundary conditions in each test site. Section 4.2.4 compares and analyses the results from preceding sections to identify the most essential boundary conditions for simulating shoreline evolution in managed sandy coastal systems.

Statistics in proceeding sections are based on net shoreline change observed and predicted in transects every 5 m longshore, excluding those in groyne locations as MIKE21 and the Bruun Rule assume the active coastal profile moves from changes in sediment balance regardless of bed topography. As a result, hard defences within a migrating active coastal profile will also move with the profile, giving an erroneous change in shoreline position (Fig. 4.1; Kristensen, 2013; Roelvink et al., 2016). Appendix A contains all spatial distribution plots of net shoreline change predictions and residuals from model sensitivity simulations associated with statistics in subsequent sections for reference, excluding those included in this chapter. Appendix A also shows the effects of boundary conditions on MIKE21 net littoral drift predictions in each test site for reference as net littoral drift is the primary driving flux of shoreline evolution in MIKE21. However, I do not consider net littoral drift predictions in MIKE21 evaluations as there are no sediment transport data to verify these predictions.

4.2.1 Boundary condition effects in the New York test site

Fig. 4.2 and Table 4.1 illustrate the sensitivity of net shoreline change predictions to nearshore discretisation, bathymetry data spatial resolution, coastal processes time series data, and free parameters in the New York test site. All results in Fig. 4.2 and Table 4.1 are based on net shoreline change observed and predicted from 01-Jan-2014 to 01-Feb-2016, and grouped according to the order used for calibrating the various boundary conditions. Results in Fig. 4.2 and Table 4.1 indicate:

45 m is the optimal (coarsest) nearshore discretisation for simulating shoreline evolution in the New York test site. MIKE21 BSS falls from 0.38 (good) to below zero (bad) as nearshore discretisation gets coarser than 45 m in the New York test site (Fig. 4.2a; Table 4.1). These BSS results follow a consistent increase in net shoreline change prediction noise (outliers), observed in < 5% of transects mostly near the west boundary, as nearshore discretisation coarsens beyond 45 m (Fig. 4.3). The Kruskal-Wallis test, however, finds no significant differences in net shoreline change predictions from coarsening nearshore discretisation in the New York test site ($p = 0.863$). The Kruskal-Wallis test is robust against outliers as it ranks each value in a sample and uses the median of ranks to determine if two or more samples are significantly different (Kruskal and Wallis, 1952). Therefore, the Kruskal-Wallis test will find no significant differences between net shoreline change prediction samples if numerical noise in some samples is confined to a small area of the model space. On the other hand, the BSS detects prediction noise because it is based on a sample's mean. Detecting prediction noise, minor or otherwise, is important as the sudden increase or emergence of noise in model predictions indicates disequilibrium between boundary conditions in the model space. Caution is thus needed when interpreting Kruskal-Wallis (and similar) test results. The consistent increase in MIKE21 net shoreline change prediction noise as nearshore discretisation coarsens beyond 45 m provides further evidence illustrating 45 m is the optimal (coarsest) nearshore discretisation in the New York test site.

Bathymetry data resolutions ≤ 100 m appear suitable for modelling shoreline change in the New York test site. MIKE21 BSS varies between 0.36 and 0.38 (good) from bathymetry data resolutions ≤ 100 m and rises to 0.44 from bathymetry data coarser than 100 m in the New York test site (Fig. 4.2b). In contrast, the Bruun Rule BSS is ~ 0.2 (reasonable) from bathymetry data resolutions ≤ 100 m and falls to ~ 0.1 from bathymetry data coarser than 100 m (Fig. 4.2b). The rise in MIKE21 BSS follows a small decline in its net shoreline change prediction noise, and the fall in the Bruun Rule BSS corresponds to spatial differences in its predictions as bathymetry data get coarser than 100 m (Table 4.1; Fig. 4.4). MIKE21 and the Bruun Rule net shoreline change predictions are consistent from bathymetry data resolutions ≤ 100 m most likely because the New York test site's average coastal profile only significantly degenerates from bathymetry data coarser than 100 m (Fig. 4.5). The coastal profile degeneration explains the associated decline in the Bruun Rule BSS but cast doubt on the related rise in MIKE21 BSS (Fig. 4.2b). Shoreline evolution predictions must relate to observed coastal morphology to be useful for guiding coastal management. However, it is difficult to determine *a priori* if similarities between average coastal profiles from different bathymetry data resolutions will produce equally good shoreline change predictions. The average coastal profile may obscure spatial differences among individual profiles that can affect shoreline change prediction accuracy. Therefore, evaluating model sensitivity against bathymetry data is necessary to calibrate shoreline evolution models appropriately. Altogether, the model sensitivity results discussed here show that bathymetry data resolutions ≤ 100 m are appropriate for simulating shoreline evolution in the New York test site.

Tide data resolutions ≤ 60 min appear suitable for simulating shoreline evolution in the New York test site. MIKE21 BSS is ~ 0.4 (good) from tide data resolutions ≤ 60 min, but falls in response to daily high/low tide data (~ 0.2) and NOAA tide predictions (~ -0.4) (Fig. 4.2c; Table 4.1). The fall in BSS follows a sudden spike in MIKE21 net shoreline change prediction noise, near the east boundary, as tide data change to daily high/low tide frequency and NOAA predictions (Fig. 4.6). MIKE21 consistent BSS from tide data resolutions ≤ 60 min is linked to no significant spatial differences between associated net shoreline change predictions (Fig. 4.6). MIKE21 consistent BSS and shoreline change predictions from tide data resolutions ≤ 60 min correspond to negligible differences in tidal variations as tide data coarsen from 6 to 60 min in the New York test site (Fig. 3.15). However, the New York test site's tide levels are more variable and higher relative to mean high water (MHW) than NOAA's predictions and become linearised between daily extremes in the daily high/low tide dataset (Fig. 3.15). Thus, tide forcing from daily high/low tide data and NOAA predictions may not be in complete equilibrium with the New York test site's morphology, which can explain the related fall (spike) in MIKE21 BSS (prediction noise). Altogether, the MIKE21 sensitivity results discussed here show that tide data resolutions ≤ 60 min are suitable for modelling shoreline change in the New York test site.

The Bruun Rule predictions are sensitive to NOAA tide predictions in the New York test site. Statistical and spatial differences appear in the Bruun Rule predictions as tide data change from unadjusted and seasonally adjusted to NOAA predictions in the New York test site (Fig. 4.2d; Table 4.1; Fig. 4.7). Tide data influence sea-level rise (SLR) estimations, the primary forcing in the Bruun Rule. Unadjusted and seasonally adjusted tide data are observed tide levels with and without effects from seasonal variations in meteorological conditions, respectively (NOAA, 2017d). SLR estimations from the unadjusted (0.0078 m) and seasonally adjusted (0.008 m) tide data are almost equivalent, and higher than the SLR estimation from NOAA tide predictions (-0.0004 m) over the New York test site's sensitivity testing period. A lower SLR is estimated from NOAA tide predictions because the New York test site's observed tide levels are higher than those predicted by NOAA (Fig. 3.15; NOAA, 2017d). The small difference (0.0002 m) between the unadjusted and seasonally adjusted SLR is the main reason behind the consistent Bruun Rule results from both observed tide datasets. In contrast, Dunn's test shows significant differences in the Bruun Rule predictions from each tide dataset (Table 4.1). The Bruun Rule comprises four constants, including SLR (Eqn. 3.2). Any change in any constant will modify the Bruun Rule results spatially and show statistical significance. Fig. 4.7 shows a small spatial difference of ~ 0.01 m between the Bruun Rule predictions from unadjusted and seasonally adjusted tide data. Although statistically significant, such a small spatial difference between shoreline evolution predictions is not practically significant. Thus, caution is necessary when interpreting statistically significant differences among net shoreline change predictions. Meso timescale SLR estimations from each tide dataset will likely result in the Bruun Rule predictions being considerably different. However, the Bruun Rule sensitivity results do not reveal an optimal tide dataset for predicting shoreline evolution in the New York test site. Instead, it highlights the importance of considering the impact of tide data on SLR estimations when interpreting the Bruun Rule predictions.

Based on the range of values considered, wind and wave climate resolution do not affect the New York test site's shoreline change predictions. There are no statistical differences in shoreline change predictions from coarsening wind and wave data in the New York test site (Figs. 4.2 e – f; Table 4.1). Appendix A verifies these findings showing no spatial differences in MIKE21 net shoreline change and littoral drift predictions from coarsening wind and wave data in the New York test site (Figs. A4.1; A4.2; A5.1; A5.2). These results follow no discernible changes in wind and wave climate variations from coarsening time series data on these variables in the New York test site (see Figs. 3.16; 3.17).

All free parameters affect the New York test site's shoreline change predictions, except the weir coefficient. MIKE21 BSS rises from increasing sand grain diameter; falls from increasing Manning's n reciprocal, sand porosity, and sediment grading coefficient; and marginally declines from increasing weir coefficient in the New York test site (Fig. 4.2 g – k; Table 4.1). Appendix A corroborates these results by showing an increase in net shoreline change prediction noise from decreasing sand grain diameter, and increasing Manning's n reciprocal, sand porosity, and sediment grading coefficient; and no apparent spatial differences in net shoreline change predictions from increasing weir coefficient in the New York test site (Figs. A6.2; A7.2; A8.2; A9.2; Fig. A10.2). MIKE21 most optimal performance and shoreline evolution predictions in the New York test site are derived from a Manning's n reciprocal of 29 $m^{1/3}/s$, sand porosity of 0.4, sand grain diameter of 1 mm, sediment grading coefficient of 1.1, and weir coefficient of 1.21 $m^{1/2}/s$ (see Fig. 4.2 g – k; Table 4.1).

4.2.2 Boundary condition effects in the Puerto Rico test site

Fig. 4.8 and Table 4.2 illustrate the sensitivity of shoreline evolution predictions to nearshore discretisation, bathymetry data resolution, coastal processes data, and free parameters in the Puerto Rico test site. All statistical outputs in Fig. 4.8 and Table 4.2 are based on net shoreline change observed and predicted from 10-Oct-2014 to 31-Mar-2016. Analysing Fig. 4.7 and Table 4.2 reveal:

MIKE21 performance in the Puerto Rico test site is poor despite calibration attempts. Fig. 4.8 and Table 4.2 show MIKE21 BSS incrementally improves from below zero (bad) to 0.03 (poor) as the various boundary conditions become calibrated. These incremental improvements in MIKE21 BSS occur in response to boundary condition specifications that match the Puerto Rico test site morphology (details in section 4.2.4). Thus, this finding provides confidence in using the most accurate specifications of boundary conditions identified from Fig. 4.8 and Table 4.2 in subsequent MIKE21 applications in the Puerto Rico test site. MIKE21 overall poor performance in the Puerto Rico test site stems from its inability to handle longshore variations in the closure depth, which becomes apparent from results in Chapter 6. Chapter 6 evaluates the importance of a space-varying closure depth for simulating shoreline evolution in complex planform morphologies. It is difficult to determine *a priori* the parameters and variables that will be most instrumental in influencing model predictions, hence the need for evaluating model sensitivity to all potentially key boundary conditions.

45 m is plausibly the optimal (coarsest) nearshore discretisation for simulating shoreline evolution in the Puerto Rico test site. MIKE21 BSS generally stays constant around -0.05 (bad) from nearshore discretisations ≤ 40 m, incrementally improves closer to 0 (poor) from a nearshore discretisation of 45 m, and consistently worsens as nearshore discretisation gets coarser than 45 m in the Puerto Rico test site (Fig. 4.8a; Table 4.2). MIKE21 BSS incremental improvement from a nearshore discretisation of 45 m in the Puerto Rico test site follows an associated decline in its net shoreline change prediction MAE (Table 4.2). Apart from BSS and MAE estimations, there is no discernible trend in the magnitude and spatial variations of MIKE21 net shoreline change predictions from coarsening nearshore discretisation in the Puerto Rico test site (Table 4.2; Fig. 4.9). For example, MIKE21 MNC predictions from coarsening nearshore discretisation in the Puerto Rico test site are negligible compared to the observed MNC (3.22 m), varying within a small range of values (0.13 to 0.17 m) close to zero (m). Notwithstanding MIKE21 bad performance, BSS and MAE estimations indicate that MIKE21 net shoreline change predictions improve from a nearshore discretisation of 45 m in the Puerto Rico test site (Fig. 4.8a; Table 4.2). Therefore, 45 m is most plausibly the optimal (coarsest) nearshore spatial discretisation for modelling shoreline change in the Puerto Rico test site.

Bathymetry data resolutions ≤ 27 m appear suitable for simulating shoreline evolution in the Puerto Rico test site. MIKE21 BSS rises incrementally from -0.02 (bad) to 0 (poor) as bathymetry data coarsen from 3 to 27 m, and falls from bathymetry data coarser than 27 m in the Puerto Rico test site (Fig. 4.8b; Table 4.2). However, the Bruun Rule BSS only changes (declines) as bathymetry data become coarser than 100 m in the Puerto Rico test site (Fig. 4.8b; Table 4.2). Fig. 4.10 shows the Puerto Rico test site's average upper beach profile degenerates from bathymetry data coarser than 27 m, which explains the corresponding fall in MIKE21 BSS. There are spatial differences in MIKE21 and the Bruun Rule net shoreline change predictions from bathymetry data coarser than 27 m in the Puerto Rico test site (see Fig. 4.11) that also correspond to the degeneration of the average upper beach profile. Therefore, 27 m is plausibly the optimal (coarsest) bathymetry data resolution for modelling shoreline change in the Puerto Rico test site. Spatial differences in the Bruun Rule predictions from bathymetry data coarser than 27 m in the Puerto Rico test site are far too small (~ 0.2 m) to modify its BSS (Fig. 4.11; Table 4.2). It is possible that bathymetry data coarser than 27 m will significantly affect the Bruun Rule predictions over meso timescales in the Puerto Rico test site.

Based on the range of values considered, tide, wind and wave climate data resolution do not affect MIKE21 shoreline change predictions in the Puerto Rico test site. There are insignificant statistical differences in MIKE21 net shoreline change predictions from coarsening tide, wind and wave data in the Puerto Rico test site (Fig. 4.8; Table 4.2). NOAA tide predictions also do not affect MIKE21 net shoreline change predictions in the Puerto Rico test site (Fig. 4.8c; Table 4.2). Appendix A verifies these results by showing no longshore differences in MIKE21 net shoreline change and littoral drift predictions from changes in tide, wind and wave climate data in the Puerto Rico test site (Figs. A3.1; A3.2; A4.1; A4.3; A5.1; A5.3). MIKE21 insensitivity to coastal processes data resolution in the Puerto Rico test site is linked to no associated changes in tide, wind and wave climate variations from coarsening time series data on these coastal variables (Figs. 3.15; 3.16; 3.17). MIKE21 insensitivity to NOAA tide predictions in the Puerto Rico test site corresponds to the micro tide range (~ 0.34 m) and negligible difference (≤ 0.1 m) between tide levels observed and predicted there (NOAA, 2017c).

The Bruun Rule predictions are sensitive to tide data in the Puerto Rico test site. The Bruun Rule predictions decline in magnitude as tide data change from unadjusted to seasonally adjusted to NOAA predictions in the Puerto Rico test site (Table 4.2). The decline in the magnitude of the Bruun Rule predictions is linked to a fall in SLR over the Puerto Rico test site's sensitivity testing period as tide data change from unadjusted (0.0048 m) to seasonally adjusted (0.0041 m) to NOAA predictions

(-0.001 mm). However, the Bruun Rule predictions are negligible, varying very close to zero (m) longshore, regardless of tide data (Fig. 4.12) as associated SLR estimations are close to zero (m). Therefore, the Bruun Rule BSS remains approximately zero despite changes in tide data (Fig. 4.8d). It is likely that differences in meso timescale SLR estimations from each tide dataset will significantly affect the Bruun Rule performance and net shoreline change predictions in the Puerto Rico test site.

Net shoreline change predictions in the Puerto Rico test site are sensitive to all free parameters, except the weir coefficient. MIKE21 BSS decreases from increasing Manning's n reciprocal, sand porosity, and sediment grading coefficient; rises and marginally changes from sand grain diameters > 0.1 mm; and stays relatively constant from increasing weir coefficient in the Puerto Rico test site (Fig. 4.8 g – k; Table 4.2). Appendix A supports these BSS results by showing an increase in net shoreline change prediction noise from increasing Manning's n reciprocal, sand porosity, and sediment grading coefficient; a sharp (gradual) decline in net shoreline change prediction noise as sand grain diameter increases to 0.2 mm (beyond 0.2 mm); and no apparent spatial differences in net shoreline change predictions from increasing weir coefficient in the Puerto Rico test site (Figs. A6.3; A7.3; A8.3; A9.3; A10.3). MIKE21 best performance in the Puerto Rico test site is obtained from a Manning's n reciprocal of 29 $m^{1/3}/s$, sand porosity of 0.3, sand grain diameter of 0.25 and 0.5 mm, sediment grading coefficient of 1.1, and weir coefficient of 0.55 $m^{1/2}/s$ (Fig. 4.8 g – k; Table 4.2).

4.2.3 Boundary condition effects in the Southern California test site

Fig. 4.13 and Table 4.3 illustrate the sensitivity of shoreline evolution predictions to nearshore discretisation, bathymetry data resolution, coastal processes time series data and free parameters in the Southern California test site. Fig. 4.13 and Table 4.3 results are based on net shoreline change observed and predicted from 01-Jan-2009 to 02-Aug-2011. It is important to note that shoreline evolution in the Southern California test site is influenced by annual temporary sand berms (Gallien et al., 2015). MIKE21 and the Bruun Rule do not consider temporal variations in beach berms, which prevent an objective evaluation of their performance and net shoreline change predictions in the Southern California test site. Thus, I only use the Southern California test site's observed shoreline change as a baseline for evaluating MIKE21 and the Bruun Rule response to boundary condition variations to understand the controls on shoreline evolution in different coastal morphologies. Therefore, Fig. 4.13 and Table 4.3 results should only be interpreted in terms of MIKE21 and the Bruun Rule sensitivity rather than their overall predictability. Analysing Fig. 4.13 and Table 4.3 reveal:

30 m is the optimal (coarsest) nearshore discretisation for simulating shoreline evolution in the Southern California test site. MIKE21 BSS incrementally increases from 0.14 to 0.15 (reasonable) as nearshore discretisation coarsens from 25 to 30 m, and falls below zero (bad) as nearshore discretisation gets coarser than 30 m in the Southern California test site (Fig. 4.13a; Table 4.3). These BSS results correspond to an increase in the magnitude and noisiness of MIKE21 net shoreline change predictions as nearshore discretisation gets coarser than 30 m in the Southern California test site (Table 4.3; Fig. 4.14). The increase in noisiness indicates disequilibrium between the mesh geometry and processes operating within the model space, providing further evidence of 30 m being the optimal (coarsest) nearshore spatial discretisation in the Southern California test site.

The optimal (coarsest) bathymetry data resolution for simulating shoreline evolution in the Southern California test site is likely ≤ 10 m. MIKE21 BSS declines from 0.15 (reasonable) to below zero (bad) as bathymetry data get coarser than 10 m in the Southern California test site (Fig. 4.13b; Table 4.3). The decline in MIKE21 BSS corresponds to constant changes in MIKE21 net shoreline change prediction magnitude from coarsening bathymetry data in the Southern California test site (Fig. 4.15; Table 4.3). In contrast, the Bruun Rule BSS is constant at 0.01 (poor) even though the Bruun Rule predictions vary spatially from coarsening bathymetry data in the Southern California test site (Figs. 4.13b; 4.15). The constant Bruun Rule BSS is a consequence of the Bruun Rule predictions ranging from 0.1 to 0.3 m longshore regardless of bathymetry data resolution as SLR is negligible (0.006 m) over the associated sensitivity testing period (Fig. 4.15). Therefore, spatial differences in the Bruun Rule predictions from coarsening bathymetry data in the Southern California test site are too small to modify its BSS. The spatial differences in the Bruun Rule predictions from coarsening bathymetry data in the Southern California test site will likely become significant as the magnitude of SLR increases. The constant spatial changes in MIKE21 and the Bruun Rule net shoreline change predictions from coarsening bathymetry data in Fig. 4.15 imply that the optimal (coarsest) bathymetry data resolution for modelling shoreline evolution in the Southern California test site is likely ≤ 10 m.

Tide (including NOAA predictions), wind, and wave climate time series data have a negligible effect on MIKE21 net shoreline change predictions in the Southern California test site. There are small (insignificant) statistical differences in MIKE21 net shoreline change predictions from changes in tide, wind, and wave climate time series data in the Southern California test site (Fig. 4.13; Table 4.3). Appendix A verifies these results by showing negligible spatial differences in MIKE21 net shoreline change and net littoral drift predictions from changes in tide, wind, and wave climate time series data in the Southern California test site (Figs. A3.1; A3.3; A4.1; A4.4; A5.1; A5.4). These findings correspond to consistent variations, daily and seasonal, in all coastal processes time series data used for evaluating MIKE21 sensitivity in the Southern California test site (see Figs. 3.15; 3.16; 3.17).

The Bruun Rule is sensitive to tide data in the Southern California test site. The Bruun Rule predicts a larger MNC as tide data change from NOAA predictions (~ 0.00 m) to unadjusted (-0.09 m) to seasonally adjusted (-0.15 m) in the Southern California test site (Table 4.3; Fig. 4.16). The constant change in the Bruun Rule MNC follows an increase in SLR estimated over the associated sensitivity testing period as tide data change from NOAA predictions (-0.0024 mm) to unadjusted (0.004 m) to seasonally adjusted (0.006 m). However, spatial differences between the Bruun Rule predictions from each tide dataset are too small (≤ 0.22 m) to modify its BSS (Fig. 4.16) as associated SLR (m) estimates are negligible. It is highly likely that differences in meso timescale SLR estimates from each tide dataset will significantly influence the Bruun Rule predictions in the Southern California test site.

Shoreline evolution predictions in the Southern California test site are sensitive to all free parameters, except the weir coefficient. MIKE21 BSS falls sharply from Manning's n reciprocals > 33 $m^{1/3}/s$; rises (falls) as sand porosity increases to 0.5 (0.7); declines as sand grain diameter and sediment grading coefficient increases; and stays relatively constant from increasing weir coefficient in the Southern California test site (Fig. 4.13 g – k; Table 4.3). Appendix A supports these BSS results showing a significant increase in net shoreline change prediction noise from Manning's n reciprocals > 33 $m^{1/3}/s$ and sand porosities > 0.5; an overall decline in net shoreline change prediction magnitude from sand grain diameters > 0.2 mm and sediment grading coefficient > 1.1; and spatially consistent net shoreline change predictions from increasing weir coefficient in the Southern California test site (Figs. A6.4; A7.4; A8.4; A9.4; A10.4). MIKE21 best results in the Southern California test site are derived from a Manning's n reciprocal of 33 $m^{1/3}/s$, sand porosity of 0.5, sand grain diameter of 0.2 mm, sediment grading coefficient of 1.1, and weir coefficient of 0.99 $m^{1/2}/s$ (see Fig. 4.13 g – k; Table 4.3).

4.2.4 Key boundary conditions

Preceding sections reveal nearshore discretisation, bathymetry, tides, Manning's n reciprocal, and sediment properties (grain diameter, porosity, and grading) are the key boundary conditions affecting shoreline evolution predictions in each test site (Fig. 4.17). Wind, wave climate and weir coefficient have a negligible effect on shoreline evolution predictions in all three test sites. The optimal specifications of the key boundary conditions, however, are mostly site-specific (Fig. 4.17; Table 4.4):

The optimal nearshore discretisation for simulating shoreline evolution is finer in the Southern California test site (30 m) than in the New York and Puerto Rico test sites (45 m) (Fig. 4.17a; Table 4.4). This finding stems from the Southern California test site having a steeper average coastal profile morphology (slope = 2.68%) than the New York (slope = 1.82%) and Puerto Rico test site (slope = 1.75%) (Table 4.5; Fig. 2.4c). Nearshore discretisation influences how well the observed coastal profile morphology is represented in the model space (Gorman et al., 2006). For instance, coarsening nearshore discretisation smoothens the coastal profile (Gorman et al., 2006). As a result, steep coastal profiles degenerate and become numerically gradient over a smaller range of nearshore discretisations than gentle profiles because of their larger bed topography range (Meng et al., 2017).

The optimal bathymetry data resolutions for simulating shoreline evolution are ≤ 100 m in the New York test site, ≤ 27 m in the Puerto Rico test site, and ≤ 10 m in the Southern California test site (Fig. 4.17b; Table 4.4). These results are also linked to each test site's coastal profile morphology. The New York and Puerto Rico test sites have a coarser optimal range of bathymetry data than the Southern California test site because of their gentler sloping average coastal profile (Table 4.5; Fig. 2.4). However, the Puerto Rico test site has a finer optimal range of bathymetry data than the New York test site because it has a non-uniform bathymetry from coral reefs (Fig. 2.4 a – b). As a result, the Puerto Rico test site has more longshore and cross-shore fluctuations in bed topography than the New York test site's simple planform morphology over equivalent spatial distances (Fig. 2.4 a – b). Therefore, the Puerto Rico test site morphology becomes numerically gradient over a smaller range of bathymetry data resolutions than the New York test site morphology (see Figs. 4.5; 4.10).

Tide data resolutions ≤ 60 min are optimal for MIKE21 shoreline evolution simulations in the New York test site, whereas tide data (including NOAA predictions) have a negligible effect on MIKE21 simulations in the Puerto Rico and Southern California test sites (Fig. 4.17c). Tide levels observed in the New York test site are generally higher and more variable relative to MHW than those observed in the Puerto Rico and Southern California test sites (Fig. 3.15; Table 4.7). Therefore, changes in tide data (e.g. daily high/low tide frequency or NOAA predictions) will have a more significant effect on MIKE21 process simulations and resulting shoreline change predictions in the New York test site.

The Bruun Rule sensitivity results do not reveal an optimal tide dataset for predicting shoreline evolution in each test site. Instead, it highlights the importance of considering the influence of tide data characteristics (e.g. origin and time series adjustments) on SLR estimations and corresponding shoreline evolution predictions. Small (≤ 0.3 m), but apparent spatial differences in the Bruun Rule net shoreline change predictions emerge as tide data change from unadjusted to seasonally adjusted to NOAA predictions in each test site (Figs. 4.7; 4.12; 4.16). In all cases, however, the Bruun Rule net shoreline change predictions are negligible as SLR estimated from each tide dataset is almost zero (m) over the associated sensitivity testing period. The magnitude of the Bruun Rule net shoreline change predictions hinges on the magnitude of SLR (see Chapters 5 and 7) because SLR is the primary forcing term in the Bruun Rule equation (Eqn. 3.2). Therefore, meso timescale SLR estimations from different tide datasets in each test site will most likely result in very different Bruun Rule net shoreline change predictions. It is thus important to account for the influence of tide data characteristics on SLR estimations when interpreting the Bruun Rule shoreline evolution predictions.

The optimal Manning's n reciprocal for simulating shoreline evolution is 29 $m^{1/3}$/s in the New York and Puerto Rico test sites, and 33 $m^{1/3}$/s in the Southern California test site (Fig. 4.17f; Table 4.4). These Manning's n reciprocals are equivalent to a Manning's n value of ~ 0.03, which is more representative of sandy coastal systems, characteristic of the three test sites, than Manning's n reciprocals of 40 and 50 $m^{1/3}$/s (Ayres, 2008; Kaiser et al., 2011; Quataert et al., 2019). Manning's n reciprocals of 40 and 50 $m^{1/3}$/s are more representative of open water bodies (Ayres, 2008; Mattocks and Forbes, 2008), which most plausibly explains why MIKE21 net shoreline change prediction accuracy worsens from these Manning's n reciprocals in each test site (Fig. 4.17f; Tables 4.1 – 4.3).

MIKE21 sensitivity results indicate that the optimal sand grain diameter for modelling shoreline evolution is 0.2 mm in the Southern California test site, 0.25 and 0.5 mm in the Puerto Rico test site, and 1 mm in the New York test site (Fig. 4.17g; Table 4.4). A sand grain diameter of 0.2 mm is characteristic of the fine-grained beach sediments in the Southern California test site, and 0.25 and 0.5 mm are both characteristic of the medium-grained beach sediments in the Puerto Rico test site (Kaye, 1959; Farnsworth and Warrick, 2007). However, a sand grain diameter of 1 mm is not characteristic of the New York test site where the median grain size is ~ 0.2 mm (USACE and NYSDEC, 2015). Therefore, I consider 0.2 mm as the optimal sand grain diameter in the New York test site to avoid having a right model for the wrong reasons, where right refers to the best match between observed and predicted net shoreline change and wrong refers to physically unrealistic parameter values of the conceptual model describing the New York test site morphology. Coastal management decisions can be adversely affected, with inherent implications (ineffectiveness or worsening of coastal change), if shoreline evolution predictions are not based on observed coastal morphology. Caution is thus necessary when identifying calibrated values of key model parameters.

The optimal sand porosity for modelling shoreline evolution ranges from 0.3 in the New York and

Puerto Rico test sites to 0.5 in the Southern California test site (Fig. 4.17h; Table 4.4). These values fall within the range of fine (0.26 to 0.53) and medium (0.29 to 0.49) grained sand porosities (Morris and Johnson, 1967), therefore are characteristic of sand grain diameters across the three test sites.

The optimal sediment grading coefficient for modelling shoreline evolution is 1.1 in each test site (Fig. 4.17i). A sediment grading coefficient of 1.1 is representative of the very well sorted beach sediments present in all three test sites (Terry et al., 1956; Kaye, 1959; USACE and NYSDEC, 2015).

Analysing and comparing model sensitivity results from each test site reveal that the optimal specifications of the key boundary conditions for simulating shoreline evolution in managed sandy coastal systems generally correspond to observed coastal system characteristics, including morphology and processes. These sensitivity results highlight the importance of carefully considering boundary conditions alongside coastal system features when calibrating shoreline evolution models.

4.3 Calibrated net shoreline change predictions

This section first provides a spatial illustration of MIKE21 and the Bruun Rule calibrated shoreline evolution predictions in each test site (sections 4.3.1; 4.3.2). Section 4.3.3 then identifies the better model for application in managed sandy coastal systems. All model calibration results are based on the relevant specifications in Table 4.4 and the associated sensitivity testing period in each test site.

4.3.1 MIKE21

According to BSS estimations, MIKE21 calibrated shoreline evolution predictions are good in the New York test site (0.46), very poor in the Puerto Rico test site (0.03), and borderline good in the Southern California test site (0.22). Fig. 4.18 corroborates these BSS estimations by illustrating that:

There is a good fit between spatial variations in net shoreline change observed and predicted from the New York test site's calibrated MIKE21 model (Fig. 4.18a). The signs in MNC observed and predicted from the New York test site's calibrated MIKE21 model are also consistent (negative), indicating net shoreline change observations and predictions move in the same direction. However, the New York test site's calibrated MIKE21 model moderately underpredicts shoreline change, evident from the observed MAC (1.16 m) being slightly larger than the predicted MAC (0.76 m). The moderate underprediction is attributed to the Flather condition data (current velocities and free surface elevation) applied along the open boundaries. The Flather condition data are generated from pre-calibration simulations (see section 3.4.2) because observed current velocities and free surface elevation data are not available. As a result, the Flather condition data applied at the open boundaries are not likely to be in complete equilibrium with other boundary conditions in the model space, which can explain the moderate shoreline change underprediction from the New York test site's calibrated MIKE21 model. The Flather condition data directly influence shoreline evolution predictions as these data affect littoral drift. Littoral drift is the driving flux of shoreline evolution in MIKE21 (see Eqn. 3.3).

The Puerto Rico test site's calibrated MIKE21 model fails to predict observed shoreline change to an acceptable level (Fig. 4.18b). MIKE21 calibrated net shoreline change predictions in the Puerto Rico test site vary closely around zero (m) longshore compared to related observations (-12 to 16 m). As a result, the Puerto Rico test site's calibrated MIKE21 model predicts a very small MNC (0.11 m) compared to the observed MNC (3.22 m), hence the associated BSS of almost zero (see Fig. 4.18b). These considerable differences between the magnitude of net shoreline change observed and predicted stem from MIKE21 inability to incorporate the Puerto Rico test site's closure depth longshore variations (see Chapter 6). MIKE21 simulates shoreline evolution by uniformly redistributing net littoral drift gradients between the berm height and closure depth (Kaergaard and Fredsoe, 2013; Kristensen et al., 2013). Therefore, averaging out the berm height and closure depth in coastal systems with considerable longshore variations in these boundaries, particularly the closure depth, can cause a significant under- or over-prediction of net shoreline change. The closure depth is singled out because it specifies the seaward boundary of morphodynamic activity in MIKE21.

Net shoreline change observed and predicted from the calibrated MIKE21 model in the Southern California test site match reasonably well in the north but differ in trend component towards the south (Fig. 4.18c). Net shoreline change observations in the Southern California test site show accretion towards the south in line with the annual creation of temporary sand berms. The yearly temporary sand berms mean the berm height changes yearly towards the south of the Southern California test site (Fig. 2.3; Gallien et al., 2015), violating MIKE21 assumption of a fixed berm height. As a result, MIKE21 (calibrated or uncalibrated) cannot predict the accretion levels associated with the Southern California test site's annual berms. However, the Southern California test site's calibrated MIKE21 model still predicts net accretion (MNC = 1.37 m) in line with the observed trend (MNC = 15.15 m) and a fluctuating pattern of accretion (mostly) and erosion similar to the fluctuating accretion pattern observed towards the south (Fig. 4.18c). MIKE21 may thus replicate the Southern California test site's shoreline change trends very well if developed to handle a time and space-varying berm height.

Considering the framework of MIKE21 (section 3.3.1), it is clear that MIKE21 calibrated performance is best in areas that match the one-line theory assumptions of shore-parallel contours and spatially invariable berm height and closure depth. The one-line theory forms the basis of MIKE21 shoreline continuity equation (Eqn. 3.3). As the New York test site fully matches the one-line theory morphology assumptions, MIKE21 associated performance is good (BSS = 0.46) (Figs. 4.17; 4.18a). In slight contrast, the Southern California test site partly matches the one-line theory morphology assumptions, hence MIKE21 associated performance is borderline good (BSS = 0.22) (Figs. 4.17; 4.18c). Although the Southern California test site has shore-parallel contours and a spatially invariable closure depth, it has a time and space-varying berm height. The Puerto Rico test site does not conform to the one-line theory morphology assumptions, hence MIKE21 associated performance is very poor (BSS = 0.03) (Figs. 4.16; 4.17b). The Puerto Rico test site has a complex planform morphology, characterised by non-parallel depth contours and a space-varying closure depth. Developing MIKE21 to allow a time and space-varying active coastal profile may improve and extend its applicability beyond simple planform morphologies, such as the New York test site morphology.

4.3.2 The Bruun Rule

Fig. 4.19 shows that the Bruun Rule calibrated predictions in each test site are negligible compared to related observations. The only correspondence between net shoreline change observations and the Bruun Rule calibrated predictions is the MNC in the New York test site (Fig. 4.19a). MNC observed and predicted from the New York test site's calibrated Bruun Rule model are negative, indicating shoreline change observations and predictions move in the same direction (erosion). The negligible net shoreline change predictions from the calibrated Bruun Rule in each test site are due to SLR being approximately zero (m) over the associated calibration period (see Chapters 5 and 7).

4.3.3 Optimal modelling approach

MIKE21 and the Bruun Rule calibrated shoreline evolution predictions in each test site indicate that:

The MIKE21 modelling approach is more appropriate for simulating shoreline evolution in the New York and Southern California test sites (Figs. 4.18; 4.19). MIKE21 calibrated net shoreline change predictions generally follow the New York and Southern California test sites observed shoreline change trends. In contrast, the Bruun Rule calibrated predictions are negligible in each test site due to negligible SLR over the associated calibration period (Figs. 4.18; 4.19). These results indicate that littoral drift has a more endogenous influence on shoreline evolution than SLR, at least over the micro timescales used for sensitivity testing and calibration in each test site. Littoral drift is the driving flux of shoreline evolution in MIKE21, whereas SLR is the primary forcing in the Bruun Rule. SLR, however, will likely be a more endogenous factor in meso timescale shoreline evolution (Stive et al., 2002). Therefore, the Bruun Rule predictions may improve over such timescales in all three test sites.

Neither MIKE21 nor the Bruun Rule is optimal for modelling shoreline change in the Puerto Rico test site. Both models fail to predict the observed net shoreline change in the Puerto Rico test site to an acceptable level despite calibration attempts (Figs. 4.8; 4.18b; 4.19b). MIKE21 poor performance in the Puerto Rico test site stems from its inability to handle spatial variations in the closure depth (see Chapter 6), whereas the Bruun Rule poor performance is due to negligible SLR over the calibration period. In contrast to the calibrated Bruun Rule, however, the calibrated MIKE21 model predicts net shoreline accretion in line with the Puerto Rico test site's observed MNC trend (Fig. 4.18b; 4.19b).

4.4 Summary

This chapter presents the main results from calibrating and assessing MIKE21 and the Bruun Rule sensitivity to boundary conditions in each test site. The key findings from analysing these results are:

1. Nearshore spatial discretisation, bathymetry, tides, Manning's n reciprocal (friction), and sediment properties (grain diameter, porosity, and grading) are the key boundary conditions influencing shoreline evolution predictions in each test site. Wind, wave climate, and weir coefficient have no significant effect on shoreline evolution predictions across all three test sites.

2. The optimal specifications of the key boundary conditions for modelling the evolution of managed sandy shorelines correspond to coastal system features, including morphology and processes.

3. MIKE21 performance and predictions are best in areas that match the one-line theory

assumptions of shore-parallel contours and spatially invariable berm height and closure depth, which underlie its shoreline continuity equation (Eqn. 3.3). This finding is clear from MIKE21 calibrated net shoreline change predictions being good in the New York test site (BSS = 0.46), poor in the Puerto Rico test site (BSS = 0.03), and borderline good in the Southern California test site (BSS = 0.22). The one-line theory morphology assumptions fully and partly characterise the New York and Southern California test site morphology, respectively. On the other hand, the Puerto Rico test site does not conform to any of the one-line theory morphology assumptions.

4. The Bruun Rule fails to predict the observed net shoreline change to an acceptable level in each test site because of an almost zero (m) SLR over the associated sensitivity testing and calibration period. However, there is a chance that the Bruun Rule accuracy and predictions may improve over meso timescales where SLR is expected to become an endogenous factor in shoreline evolution. Chapters 5 and 7 apply and gauge the Bruun Rule capabilities over such timescales.

5. MIKE21 is more appropriate than the Bruun Rule for simulating shoreline evolution in the New York and Southern California test sites, whereas neither model is optimal in the Puerto Rico test site. This finding is clear from MIKE21 ability to replicate observed net shoreline change trends in the New York and Southern California test sites compared to the Bruun Rule, which further indicates the importance of littoral drift gradients in shoreline evolution simulations. In the Puerto Rico test site, MIKE21 and the Bruun Rule both fail to predict the observed net shoreline change to an acceptable level despite calibration attempts. However, the Puerto Rico test site's calibrated MIKE21 model still predicts net accretion in line with the observed net shoreline change trend in contrast to its calibrated Bruun Rule model. MIKE21 poor performance in the Puerto Rico test site stems from its inability to handle spatial variations in the closure depth. Chapter 6 gauges and defines the importance of a space-varying closure depth for simulating shoreline evolution in complex planform morphologies, characteristic of the Puerto Rico test site.

05
Incorporating sea-level rise

'For no two successive days is the shoreline precisely the same. Not only do the tides advance and retreat in their eternal rhythms, but the level of the sea itself is never at rest…Today a little more land may belong to the sea, tomorrow a little less.'

– Rachel Carson

5.1 Introduction

This chapter presents the results from hindcasting and forecasting meso timescale shoreline evolution in the New York test site using a constant and time-varying closure depth in MIKE21, and the Bruun Rule. I use these results to determine if a time-varying closure depth in MIKE21 improves meso timescale shoreline evolution predictions under sea-level rise to address research question two: *How can sea-level rise be incorporated in shoreline evolution models for mesoscale application in managed sandy coastal systems*? Section 3.8 explains that sea-level rise can alter the offshore part of the active coastal profile shape, in particular, by affecting cross-shore sediment mass balance through its influence on the wave setup and associated undertow. Changes in coastal profile shape inevitably affect shoreline morphology. However, advanced mesoscale shoreline evolution models grossly simplify their morphology update by assuming an equilibrium coastal profile, consequently failing to account for sea-level rise. An equilibrium coastal profile implies a fixed berm height and closure depth, with the closure depth marking the seaward extent of morphodynamics. Although a gross simplification, the equilibrium profile assumption prevents coastal profile degeneration (and ensuing unreliable shoreline change predictions) that stem from the inability of existing mesoscale shoreline evolution models to represent undertow currents (see section 3.8). Slightly modifying this assumption to include a time-varying closure depth may offer a plausible simple solution to mirror sea-level rise effects on the offshore part of the coastal profile in mesoscale shoreline evolution models. The workflow used to test this solution entailed running MIKE21 annually using a different closure depth, with outputs (morphology and hydrodynamic) from each annual simulation hot-starting the next annual simulation (Fig. 3.19). This approach does not modify MIKE21 code. It simply forces MIKE21 to simulate meso timescale shoreline evolution iteratively over one-year intervals, which include a change in the active coastal profile offshore limit in response to changing hydrodynamics.

Section 5.2 quantifies and compares the results of five different modelling approaches used to hindcast meso timescale shoreline evolution in the New York test site (01-Jan-1966 to 01-Feb-2016):

1. **Model one** applies a constant closure depth and partially enforces the one-line theory in line with MIKE21 current approach. At present, MIKE21 applies the one-line theory to update the shoreface and shoreline morphology (Eqn. 3.3). The one-line theory, however, is not applied in MIKE21 processes simulations. Model one is based on the New York test site's 1966 bathymetry (Fig. 2.9a), coastal profiles, and closure depth (4.2 m). The closure depth in model one is the most seaward contour with shoreline undulations in the New York test site's 1966 bathymetry.

2. **Model two** applies a constant closure depth and fully enforces the one-line theory in MIKE21. Model two is based on a modified bathymetry, created by interpolating the New York test site's 1966 bathymetry data points (x, y) with the depth values (z) from its 2014 bathymetry (Fig. 2.5a). According to the one-line theory, this interpolation shifts the New York test site's 2014 coastal profiles back to their 1966 position. The one-line theory assumes the coastal profile maintains its shape while moving from a change in sediment balance (Pelnard-Considere, 1956). Model two is thus based on the New York test site's 2014 profiles. Model two closure depth is 6 m, the most seaward depth contour with shoreline undulations in the modified bathymetry. The modified

bathymetry ensures that the one-line theory is also included in MIKE21 processes simulations.

3. **Model three** applies a time-varying closure depth in MIKE21. Initial conditions in model three include the modified bathymetry and closure depth (6 m) specified in model two. The novelty in model three is that the closure depth is updated yearly based on nearshore significant wave heights calculated in MIKE21. All closure depth updates are based on Birkemeier (1985) formula.

4. **Model four** applies the Bruun Rule (Eqn. 3.2) using the coastal profiles derived from the New York test site's 1966 bathymetry. The closure depth in model four is 4.2 m, which is the most seaward depth contour with shoreline undulations in the New York test site's 1966 bathymetry.

5. **Model five** applies the Bruun Rule using the coastal profiles derived from the modified bathymetry specified in model two (shifted 2014 coastal profiles). Model five closure depth is 6 m, the most seaward depth contour reflecting shoreline undulations in the modified bathymetry.

All meso timescale hindcasts above include a relative sea-level rise of 0.2 m from the New York test site 1966 to 2016 tide data (Fig. 2.9c; NOAA, 2017d). The objective of these hindcasts is to determine if a time-varying closure depth improves shoreline evolution predictions in the New York test site over a 50-year period that had relative sea-level rise and presumably a change in the offshore profile. Sections 3.8.1 and 3.8.2 outline each meso timescale hindcast carried out in the New York test site.

Section 5.3 quantifies and compares shoreline evolution projections derived from applying a constant closure depth in MIKE21, a time-varying closure depth in MIKE21, and the Bruun Rule to forecast meso timescale shoreline evolution in the New York test site (01-Jan-2014 to 01-Jan-2064). The initial conditions in these forecasts include the New York test site's 2014 bathymetry, coastal profiles, and closure depth (5.8 m). All meso timescale forecasts in the New York test site assume a 0.28 m sea-level rise. 0.28 m is the Intergovernmental Panel on Climate Change (IPCC) global median sea-level rise projection for 2046 to 2065 (Church et al., 2013). The objective of these meso timescale forecasts is to compare shoreline evolution projections for a theoretical future sea-level environment from three different modelling approaches with respect to implications for coastal management decisions. Section 3.8.3 outlines each meso timescale forecast carried out in the New York test site.

Sections 5.2 and 5.3 focus on a 7 km coastal stretch in the New York test site, spanning from ~ 3 400 m west of the east boundary to ~ 1 800 m east of the west boundary (Fig. 5.1), because MIKE21 meso timescale shoreline evolution predictions in transects outside this area are sensitive (noisy) to the Flather condition data applied at the open boundaries. As before, all shoreline change statistics in this chapter are derived from transects every 5 m longshore, excluding those in groyne locations.

5.2 Meso timescale hindcasts of shoreline evolution in the New York test site

This section quantifies and analyses the results derived from hindcasting meso timescale shoreline evolution in the New York test site (01-Jan-1966 to 01-Feb-2016) using a constant closure depth based on the one-line theory in MIKE21 (section 5.2.1), a time-varying closure depth in MIKE21 (section 5.2.2), and the Bruun Rule (section 5.2.3). In all cases, net shoreline change predictions are compared with related observations. Section 5.2.4 summarises the findings from preceding sections.

5.2.1 Using a constant closure depth in MIKE21

There is a relatively good fit between net shoreline change observations and predictions from models one (4.2 m closure depth based on 1966 coastal profiles) and two (6 m closure depth based on shifted 2014 coastal profiles) over the 50-year hindcast (Fig. 5.2 a – b). The key difference between both models is that model one applies the one-line theory in the shoreline morphology update only, while model two applies the one-line theory in both processes simulations and morphology update. Models one and two net shoreline change predictions have a Brier Skill Score (BSS) of ~ 0.2 (Fig. 5.2 a – b), indicating that the one-line theory as included in MIKE21 provides borderline good meso timescale shoreline evolution predictions (Sutherland et al., 2004). Models one and two borderline good BSSs correspond to associated shoreline change observations and predictions demonstrating:

1. *Net shoreline accretion*, which is evident from the positive MNC observed (1.69 m; SD: 4.16) and predicted from models one (1.08 m; SD: 4.45) and two (1.79 m; SD: 6.14) over the 50-year hindcast (Fig. 5.2 a – b). In terms of longshore trends in shoreline morphology, shoreline evolution observations (67% accretion; 33% erosion) and predictions from models one (60% accretion; 40% erosion) and two (62% accretion; 38% erosion) all indicate that accretion dominates ≥ 60% of the New York test site focus area from 1966 to 2016. The longshore range of net shoreline change observations (-18.8 to 30.2 m) and predictions from models one (-11.9 to 14.6 m) and two (-14.4 to 23.1 m) also show overall higher shoreline accretion magnitudes than erosion magnitudes from 1966 to 2016 in the New York test site focus area.

2. *A similar longshore pattern of accretion and erosion* (Fig. 5.2 a – b). Net shoreline change observed and predicted from models one and two show an alternating pattern of accretion and erosion over the 50-year hindcast, with accretion mainly between groynes and erosion mostly in groynes immediate vicinity (Fig. 5.2 a – b). This alternating pattern is common in sandy coastal systems that have groyne fields for intercepting littoral drift to facilitate shoreline stabilisation and expansion of beach width (Hapke et al., 2013; Ruiz-Martínez et al., 2016).

The net accretion observed over the 50-year hindcast in the New York test site is primarily attributed to groynes constructed between 1930 and 1961, and secondarily attributed to periodic beach feeding in Point Lookout between 1990 and 2014 (Tanski, 2012; Catania, 2015; USACE and NYSDEC, 2015). The groynes and periodic beach feeding were used to offset sediment deficit and sea-level rise effects in the New York test site (Tanski, 2012; USACE and NYSDEC, 2015). Before groynes construction, the New York test site's Atlantic shoreline was naturally retreating (Gornitz et al., 2002; Tanski, 2012). Therefore, models one and two ability to predict the net accretion and general alternating pattern of accretion and erosion observed from 1966 to 2016 in the New York test site indicate that MIKE21 can successfully simulate the effects of groynes and beach feeding on shoreline evolution under sea-level rise. MIKE21 incorporates groynes as subgrid polyline features (Fig. 3.9), and beach feeding by assuming an adequate sand supply at the open boundaries (see section 3.4.2).

Models one and two assumption of a constant closure depth in accordance with the one-line theory is the most plausible reason that prohibited a better fit between corresponding net shoreline change observations and predictions. Models one and two constant closure depth averages out the temporal variability of the New York test site's active coastal area over the 50-year hindcast (Table 5.1). Table 5.1 shows annual variations in the New York test site's closure depth from 1980 to 2012. There are no closure depth data before and after this period. The closure depth defines the offshore extent of morphodynamic activity in MIKE21, influencing the horizontal dimension of the active coastal area over which MIKE21 distributes littoral drift gradients to calculate shoreline change. Therefore, the achievable goodness of fit between shoreline evolution predictions and observations from using a constant closure depth in MIKE21 will reduce as timescales increase and the active coastal area changes. This became evident from the New York test site's calibrated MIKE21 model (2014 to 2016) having a good BSS of 0.46 (Fig. 4.17a), whereas models one and two (1966 to 2016) have borderline good BSSs (~ 0.2). Models one and two are meso timescale extensions of the New York test site's calibrated MIKE21 model. Closure depth changes usually occur in response to a change in wave climate or sea-level (Nicholls et al., 1996; Hallin et al., 2019). Thus, the use of a constant closure depth means that sea-level rise effects over the 50-year hindcast are not fully incorporated in models one and two. However, tide forcing from the New York test site's 1966 to 2016 tide gauge data ensures that models one and two account for sea-level rise in sediment transport simulations (details in section 3.8.1). Establishing a method that enables a time-varying closure depth in MIKE21 will likely improve our ability to simulate meso timescale shoreline evolution under relative sea-level rise.

5.2.2 Using a time-varying closure depth in MIKE21

MIKE21 net shoreline change predictions worsen in response to a time-varying closure depth (model three) over the 50-year hindcast period in the New York test site (Fig. 5.2). This is evident from model three having a BSS of 0.12 (reasonable), whereas models one and two (constant closure depth) have a BSS slightly above 0.2 (borderline good) (Fig. 5.2 a – c). The reasonable BSS from model three corresponds to associated net shoreline change predictions (MNC: 0.01 m) and observations (MNC: 1.69 m) showing net accretion and a fairly similar alternating pattern of accretion and erosion, with accretion mainly between groynes and erosion mainly in the groynes direct vicinity (Fig. 5.2c). These consistencies between net shoreline change observed and predicted from model three provide further evidence of MIKE21 ability to successfully simulate groynes and beach feeding effects on shoreline evolution under relative sea-level rise. However, longshore trends in model three net shoreline change predictions (51% accretion; 49% erosion) show more erosion than observed (67% accretion; 33% erosion) and predicted from models one (60% accretion; 40% erosion) and two (62% accretion; 38% erosion), which explains the corresponding fall in MIKE21 BSS (Fig. 5.2 a – c).

Model three overprediction of shoreline erosion corresponds to mean closure depth overestimation from 1980 to 2012 (Table 5.1). Closure depth overestimations are evident from 1981 to 1990 (range: 0.22 to 3.23 m) and 1997 to 2008 (range: 0.03 to 2.23 m) (Fig. 5.3). Table 5.1 and Fig. 5.3 also show closure depth underestimations from 1991 to 1996 (range: 0.41 to 2.54 m) and 2009 to 2012 (range: 0.49 to 3.71 m). In MIKE21, closure depth overestimations push the observed seaward extent of the active coastal profile further offshore, causing sediment distribution in morphologically inactive areas

(Kristensen, 2013; DHI, 2017b). Closure depth overestimations consequently reduce the sediment volume available for inshore distribution, which causes an overprediction (underprediction) of erosion (accretion) (De Figueiredo et al., 2020). This finding is apparent from comparing models two and three net shoreline change predictions (Fig. 5.2 b – c). Model three predicts more erosion than model two (Fig. 5.2 b – c) as it has a mean deeper closure depth (range: 5.23 to 7.93 m; mean: 6.86 m; SD: 0.68) than model two (6 m). All other inputs in models two and three are the same. Thus, shoreline evolution predictions in response to model three time-varying closure depth are within expectations.

All closure depth estimations applied in model three are derived from Birkemeier (1985) formula using nearshore significant wave heights calculated by MIKE21. Nearshore significant wave heights calculated in MIKE21 are influenced by the model domain's boundary conditions, including mesh bathymetry, tides, wind and wave climate. Therefore, closure depth overestimations in model three are most plausibly a consequence of repeating the New York test site's 2014 to 2016 wave climate data over the 50-year hindcast (see section 3.8.1 for details). Fig. 5.4 illustrates an increasing trend in the New York test site's annual median and mean significant wave height from 1980 to 2012. There are no wave climate statistics before and after this period. Considering the overall increase in significant wave heights from 1980 to 2012, repeating the 2014 to 2016 wave climate data in model three most plausibly resulted in MIKE21 overestimating nearshore significant wave heights in the New York test site over the 50-year hindcast, which can explain the overestimated closure depths.

Considering wave climate data limitations and related closure depth overestimations, the reasonable agreement between model three shoreline evolution predictions and associated observations imply that a time-varying closure depth *may* improve MIKE21 meso timescale shoreline evolution predictions if closure depth time series estimates can be accurately prescribed. A time-varying closure depth will allow MIKE21 to account for the effects of sea-level rise in meso timescale shoreline evolution simulations, which so far has only been possible in the Bruun Rule (Sharaan and Udo, 2020). As previously mentioned, an effect of sea-level rise is temporal changes in the closure depth (Ortiz and Ashton, 2016; Hallin et al., 2019). However, obtaining physically realistic closure depth time series estimates depend on the availability and quality (accuracy) of wave climate data or predictions. In the absence of observed wave climate data or accurate wave climate predictions, estimating and applying a time-varying closure depth instead of a constant closure depth in MIKE21 will generate greater uncertainty in resulting meso timescale shoreline evolution predictions (Fig. 5.2). Verifiable wave climate and closure depth data are needed to more objectively evaluate if a time-varying closure depth can significantly improve meso timescale shoreline evolution simulations.

5.2.3 Using the Bruun Rule

There is no agreement between net shoreline change observations and predictions from models four and five over the 50-year hindcast in the New York test site (Fig. 5.2 d – e). Models four and five apply the Bruun Rule, except model four is based on the 1966 coastal profiles (closure depth: 4.2 m), and model five is based on the shifted 2014 coastal profiles (closure depth: 6 m). Models four and five shoreline evolution predictions have a BSS < 0 (bad), which indicates that the Bruun Rule fails to predict meso timescale shoreline evolution to an acceptable level. The bad BSSs from models four and five are a consequence of the Bruun Rule only predicting shoreline erosion longshore compared to the net accretion observed (Fig. 5.2 d – e). The Bruun Rule assumes a linear relationship between sea-level rise and shoreline evolution, therefore, will always predict shoreline erosion (accretion) in response to a positive (negative) sea-level rise (Bruun, 1962; Ranasinghe et al., 2012; Le Cozannet et al., 2016). Sea-level rise over the 50-year hindcast (1966 to 2016) in the New York test site is 0.2 m based on a rate of 0.004 m yr^{-1} from 1932 to 2019 (NOAA, 2017d). The bad shoreline evolution predictions obtained from models four and five only clearly demonstrate that:

1. *The Bruun Rule cannot simulate meso timescale shoreline evolution in sandy coastal systems where groynes and beach feeding, for example, are used to offset sediment deficit and sea-level rise effects*. As aforementioned, the New York test site's Atlantic shoreline was eroding before the groynes were constructed. Periodic beach feeding also occurred over the 50-year hindcast period to offset erosion in the New York test site (see section 2.2). In contrast to MIKE21, the Bruun Rule cannot account for coastal management defences as it assumes linearity between sea-level rise and shoreline change, hence models four and five bad BSSs.

2. *Sea-level rise is not the primary driver of meso timescale shoreline evolution as the Bruun Rule assumes, at least in managed sandy coastal systems*. This is evident from comparing models one to five net shoreline change predictions and corresponding observations (Fig. 5.2 a – c). Models one to five incorporate a relative sea-level rise of 0.2 m from the New York test site 1966 to 2016 tide data (Fig. 2.9a). The key difference between models one to five is the approach used for simulating shoreline evolution. Models one to three (MIKE21) simulate shoreline evolution based on littoral drift gradients estimated in response to local morphology, coastal management, coastal processes (tides, wind, and wave climate), and rate of sea-level rise (based on the 1966 to 2016 tide time series). In contrast, models four and five (Bruun Rule) simulate shoreline evolution based on the total sea-level rise (0.2 m) and the active coastal profile slope. Models one to three predict net shoreline accretion in line with the observed, whereas models four and five predict erosion longshore (Fig. 5.2). This finding demonstrates that shoreline response to sea-level rise depends on a number of local environmental factors and processes, including longshore sediment transport, coastal management (e.g. groynes and beach feeding), coastal morphology, and the rate of sea-level rise (not just the total amount as the Bruun Rule assumes). In this regard, the Bruun Rule assumption of linearity between sea-level rise and shoreline evolution does not allow for realistic meso timescale shoreline evolution predictions in managed sandy coastal systems.

3. *Sea-level rise does not necessarily threaten the existence of sandy coastlines as reported in shoreline evolution studies based on the Bruun Rule* (e.g. Hinkel et al., 2013; Sharaan and Udo, 2020; Vousdoukas et al., 2020). This is evident from the net accretion observed and predicted from models one to three over the 50-year hindcast in the New York test site (Fig. 5.2 a – c). The Bruun Rule only considers cross-shore sediment transport as it assumes that all sandy shorelines retreat shore-normal from sea-level rise (Bruun, 1962). However, longshore sediment transport can cause shoreline accretion under sea-level rise when

sediment budgets are positive (Anderson et al., 2015), as evident from the net accretion predicted from models one to three (Fig. 5.2 a – c). Models one to three simulate shoreline evolution based on longshore sediment transport and the assumption of an adequate sand supply in line with the periodic beach feeding over the 50-year hindcast period in the New York test site. These results give weight to Cooper and Pilkey (2004) and Cooper et al. (2020) argument that sandy beaches do not have a common linear response (retreat) to sea-level rise as the Bruun Rule assumes since such beaches are highly variable in form and setting.

5.2.4 Main findings

Four main findings are derived from the above results. *First*, MIKE21 assumption of a constant closure depth allows for simulating meso timescale shoreline evolution in managed sandy coastal systems to a relatively good extent (Table 5.2). The key limitation of such an approach is that a constant closure depth averages out the temporal variability of the active coastal area, masking the effects of sea-level rise. Averaging out the temporal variability of the active coastal area reduces the achievable accuracy of shoreline evolution predictions as timescales increase because temporal variations in the active coastal area define the spatial extent of sediment distribution and associated shoreline changes over time. This limitation became clear from MIKE21 calibrated model (constant closure depth; 2014 to 2016) in the New York test site having a good BSS of 0.46, whereas models one and two (constant closure depth; 1966 to 2016) have a markedly lower BSS of ~ 0.2 (Table 5.2).

The *second* main finding is that a time-varying closure depth worsens MIKE21 performance when applied to hindcast meso timescale shoreline evolution in the New York test site (Table 5.2). This finding is attributed to mean closure depth overestimation, which caused an overprediction of shoreline erosion (Figs. 5.2c; 5.3; Table 5.1). Closure depth overestimation forces sediment distribution in morphologically inactive offshore areas, leading to an overprediction of shoreline erosion by reducing the sediment volume available for inshore distribution (Cowell, 2002; De Figueiredo et al., 2020). There is thus a chance that a time-varying closure depth in MIKE21 may improve meso timescale shoreline evolution simulations if closure depth time series estimates can be accurately prescribed. Such an approach will enable MIKE21 to account for sea-level rise fully.

The *third* main finding is that MIKE21 can successfully simulate groynes and beach feeding effects on meso timescale shoreline evolution. This finding is clear from MIKE21 ability to predict the net accretion and general alternating pattern of accretion between groynes and erosion elsewhere over the 50-year hindcast in the New York test site from using a constant and time-varying closure depth (Fig. 5.2; Table 5.2). The net accretion observed over the 50-year hindcast period in the New York test site is due to groynes and periodic beach feeding (Tanski, 2012; USACE and NYSDEC, 2015). MIKE21 incorporates groynes as polyline features (Fig. 3.9), and beach feeding by assuming an adequate sand supply at open boundaries. Without groynes and beach feeding, erosion would have been naturally dominant in the New York test site from 1966 to 2016 (Tanski, 2012; Catania, 2015).

The *fourth* main finding is that the Bruun Rule fails to predict meso timescale shoreline evolution to an acceptable level in the New York test site (Table 5.2), indicating that sea-level rise is not the primary driver of shoreline evolution, at least in managed sandy coastal systems. This finding is evident from the Bruun Rule predicting shoreline erosion longshore in response to sea-level rise over the 50-year hindcast, whereas corresponding observations show net accretion (Fig. 5.2 d – e). This result is a consequence of the Bruun Rule inability to account for coastal management defences, such as groynes and beach feeding, that can offset the effects of sediment deficit and sea-level rise.

5.3 Meso timescale forecasts of shoreline evolution in the New York test site

This section quantifies and analyses the results derived from forecasting meso timescale shoreline evolution in the New York test site (01-Jan-2014 to 01-Jan-2064) using a constant and time-varying closure depth in MIKE21 (section 5.3.1), and the Bruun Rule (section 5.3.2). These forecasts all assume a 0.28 m sea-level rise (IPCC global median sea-level rise projection for 2046 to 2065). Each meso timescale forecast in MIKE21 also assumes an adequate sand supply in line with plans implemented to nourish the New York test site's Atlantic coast every five years from 2018 to 2068 (USACE and NYSDEC, 2015). Section 5.3.3 summarises the key findings from preceding sections.

5.3.1 Using a constant and time-varying closure depth in MIKE21

Forecasts one (5.8 m closure depth in MIKE21) and two (time-varying closure depth in MIKE21) predict an alternating pattern of accretion and erosion longshore, with accretion mainly between groynes and erosion mainly in the groynes direct vicinity in line with realistic expectations (Fig. 5.5 a – b). This finding further demonstrates MIKE21 ability to simulate groynes and beach feeding effects on meso timescale shoreline evolution under sea-level rise using a constant and time-varying closure depth. However, forecast one mostly predicts accretion longshore (MNC: 1.02 m; 58% accretion; 42% erosion) compared to forecast two (MNC: -2.96 m; 38% accretion; 62% erosion) (Fig. 5.5 a – b). Also, forecast one predicts a smaller MAC (4.4 m) than forecast two (6.45 m). These differences in net shoreline change prediction trend and magnitude correspond to differences between closure depth specifications in forecasts one and two. Forecast one has a 5.8 m closure depth, whereas forecast two has a mean closure depth of 6.88 m (range: 5.24 to 8.02 m; SD: 0.7) (Fig. 5.6). As a result of having a deeper mean closure depth, forecast two predicts more erosion and shoreline change than forecast one since MIKE21 distributes sediments further offshore as the closure depth deepens (DHI, 2017b). It is thus clear from forecasts one and two shoreline change predictions that:

1. *Closure depth specifications in meso timescale shoreline evolution models require careful consideration of the morphologically active coastal area*. The closure depth determines the cross-shore extent of sediment distribution, which influences shoreline evolution predictions.

2. *MIKE21 can account for groynes and beach feeding effects on meso timescale shoreline evolution under sea-level rise*. This finding is evident from the projected pattern of alternating shoreline accretion between groynes and erosion elsewhere over the 50-year forecast period.

3. *MIKE21 response to forecast two time-varying closure depth is within expectations*. This finding supports the argument that a time-varying closure depth *may* improve MIKE21 meso timescale shoreline evolution predictions if closure depth time series estimates are accurate.

5.3.2 Using the Bruun Rule II

The Bruun Rule (forecast three) only predicts erosion longshore in contrast to MIKE21 (forecasts one to two) over the 50-year forecast in the New York test site (Fig. 5.5). This finding is a consequence of the Bruun Rule inability to account for the coastal management initiatives (groynes and beach feeding) in place in the New York test site by assuming linearity between sea-level rise and shoreline evolution. Groynes and beach feeding are expected to partly or fully offset the effects of sediment deficit and sea-level rise. Forecasts one and two, for example, show that accretion is possible between groynes under sea-level rise (Fig. 5.5 a – b). Forecasts one and two are based on MIKE21, which has a much higher accuracy than the Bruun Rule (Table 5.2). Ford and Kench (2015), Brooke et al. (2019), and Cooper et al. (2020) further show that accretion is possible under sea-level rise if sediment budgets are positive. This argument is also supported by the alternating accretion and erosion predicted from forecasts one and two, both of which assume an adequate sand supply (positive sediment budget). These results show that sandy shorelines do not always have a linear (erosion) response to sea-level rise as the Bruun Rule assumes. It is thus clear from the results in Fig. 5.5 (and Fig. 5.2) that the Bruun Rule fails to provide realistic meso timescale shoreline evolution predictions under sea-level rise in sandy coastal systems managed by either hard or soft defences.

5.3.3 Main findings II

The above results reaffirm section 5.2.4 findings that: (a) MIKE21 can successfully simulate the effects of groynes and beach feeding on meso timescale shoreline evolution; (b) MIKE21 response to a time-varying closure depth is within expectations; and (c) the Bruun Rule fails to provide realistic predictions of meso timescale shoreline evolution in managed sandy coastal systems under relative sea-level rise. The above results also demonstrate that the closure depth plays a crucial role in influencing meso timescale shoreline evolution predictions, which is particularly evident from the increase in shoreline erosion predicted as the overall closure depth becomes deeper (Fig. 5.5 a – b).

5.4 Summary

This chapter presents the results from hindcasting and forecasting meso timescale shoreline evolution in the New York test site using MIKE21 applied with a constant and time-varying closure depth and the Bruun Rule. The primary conclusions obtained from analysing these results include:

1. *The one-line theory incorporated in MIKE21 allows for simulating mesoscale shoreline evolution to a relatively good extent.* The limitation of this approach is that the closure depth is constant. A constant closure depth limits the achievable accuracy of mesoscale shoreline evolution predictions by averaging out the time variability of the active coastal area, masking sea-level rise effects. For example, the New York test site's calibrated MIKE21 BSS falls from 0.46 (good) to ~ 0.2 (borderline good) over meso timescales. The time variability of the active coastal area influences the spatial extent of sediment distribution and associated shoreline change over time.

2. *The closure depth influences meso timescale shoreline evolution predictions and projections.* This finding is evident from MIKE21 hindcasting and forecasting more shoreline erosion over meso timescales as the overall closure depth deepens in the New York test site. Closure depth

specifications in mesoscale shoreline evolution models, therefore, require careful consideration.

3. *MIKE21 response to a time-varying closure depth is within expectations even though a time-varying closure depth causes MIKE21 to overpredict shoreline erosion in the New York test site.* The overprediction of shoreline erosion stems from mean closure depth overestimation. Closure depth overestimation forces sediment distribution in morphologically inactive offshore areas, inflating shoreline erosion prediction by reducing the sediment volume available for inshore distribution. There is thus a chance that a time-varying closure depth may improve MIKE21 meso timescale shoreline evolution simulations if closure depth time series estimations are accurate.

4. *MIKE21 can simulate groyne and beach feeding effects on meso timescale shoreline evolution*. For instance, MIKE21 successfully hindcasts the net shoreline accretion and general alternating accretion (between groynes) and erosion (at groyne locations) pattern observed in the New York test site (1966 – 2016) using a constant and time-varying closure depth. MIKE21 also forecasts a similar longshore pattern of alternating accretion and erosion in the New York test site (2014 – 2064) using a constant and time-varying closure depth. Without groynes and beach feeding, the New York test site's shoreline will be in a natural retreat state (USACE and NYSDEC, 2015).

5. *The Bruun Rule fails to provide realistic meso timescale shoreline evolution predictions in managed sandy coastal systems because it assumes linearity between sea-level rise and shoreline change*. Such an assumption does not account for coastal management schemes that can partly or fully offset sediment deficit and sea-level rise effects. This is evident from the Bruun Rule predicting only erosion in response to sea-level rise from 1966 to 2016 in the New York test site, whereas related observations show net accretion. The observed accretion over the 50-year hindcast period in the New York test site is attributed to groynes and beach feeding. Sea-level rise is, therefore, not the primary driver of shoreline evolution as the Bruun Rule assumes.

06
Handling complex planform morphologies

'The shoreline is such a place of unexpected change and flux, that if it is not carefully and consistently managed, it is easy to make spontaneous changes that will disrupt the centuries old cycles that are as delicately balanced as the most intricate mobile.'

– Joy Rudder

6.1 Introduction

This chapter presents the results from hindcasting shoreline evolution (10-Oct-2014 to 31-Mar-2016) in the Puerto Rico test site using a constant closure depth in MIKE21 and a space-varying closure depth in MIKE21 and the Bruun Rule. I use these results to determine if a space-varying closure depth can improve MIKE21 shoreline evolution predictions in a complex planform morphology to address research question three: *How can complex planform morphologies be accounted for in shoreline evolution predictions?* Complex planform morphologies are defined by non-parallel contours, typical of coral reef systems. Section 3.9 explains that wave transformation over non-parallel contours generates spatial variations in wave heights approaching the shoreline, resulting in some areas having a shallower closure depth than others. Wave energy dissipation over non-parallel contours has an endogenous influence on shoreline evolution in reef environments, in particular. However, the equilibrium profile assumption driving the morphology update in advanced mesoscale shoreline evolution models does not allow these models to account for closure depth spatial variations, preventing realistic longshore shoreline evolution simulations in complex morphologies. It is important to remember that the closure depth defines the offshore extent of morphodynamics in these models. Acknowledging the equilibrium profile assumption role in preventing coastal profile degeneration, slightly modifying it to include a space-varying closure depth may enable us to mirror the effects of wave dissipation over non-parallel contours on coastal profiles longshore. Doing so can allow mesoscale shoreline evolution models to better account for complex planform morphologies whilst ensuring a stable morphology update. The workflow used to test this theory entailed applying MIKE21 process-driven modules over the same mesh bathymetry while applying its shoreline morphology module on smaller coastal segments with the same closure depth (see section 3.9.1). This process does not modify MIKE21 code. Instead, it forces MIKE21 to update the shoreline morphology iteratively over irregular spatial intervals, with each interval having a defined offshore limit for the active coastal profile based on their underlying morphology and wave climate conditions.

Section 6.2 evaluates whether a space-varying closure depth significantly improves MIKE21 shoreline evolution predictions in a complex planform morphology by comparing the results of three modelling approaches used to hindcast shoreline evolution in the Puerto Rico test site (2014 to 2016):

1. **Model one** maintains the one-line theory principles underlying MIKE21 shoreline morphology update, assuming a constant closure depth of 5.5 m longshore. 5.5 m is the deepest general shore-parallel contour landward of coral reefs in the Puerto Rico test site's 2014 bathymetry.

2. **Model two** has the same mesh and boundary conditions as model one, except iteratively applies MIKE21 Shoreline Morphology module (MIKE21 SM) to seven segments of the Puerto Rico test site's coast to account for its closure depth variability (Fig. 6.1). Thus, model two has seven iterative simulations, each with their own MIKE21 SM domain and closure depth.

3. **Model three** applies the Bruun Rule in transects every 5 m longshore. The closure depth in each transect fluctuates according to reef substrate distribution. The closure depth in reef areas is the depth contour nearest the shoreline where reef substrate first appears. The

closure depth in non-reef areas is the most seaward contour reflecting shoreline undulations.

Section 3.9 outlines each of the above hindcasts. A micro timescale period is used in these hindcasts to assess the viability of incorporating a space-varying closure depth in MIKE21 before extending such an approach over meso timescales. As before, all net shoreline change statistics presented in this chapter are obtained from transects every 5 m longshore, excluding those in groyne locations.

6.2 Shoreline evolution hindcasts in the Puerto Rico test site

This section quantifies and analyses the results derived from hindcasting shoreline evolution in the Puerto Rico test site (10-Oct-2014 to 31-Mar-2016) using a constant closure depth in MIKE21 (section 6.2.1), a space-varying closure depth in MIKE21 (section 6.2.2), and a space-varying closure depth in the Bruun Rule (section 6.2.3). In all cases, net shoreline change predictions are compared against related observations. Section 6.2.4 summarises the key findings from the preceding sections.

6.2.1 Using a constant closure depth in MIKE21

There is a poor fit between model one (5.5 m constant closure depth in MIKE21) net shoreline change predictions and associated observations (Fig. 6.2a). Model one net shoreline change predictions have a very poor Brier Skill Score (BSS) of 0.03, which implies that model predictions are roughly equivalent to initial model conditions (Van Rijn et al., 2003; Sutherland et al., 2004). This finding is due to model one significantly underpredicting net shoreline change magnitude (Fig. 6.2a). For instance, model one net shoreline change predictions are generally negligible longshore (range: -4 to 5.7 m; MNC: 0.11 m; SD: 1.17) compared to corresponding observations (range: -12 to 16 m; MNC: 3.22 m; SD: 5.7). Additionally, there is no discernible similarity between the longshore variations of model one net shoreline change predictions and corresponding observations (Fig. 6.2a).

Model one significantly underpredicts net shoreline change magnitude most plausibly because it assumes a 5.5 m constant closure depth. Fig. 6.1 shows that the Puerto Rico test site's closure depth ranges from 3.3 to 8 m longshore (mean: 6.7 m; SD: 1.23). Therefore, model one assumption of a 5.5 m constant closure depth averages out and underestimates the Puerto Rico test site's active coastal area. The closure depth constrains the active coastal area in MIKE21 by specifying the seaward extent of morphodynamics (Kaergaard and Fredsoe, 2013; Kristensen et al., 2013). MIKE21 divides the active coastal area (shoreface) into shore-perpendicular strips (Fig. 3.10). Each strip has one predefined active coastal profile. To simulate shoreline evolution, MIKE21 uniformly redistributes littoral drift gradients generated within each shoreface strip over their predefined active coastal profile (see section 3.4.2). Thus, underestimating the active coastal area causes MIKE21 to underestimate the sediment volume available for longshore transport from one shoreface strip to another and the vertical area of sediment redistribution per strip (Kaergaard, 2011; DHI, 2017b), which can explain why model one significantly underpredicts shoreline change magnitude longshore (cf. Hands, 1981).

A positive MNC is the only similarity between model one shoreline evolution predictions and associated observations. A positive MNC indicates net accretion. The net accretion observed over the 2014 to 2016 hindcast period in the Puerto Rico test site is attributed to fringing coral reefs, which provide a constant sand supply and protection against waves impact (Garcia-Sais et al., 2008; Bird, 2010). Without the coral reefs, the Puerto Rico test site will lose its sand supply and protection and be in a natural state of erosion (Barreto, 1997; Bird, 2010; Barreto, 2017). Model one is able to predict the net accretion in the Puerto Rico test site as MIKE21: (a) assumes an adequate sand supply at the open boundaries, which implicitly accounts for natural and anthropogenic beach feeding (see section 3.4.2); and (b) accounts for the reefs impact on wave action in processes simulations, as illustrated and discussed in Chapter 7. However, model one ability to predict the accurate net shoreline change trend alone in the Puerto Rico test site is not adequate for guiding coastal management, which requires realistic predictions of net shoreline change magnitudes and patterns.

Model one poor results indicate that MIKE21, in its current form, cannot predict shoreline evolution to an acceptable level in complex planform morphologies. This finding is likely due to the one-line theory assumption of a constant closure depth embedded in MIKE21, which can significantly underestimate or overestimate the active coastal area, especially in complex planform morphologies.

6.2.2 Using a space-varying closure depth in MIKE21

There is a much better agreement between net shoreline change observations and predictions from model two (space-varying closure depth in MIKE21) (see Fig. 6.2b). Model two net shoreline change predictions have a good BSS of 0.37, a significant improvement from model one (constant closure depth in MIKE21) very poor BSS of 0.03. The good BSS from model two corresponds to:

1. *Model two net shoreline change predictions and corresponding observations having the same general longshore pattern* (Fig. 6.2b). This finding is reflected with a Spearman's rank correlation (r_s) test, which shows a moderate linear relationship (r_s = 0.6) between model two net shoreline change predictions and associated observations longshore. There is a stronger linear relationship between model two net shoreline change predictions and associated observations (r_s = 0.8) in the western part of the site from transects one to 350 compared to the eastern part from transects 351 to 700 (r_s = 0.5). The weaker linear correlation in the eastern part of the site is due to model two underpredicting net shoreline change magnitude in MIKE21 SM domains five and six (Fig. 6.2b). MIKE21 SM domains five and six are located from transects 485 to 640 (Fig. 6.1). Model two underpredicts net shoreline change in these domain areas most plausibly because they have the largest observed closure depth variability and the most generalised (mostly too shallow) closure depth specifications (Fig. 6.1; Table 6.1). An overly shallow closure depth causes MIKE21 to underestimate the sediment volume available for longshore transport and the vertical area of sediment redistribution, which result in net shoreline change underprediction as aforementioned (Kaergaard, 2011; DHI, 2017b). Model two underprediction of net shoreline change in MIKE21 SM domains five and six consequently prohibited a better fit between associated shoreline change predictions and observations. Model two BSS increases from 0.37 to 0.42 if these two domains are excluded.

2. *Model two shoreline evolution predictions and associated observations indicating net accretion* (Fig. 6.2b). This finding is evident from the positive MNC observed (3.22 m) and predicted

from model two (0.91 m) over the 2014 to 2016 hindcast period in the Puerto Rico test site. In terms of longshore trends in shoreline morphology, model two net shoreline change predictions (39% erosion; 61% accretion) and associated observations (31% erosion; 69% accretion) show that accretion dominates > 60% of the Puerto Rico test site. Also, the longshore variations of model two net shoreline change predictions (-8.76 to 13.27 m) and corresponding observations (-11.26 to 16.23 m) indicate net higher accretion magnitudes than erosion magnitudes longshore (Fig. 6.2b). The net accretion observed in the Puerto Rico test site is attributed to coral reefs providing a constant sand supply and protection against waves impact, as previously mentioned. Without reefs, the Puerto Rico test site's shoreline will erode. Model two predicts the net accretion in the Puerto Rico test site because MIKE21 simulates the reefs effects on wave action (see Chapter7) and assumes an adequate sand supply at the open boundaries, which indirectly accounts for the natural steady sand supply from the reefs.

The above consistencies between model two net shoreline change predictions and corresponding observations are attributed to using a space-varying closure depth in MIKE21. This finding is derived from the fact that a space-varying closure depth is the only difference between models one and two. As previously discussed, the closure depth defines the seaward limit of morphodynamics in MIKE21, which affects the sediment volume available for longshore transport and the vertical area of sediment redistribution (Kaergaard, 2011; Kristensen et al., 2013; DHI, 2017b). As a result, model two has a much higher BSS of 0.37 than model one (0.03) because it incorporates the Puerto Rico test site's general closure depth longshore variability. It is evident from these results that model one significant underprediction of net shoreline change mainly stems from its assumption of a 5.5 m constant closure depth, which masks the spatial variability of the Puerto Rico test site's active coastal area (Fig. 6.1). These results demonstrate that averaging out the active coastal area can generate considerable uncertainty in MIKE21 shoreline evolution predictions, especially in complex planform morphologies.

Model two net shoreline change predictions and associated observations primarily differ in magnitude (Fig. 6.2b). Model two generally predicts a moderately lower magnitude of net shoreline change longshore (range: -8.76 to 13.27 m; MNC: 0.91 m) than observed (range: -11.26 to 16.23 m; MNC: 3.22 m) (Fig. 6.2b). Model two moderate underprediction of net shoreline change is attributed to its closure depth generalisations (Fig. 6.1; Table 6.1). Table 6.1 shows that the MIKE21 SM domains used in model two have a shallower closure depth specified than observed. Shallow closure depths naturally result in MIKE21 underpredicting net shoreline change, as previously discussed. Therefore, model two response to the space-varying closure depth specified is within practical expectations.

Using smaller MIKE21 SM domains to include more closure depth variations might have prevented model two from moderately underpredicting net shoreline change. However, incorporating smaller (more) MIKE21 SM domains increases the computing cost of shoreline evolution simulations. Littoral drift calculations determine the computational cost of MIKE21 shoreline evolution simulations. The shoreline morphology update does not affect MIKE21 computing cost. As a result, each of the seven iterations comprising model two has the same computing cost (~ 18 hours utilising four cores on a 2.8 GHz 16 core processor CPU) despite differences in MIKE21 SM domain extent. Model two is consequently seven times more computationally demanding (~ 126 hours) than model one (~ 18 hours). Using multiple MIKE21 SM domains to simulate mesoscale shoreline evolution with a space-varying closure depth will therefore be computationally costly, which may not be practical or feasible. Developing a method that allows the closure depth to vary freely in space may improve our ability to simulate shoreline evolution in complex planform morphologies at a reasonable computational cost.

Considering model two closure depth generalisations, the generally good fit between its shoreline evolution predictions and related observations indicates that enabling a space-varying closure depth in MIKE21 offers a suitable approach for simulating shoreline evolution in complex planform morphologies. Such an approach can facilitate the application of shoreline evolution models in many vulnerable Caribbean and Pacific islands where sandy coastal systems have coral reefs. No model has yet been able to fully account for complex planform morphologies in mesoscale shoreline evolution predictions. Therefore, enabling a space-varying closure depth in MIKE21 likely offers a novel viable approach to account for such morphologies in mesoscale shoreline change predictions.

6.2.3 Using a space-varying closure depth in the Bruun Rule

Model three (space-varying closure depth in the Bruun Rule) net shoreline change predictions are negligible compared to associated observations, thus have a bad BSS of -0.03 (Fig. 6.2c). Model three negligible predictions are due to negligible SLR over the 2014 to 2016 hindcast period in the Puerto Rico test site (0.0041 m) (NOAA, 2017c). The magnitude of the Bruun Rule predictions depends on the amount of SLR, its forcing variable (Eqn. 3.2; Bruun, 1962), hence these results are expected. Therefore, the Bruun Rule predictions in the Puerto Rico test site may improve over meso timescales where SLR will most probably have a more endogenous influence on shoreline evolution.

Fig. 6.2c also shows that the Bruun Rule predicts erosion longshore (MNC: -0.18 m) in contrast to the net accretion observed (MNC: 3.22 m), hence the negative BSS (-0.03). This is because the Bruun Rule fails to account for the sand supply and natural protection from the reefs by assuming that sandy beaches have a linear (erosion) response to sea-level rise (Bruun, 1962; Ranasinghe et al., 2012). This assumption implies that there is always sediment deficit (gain) from sea-level rise (fall), which prohibits the Bruun Rule from incorporating the effects of natural and anthropogenic: (a) sediment supply and (b) coastal defences on net shoreline change predictions (Cooper et al., 2020).

6.2.4 Primary findings

Three main findings are derived from the above results. *First*, the closure depth plays a critical role in influencing shoreline evolution in complex planform morphologies. This finding is evident from model one predicting much less shoreline change longshore (range: -4 to 5.74 m; MNC: 0.11 m; SD: 1.17) than model two (range: -8.76 to 13.27 m; MNC: 0.91 m; SD: 3.63) (Table. 6.2). These results are linked to model one averaging out the Puerto Rico test site's active coastal area spatial variability by having a 5.5 m closure depth compared to model two, which has a space-varying closure depth. Underestimating the active coastal area causes MIKE21 to overpredict erosion by underestimating the sediment volume available for longshore transport and the vertical area of sediment distribution.

The *second* main finding is that enabling a space-varying closure depth in MIKE21 provides an improved approach for simulating shoreline evolution in complex planform morphologies (Table 6.2). This finding is evident from model two (space-varying closure depth in MIKE21) having a good BSS of 0.37, whereas models one (5.5 m closure depth in MIKE21) and three (space-varying closure depth in the Bruun Rule) have BSSs equivalent to zero. Fig. 6.3 further shows that model two net shoreline change prediction errors are generally lower in magnitude longshore (range: -8.88 to 15.16 m; mean: 2.3 m; SD: 4.85) than those from model one (range: -12.37 to 16.79 m; mean: 3.1 m; SD: 5.77). These results illustrate the importance of a space-varying closure depth for simulating shoreline evolution in complex planform morphologies. Model three (Bruun Rule), however, incorporates a space-varying closure depth but performs worse (BSS: -0.03) than models one (BSS: 0.03) and two (BSS: 0.37). Model three predicts almost no shoreline change because SLR is negligible over the 2014 to 2016 hindcast period in the Puerto Rico test site. The amount of SLR influences the magnitude of the Bruun Rule predictions as SLR is the primary forcing in the Bruun Rule. It is thus clear from comparing model three (Bruun Rule) shoreline evolution predictions with those from models one and two (MIKE21) that littoral drift gradients have an endogenous influence on shoreline evolution, at least over micro timescales. Littoral drift gradients are the primary driving flux of shoreline evolution in MIKE21, whereas the magnitude of SLR primarily drives the Bruun Rule.

The *third* main finding is that the Bruun Rule is not suitable for application in sandy coastal systems with natural protection from reefs, for example, compared to MIKE21. This finding is clear from models one (constant closure depth in MIKE21) and two (space-varying closure depth in MIKE21) predicting the observed net accretion (2014 to 2016) in the Puerto Rico test site in contrast to model three (space-varying closure depth in the Bruun Rule). The net accretion observed in the Puerto Rico test site is due to the reefs constant sand supply and protection against waves impact. MIKE21 predicts the net accretion because it inherently accounts for the reefs effects on wave propagation in its processes simulations (see Chapter 7) and assumes an adequate sand supply at the open boundaries. The Bruun Rule cannot predict the net accretion in the Puerto Rico test site because it assumes linearity between SLR and shoreline change. The assumption of linearity between SLR and shoreline evolution implicitly implies that there is always sediment loss (gain) from sea-level rise (fall).

6.3 Summary

This chapter presents results from hindcasting micro timescale shoreline evolution in the Puerto Rico test site using a constant closure depth in MIKE21, and a space-varying closure depth in MIKE21 and the Bruun Rule. These results demonstrate that enabling a space-varying closure depth in MIKE21 considerably improves micro timescale shoreline evolution predictions in a complex planform morphology. Therefore, it is likely that such an approach will also offer a novel viable solution that accounts for complex planform morphologies in mesoscale shoreline evolution predictions. At present, there is no mesoscale shoreline evolution model available that effectively accounts for such morphologies. Chapter 7 evaluates if a space-varying closure depth in MIKE21 enables realistic meso timescale shoreline evolution predictions in a complex planform morphology.

07
Accounting for sea-level rise and complex planform morphologies

> *'Modelling is not an alternative to observation but, under certain circumstances, can be a powerful tool in understanding observations and in developing and testing theory.'*
>
> – Mulligan and Wainwright (2013)

7.1 Introduction

This chapter presents the results from forecasting meso timescale shoreline evolution (10-Oct-2014 to 10-Oct-2064) in the Puerto Rico test site using (a) a time and space-varying closure depth in MIKE21, (b) MIKE21 in its present form, and (c) the Bruun Rule. I use these results to address research question four: *Can shoreline evolution models be developed to incorporate both sea-level rise and complex planform morphologies over meso timescales?* Chapter 5 shows that enabling a time-varying closure depth in MIKE21 provides a much better alternative to the Bruun Rule for simulating meso timescale shoreline evolution under sea-level rise. Chapter 6 subsequently shows that enabling a space-varying closure depth in MIKE21 provides a suitable approach to account for complex planform morphologies in micro timescale shoreline evolution predictions. Incorporating a time and space-varying closure depth in MIKE21 should thus, in theory, allow us to simulate meso timescale shoreline evolution under sea-level rise in complex planform morphologies. The workflow used to test this theory entailed annually running MIKE21 process-driven modules on the same mesh while applying its shoreline morphology module to smaller coastal segments with the same closure depth (see section 3.10.1). The closure depth in all coastal segments is updated in each annual simulation based on their wave climate conditions in the preceding annual simulation. This user-driven iterative process simply forces MIKE21 to update the shoreline morphology annually over irregular spatial intervals in response to changing hydrodynamics without any modifications to its code. If successfully incorporated, a time and space-varying closure depth will allow MIKE21 to simulate coastal profile evolution more realistically than its current one-line theory morphology updating approach. If it theoretically works, such an approach will enable the mesoscale application of shoreline evolution models in many vulnerable Caribbean and Pacific small islands, where sandy coastal systems have non-parallel contours due to coral reefs. Arguably, mesoscale shoreline evolution models are most needed to guide coastal management decision-making in such locations.

Section 7.2 quantifies and compares the results of three different modelling approaches used to forecast meso timescale shoreline change (2014 to 2064) in the Puerto Rico test site. These include:

1. **Model one** comprises 50 annual simulations in MIKE21 (10-Oct-2014 to 10-Oct-2064) to account for time and space variations in the closure depth. Each annual simulation applies MIKE21 shoreline morphology module to seven smaller areas of the Puerto Rico test site's coast to incorporate its closure depth spatial variability (Fig. 6.1). Each annual simulation in model two thus comprises seven iterative simulations, each with their own MIKE21 SM domain and closure depth. The closure depth in each MIKE21 SM domain in the first annual simulation (Oct-2014 to Oct-2015) is based on reef substrate distribution. In each subsequent yearly simulation, the closure depth in each MIKE21 SM domain is derived from Birkemeier (1985) formula using wave heights calculated by MIKE21 in their respective nearshore over the preceding annual simulation. Table 7.1 and Fig. 7.1 show the closure depth specifications used in each MIKE21 SM domain over the 50-year forecast. Model one objective is to test if the two approaches introduced in this thesis – time and space varying closure depth – can be extended to model meso timescale shoreline evolution in complex planform morphologies.

2. **Model two** upholds MIKE21 one-line theory principles and assumes a 5.5 m closure depth. Chapter 6, however, shows that a 5.5 m closure depth significantly underpredicts the Puerto Rico test site's net shoreline change magnitude (10-Oct-2014 to 31-Mar-2016) by averaging out its active coastal area (Fig. 6.1). However, the 5.5 m depth contour is the deepest shore-parallel contour landward of the reefs in the Puerto Rico test site's 2014 bathymetry (Fig. 2.5b). As MIKE21 assumes shore-parallel contours in its morphology update, specifying a closure depth deeper than 5.5 m will cause errors in associated shoreline continuity solutions. Shoreline continuity errors occur in one-line theory models when depth contours are not shore-parallel because multiple shore-perpendicular coordinates share a common shore-parallel coordinate. Hence, there is no better alternative than using a 5.5 m closure depth in MIKE21 to forecast meso timescale shoreline evolution in the Puerto Rico test site. The results of this simulation will show the best meso timescale shoreline evolution predictions we can get from applying MIKE21 in its present form in the Puerto Rico test site. Model two objective is to test the importance of a time and space-varying closure depth for simulating meso timescale shoreline evolution under sea-level rise in a complex planform morphology.

3. **Model three** applies the Bruun Rule in transects every 5 m longshore. The closure depth in each transect varies based on reef substrate distribution (Fig. 6.1). Closure depth variations in this model are thus higher in spatial resolution than in model one. The closure depth in reef areas is the depth nearest the shoreline where reef substrate first appears. The closure depth in non-reef areas is the most seaward contour with shoreline undulations. Model three is used for comparison against both models above to gauge the importance of littoral drift in meso timescale shoreline evolution. Models one and two are driven by littoral drift gradients in MIKE21, whereas the Bruun Rule is driven by the total amount of relative sea-level rise (m).

All models above are outlined in section 3.10 and assume a 0.28 m sea-level rise, the IPCC global median sea-level rise projection for 2046 to 2065. As before, all net shoreline change statistics in this chapter are obtained from transects every 5 m longshore, excluding those in groyne locations.

7.2 Meso timescale shoreline evolution forecasts in the Puerto Rico test site

This section quantifies and analyses the results from forecasting meso timescale shoreline evolution in the Puerto Rico test site (2014 to 2064) using a time and space-varying closure depth in MIKE21 (section 7.2.1), a constant closure depth in MIKE21 (section 7.2.2), and a space-varying closure depth in the Bruun Rule (section 7.2.3). Section 7.2.4 summarises the key findings from this analysis.

7.2.1 Using a time and space-varying closure depth in MIKE21

Model one (time and space-varying closure depth in MIKE21) shoreline evolution predictions show net accretion (MNC: 4.6 m; SD: 21.78) over the 50-year forecast (Fig. 7.2a). In terms of longshore trends in shoreline morphology, model one predictions indicate that shoreline accretion dominates 59% of the Puerto Rico test site, whereas erosion dominates the latter 41% of the site, as shown in Fig. 7.3. Model one also forecasts higher shoreline accretion magnitudes (mean: 18.16 m) than erosion magnitudes (mean: 15.12 m) longshore (Fig. 7.2a). These results are most likely a result of:

1. *MIKE21 assumption of an adequate sand supply* (see section 3.4.2). This assumption indirectly accounts for the natural sand supply from the reefs in the Puerto Rico test site. Without such sand supply, the Puerto Rico test site's shoreline will be in a natural state of retreat (Kaye, 1959; Goenaga and Cintron, 1979; Morelock and Barreto-Orta, 2003). Model one prediction of net accretion in response to an adequate sand supply illustrates that sandy beaches can survive relative sea-level rise when sediment budgets are positive. This finding is in line with those of Ford and Kench (2015), Brooke et al. (2019), and Cooper et al. (2020).

2. *The presence of reefs in the model bathymetry* (see Fig. 7.4). The reefs in the model bathymetry dissipate wave energy through wave breaking and bed friction, reducing the wave energy reaching the shoreline. This is clear in Fig. 7.5, which shows that wave heights in the model space are highest towards the reefs and reduce towards the shoreline. This finding indicates that wave breaking occurs over the reefs in the mesh bathymetry in line with known wave-reef interactions (Franklin et al., 2013; Kaergaard et al., 2017). Shorelines buffered by reefs consequently remain stable or accrete as reefs reduce the erosive power of waves approaching the shoreline (Siegle and Costa, 2017), hence the longshore variations in model one net shoreline change predictions (Fig. 7.3). Fig. 7.3 shows that model one predicts accretion mainly in reef areas and erosion mostly in non-reef regions. In this regard, model one shoreline evolution predictions are consistent with theoretically plausible expectations.

Model one prediction of net accretion in response to a 0.28 m sea-level rise is consistent with historically associated meso timescale shoreline evolution trends. Historically (1936 to 2017), Puerto Rico's shoreline accreted along areas buffered by reefs and mangrove forests at rates of 0.3 to 0.5 m yr^{-1}, and eroded in areas devoid of natural protection at rates of 0.2 to 1.21 m yr^{-1} (Barreto, 1997; Morelock and Barreto-Orta, 2003; Barreto, 2017; Barreto-Orta et al., 2019). These historical trends of alternating erosion in non-reef/mangrove areas and accretion in reef/mangrove areas in Puerto Rico are generally replicated in model one (see Fig. 7.3). Also, model one predicts a mean accretion rate of 0.36 m yr^{-1} in reef areas and a mean erosion rate of 0.3 m yr^{-1} in non-reef areas in line with Puerto Rico's historical range of shoreline change rates. The key take-home message from Puerto Rico's 1936 to 2017 shoreline evolution trends is that coral reefs and mangrove forests facilitated net shoreline accretion over an 81-year period of rising sea-levels. The exact amount of sea-level rise from 1936 to 2017 in Puerto Rico is not known. However, Puerto Rico had an overall sea-level rise of 0.11 m from 1962 to 2017 based on a rate of 0.002 m yr^{-1} (NOAA, 2017c). Model one ability to predict net shoreline accretion in response to reefs protection under a 0.28 m sea-level rise in the Puerto Rico test site is, therefore, very much consistent with theoretically reasonable expectations.

7.2.2 Using a constant closure depth in MIKE21

There are considerable differences between models one (time and space-varying closure depth in MIKE21) and two (5.5 m constant closure depth in MIKE21) shoreline evolution predictions in line with Chapter 6 findings (Fig. 7.2). This finding is reflected by a Spearman's rank correlation test (r_s), which shows a poor linear relationship (r_s = 0.4) between models one and two net shoreline change predictions. The differences between models one and two net shoreline change predictions include:

1. *Model two predicts lower shoreline accretion magnitudes longshore (mean: 12.92 m) than model one (mean: 18.16 m), and hence a lower MNC and MAC* (Fig. 7.2 a – b). This finding is attributed to model two having a deeper overall closure depth (5.5 m) longshore than model one (mean: 4.64 m; SD: 0.56) (Table 7.1; Fig. 7.1). These closure depth specifications are the primary difference between models one and two. The closure depth specifies the seaward boundary of the active coastal area over which MIKE21 uniformly redistributes littoral drift gradients to simulate shoreline evolution (DHI, 2017b). Therefore, specifying a closure depth seaward of the active coastal area causes MIKE21 to average out sediment volumes over a larger cross-shore area, leading to an underprediction (overprediction) of shoreline accretion (erosion) magnitudes. Model two thus predicts lower accretion levels than model one because it averages out sediment volumes further offshore by having a deeper overall closure depth.

2. *Model two predicts accretion in the western end of the site, which falls under "MIKE21 SM one", whereas model one predicts mainly erosion* (Figs. 7.3; 7.6). San Juan's Condado Beach is located within *MIKE21 SM one*. This area is an active erosion zone because of strong longshore currents and minimal reef protection (Barreto, 1997; Bush et al., 2009). Littoral drift in the Puerto Rico test site moves east to west (Bush et al., 2009) (Fig. 7.7). As model two has a deeper closure depth than model one, it inevitably generates a larger sediment volume moving east to west, hence predicts accretion within *MIKE21 SM one*. Model two generates a gross littoral drift of 33 181.66 m^3 in *MIKE21 SM one* (west end), whereas model one generates 19 162.87 m^3. The closure depth influences the sediment volume available for longshore transport by defining the area of morphodynamic activity. An overly deep closure depth causes MIKE21 to induce sediment mobility in inactive areas, inflating the littoral drift volume (Miselis and McNinch, 2006). Therefore, model two longshore predictions of net shoreline change trends (accretion vs erosion) are not fully in line with theoretically reasonable expectations given its unrealistic accretion predictions in the Puerto Rico test site's western end. These results show that a constant closure depth in MIKE21 can generate considerable uncertainty in shoreline change predictions in a complex planform morphology.

There are some similarities, however, between models one and two shoreline evolution predictions. For instance, Fig. 7.2b shows that model two (5.5 m closure depth in MIKE21) predicts net accretion (MNC: 0.93 m; SD: 17.83) in line with model one. This finding is attributed to (a) MIKE21 assumption of an adequate sand supply at open boundaries, which implicitly accounts for the natural sand supply from the coral reefs; and (b) the coral reefs present in the mesh bathymetry, which reduce wave energies reaching the shoreline, as discussed in section 7.2.1. Excluding *MIKE21 SM one*, Fig. 7.6 shows that model two also predicts accretion mainly in reef areas and erosion manly in non-reef areas in line with model one (Fig. 7.3) and Puerto Rico's 1936 to 2017 shoreline change trends. Despite these similarities, the plausibility of model two shoreline change predictions is questionable considering: (a) its unrealistic accretion predictions in the west; (b) the higher net shoreline change magnitudes predicted from model one, which accounts for the general spatial variability of the Puerto Rico test site's active coastal area; and (c) the good BSS (0.36) derived from using a space-varying closure depth to hindcast micro timescale shoreline evolution (2014 to 2016) in the Puerto Rico test site versus the poor BSS (0.03) derived from using a 5.5 m closure depth (Fig. 6.2). Model two net shoreline change predictions are, therefore, less theoretically plausible than those from model one.

7.2.3 Using a space-varying closure depth in the Bruun Rule

Model three (space-varying closure depth in the Bruun Rule) only predicts shoreline erosion longshore (range: -7.39 to -0.97 m; MNC: -4.46 m; SD: 1.5) (see Fig. 7.2c). This finding is a consequence of the Bruun Rule failure to account for the sand supply and natural protection from coral reefs (Goenaga and Cintron, 1979; Barreto-Orta et al., 2019) due to its assumption of linearity between sea-level rise and shoreline change. This assumption implies there is always sediment deficit (gain) from a rise (fall) in sea-level. However, such a theory is not always accurate, as seen from the accretion observed along reef and mangrove areas under historical sea-level rise in Puerto Rico (Barreto, 1997; Barreto, 2017). Models one (time and space-varying closure depth in MIKE21) and two (5.5 m closure depth in MIKE21) also illustrate that accretion is possible in reef-buffered areas under a 0.28 m sea-level rise (Figs. 7.3; 7.6). Models one and two are based on MIKE21, which has a much higher prediction accuracy than the Bruun Rule (Table 7.2). It is thus clear that model three net shoreline change predictions are not in line with theoretically plausible expectations.

7.2.4 Key findings

Five key findings are derived from the above results. *First*, enabling a time and space-varying closure depth in MIKE21 allow *theoretically plausible* meso timescale shoreline evolution predictions in complex morphologies. This finding is clear from model one (time and space-varying closure depth in MIKE21) predicting accretion in reef areas and erosion elsewhere under a 0.28 m sea-level rise in the Puerto Rico test site in line with historical meso timescale shoreline change trends. Also, model one predicts accretion (mean: 0.36 m yr^{-1}) and erosion (mean: 0.3 m yr^{-1}) rates that are consistent with those observed historically from 1936 to 2017 (accretion: 0.3 to 0.5 m yr^{-1}; erosion: 0.2 to 1.21 my^{-1}) in Puerto Rico. These results show that MIKE21 can realistically simulate meso timescale shoreline evolution in a complex planform morphology using a time and space-varying closure depth. A time and space-varying closure depth allows MIKE21 to account for sea-level rise and complex morphologies in meso timescale shoreline evolution predictions, which so far has not been possible.

Second, using a constant closure depth in MIKE21 provides less plausible meso timescale shoreline evolution predictions in complex morphologies than a time and space-varying closure depth. This finding is clear from model two (5.5 m closure depth in MIKE21) predicting accretion in the known erosion zones in the western part of the Puerto Rico test site compared to model one (time and space-varying closure depth in MIKE21). These results stem from model two having a deeper closure depth than model one. As a result, model two predicts a larger sediment volume moving east to west (i.e. littoral drift direction) than model one, hence its corresponding accretion prediction in the west.

Third, the closure depth significantly influences meso timescale shoreline evolution predictions. This finding is clear from comparing models one (time and space-varying closure depth in MIKE21) and two (5.5 m constant closure depth in MIKE21) shoreline evolution predictions in Table 7.3. Closure depth specifications are the key difference between both models. As the closure depth is deeper in model two, model two predicts higher erosion magnitudes than accretion magnitudes longshore since MIKE21 distributes sediments further offshore as the closure depth deepens. It is therefore evident from models one and two shoreline evolution predictions that closure depth specifications in mesoscale shoreline evolution models require meticulous consideration of the active coastal area.

Fourth, the Bruun Rule fails to provide realistic meso timescale shoreline evolution predictions in sandy coastal systems receiving a steady sand supply from reefs, for example, compared to MIKE21. This finding is evident from models one and two (MIKE21) predicting net accretion in reef areas, whereas model three (Bruun Rule) predicts erosion longshore (Figs. 7.2; 7.3; 7.6). Models one and two are based on MIKE21, which has a higher prediction accuracy than the Bruun Rule (Table 7.1). The coral reefs provide a steady sand supply that stabilises the Puerto Rico test site's shoreline. MIKE21 implicitly accounts for the reefs sand supply by assuming an adequate sand supply at open boundaries. However, the Bruun Rule fails to account for the reefs sand supply because it assumes linearity between sea-level rise and shoreline evolution. This assumption indirectly implies that there is always sediment deficit (gain) from a rise (fall) in relative sea-level. Thus, the Bruun Rule is not appropriate for application in complex planform morphologies that have a positive sediment budget.

Fifth, littoral drift has a more endogenous influence on meso timescale shoreline evolution than sea-level rise, consistent with previous chapters conclusions. This finding is clear from models one (time and space-varying closure depth in MIKE21) and two (5.5 m constant closure depth in MIKE21) predicting considerably different shoreline change trends and magnitudes than model three (space-varying closure depth in the Bruun Rule) (Table 7.3). In contrast to model three, models one and two generally replicate the Puerto Rico test site's historical meso timescale shoreline evolution trends. Models one and two shoreline evolution predictions are thus more likely to be in line with reality than model three, which implicitly implies that littoral drift has a more endogenous influence on meso timescale shoreline evolution than sea-level rise. This inference is derived from the fact that MIKE21 is driven by littoral drift gradients, whereas the total amount of sea-level rise drives the Bruun Rule.

7.3 Summary

This chapter presents the results from forecasting meso timescale shoreline evolution in the Puerto Rico test site using a time and space-varying closure depth in MIKE21, MIKE21 in its present form, and the Bruun Rule. The key conclusion is that a time and space-varying closure depth in MIKE21 allows *theoretically plausible* meso timescale shoreline evolution predictions in complex planform morphologies. Such an approach allows MIKE21 to account for sea-level rise and complex planform morphologies in mesoscale shoreline evolution predictions, which has not been possible until now.

08
Discussion and conclusions – On modelling mesoscale evolution of managed sandy shorelines

'In every outthrust headland, in every curving beach, in every grain of sand there is a story of the earth.'

– Rachel Carson

8.1 Introduction

This chapter addresses the aim and research questions outlined in Chapter 1. The aim of this thesis is to create a method for predicting the mesoscale (10^1 to 10^2 years and 10^1 to 10^2 km) evolution of managed sandy shorelines that accounts for sea-level rise and complex morphologies. This aim stems from the growing need to predict the mesoscale evolution of managed sandy shorelines for guiding coastal management (Payo et al., 2020), particularly in small Caribbean islands (Mycoo and Donovan, 2017). To address the aim of this thesis, I use a managed sandy coastal system in New York, Puerto Rico, and Southern California as test sites to first evaluate the sensitivity of two mesoscale shoreline evolution models, MIKE21 and the Bruun Rule, for identifying the key boundary conditions influencing shoreline evolution predictions in different managed coastal morphologies. The ensuing results, presented in Chapter 4, show that nearshore discretisation, bathymetry, tides, Manning's n, and sediment properties are the key boundary conditions affecting shoreline evolution predictions in managed sandy coastal systems. I use these sensitivity results to develop and apply three shoreline evolution modelling approaches, which include introducing: (a) a time-varying closure depth in MIKE21 as a solution to account for sea-level rise; (b) a space-varying closure depth in MIKE21 as a solution to account for complex morphologies; and (c) a time and space-varying closure depth in MIKE21 as a solution to account for sea-level rise and complex morphologies. Chapter 5 shows that a time-varying closure depth overpredicts erosion in the New York test site due to net closure depth overestimation. Chapter 6 shows that a space-varying closure depth allows more realistic shoreline change predictions in the Puerto Rico test site's complex morphology relative to existing modelling approaches. Chapter 7 shows that a time and space-varying closure depth allows *theoretically plausible* meso timescale shoreline evolution predictions under sea-level rise in the Puerto Rico test site's complex morphology compared to current modelling methods. In this final chapter, section 8.1.1 first explains how the results of this thesis are transferrable to mesoscale shoreline evolution studies in small Caribbean islands. Sections 8.2 and 8.3 then discuss the insights from Chapters 4 to 7 results regarding our: (a) knowledge of the main controls on shoreline evolution in different managed morphologies; and (b) ability to realistically simulate mesoscale shoreline evolution in managed sandy coastal systems. Section 8.4 summarises the main findings of this thesis relative to each research question outlined in Chapter 1 and makes suggestions for future research.

8.1.1 Relevance of the thesis findings for Caribbean small islands

The rationale underlying the aim of this thesis is to improve and enable the mesoscale application of shoreline evolution models for informing coastal management, especially in small Caribbean islands. With this in mind, the criteria used to select test sites for addressing the aim and research questions of this thesis are: (a) the availability of high-resolution bathymetry and coastal processes data for evaluating the sensitivity of shoreline evolution models, and establishing mesoscale shoreline evolution modelling approaches that account for sea-level rise and complex planform morphologies; and (b) morphologies that broadly characterise managed sandy coastal systems in the small vulnerable islands of the Caribbean. All test sites selected are in data-rich locations and are sandy coastal systems primarily managed by groynes (details in section 2.2). The range of coastal morphologies considered in this thesis includes simple barrier island morphologies (New York test site), steep coastal profile morphologies (Southern California test site), and complex coral reef systems (Puerto Rico test site) (Figs. 2.1 to 2.4). The New York test site's simple barrier island morphology is characteristic of the gentle sloping and straight sandy beaches found along the east coast of Barbados and Trinidad (Cambers, 2005; Darsan, 2013). The Southern California test site's steep coastal profile morphology is typical of most Atlantic-facing beaches in the Caribbean (Cambers, 2005; Simpson et al., 2009). The Puerto Rico test site's complex planform morphology provides an ideal example of the many coral reef coastal systems in the Caribbean (Cambers, 2005; Simpson et al., 2012; Mycoo and Donovan, 2017). Therefore, the insights gained from all shoreline evolution modelling applications in each test site selected (see sections 8.2 and 8.3) are very relevant for informing mesoscale shoreline evolution modelling studies in the small islands of the Caribbean.

8.2 Insights from model sensitivity results

This section discusses the insights gained from assessing MIKE21 and the Bruun Rule sensitivity in each test site. Following the stepwise calibration approach detailed in section 3.6, I assess MIKE21 sensitivity to nearshore discretisation, bathymetry spatial resolution, coastal processes temporal resolution, and free parameters (Manning's n, grain diameter, porosity, sediment grading, and weir coefficient). I assess the Bruun Rule sensitivity to bathymetry and tides only, since these are the only boundary conditions implicitly included in its equation. Chapter 4 shows that each test site's shoreline evolution predictions are sensitive to all boundary conditions considered, excluding wind, waves, and weir coefficient (Fig. 4.17). However, the optimal specifications of the sensitive boundary conditions are site-specific (see Table 4.4), varying according to coastal system morphology and processes. The following sections discuss the broader implications of the results obtained from evaluating model sensitivity to nearshore discretisation (section 8.2.1), bathymetry data spatial resolution (section 8.2.2), coastal processes time series resolution (section 8.2.3), and free parameters (section 8.2.4).

8.2.1 Nearshore spatial discretisation

The nearshore spatial discretisation controls the number of mesh elements representing the nearshore zone of interest (Kristensen, 2013; Kaergaard et al., 2017). The governing equations of MIKE21 spectral wave, hydrodynamic, and sediment transport modules are solved inside each mesh element. The nearshore discretisation thus affects the spatial resolution at which MIKE21 process-driven modules are applied and, consequently, the ensuing shoreline evolution predictions (DHI, 2016a; DHI, 2017c). Model sensitivity results show that the optimal and most accurate nearshore discretisation for shoreline evolution simulations is finer in the Southern California test site (30 m) than in the New York and Puerto Rico test sites (45 m) (Fig. 4.17a). As discussed in section 4.2.4, this finding is due to the Southern California test site having a steeper coastal profile than the New York and Puerto Rico test sites (Table 4.5). Steeper profiles degenerate and become numerically gradient over a smaller nearshore discretisation range than gentler profiles (Gorman et al., 2006; Meng et al., 2017), hence the above results. These results, however, have two broader implications:

First, the finest nearshore spatial discretisation does not guarantee the most accurate shoreline evolution predictions (see Fig. 17), as often assumed in related literature (Millar et al., 2007; Williams and Esteves, 2017; Bloemendaal et al., 2018). Although MIKE21 outputs (including its convergence and mesh statistics) provide no definite reason for this finding, potential causes include the mesh growth rate (defined as the change in resolution from one element to another) and its aspect ratio (defined as the ratio of the longest to the shortest face of an element). Abrupt changes in element sizes (e.g. from offshore to nearshore) as a result of mesh growth rate and aspect ratio can cause:

1. excessively large fluxes to propagate from very coarse elements to very fine elements, forcing solutions to diverge and inducing numerical instability. For example, sudden changes in the mesh resolution in coupled wave-sediment transport models can distort wave propagation and reflection properties, causing unreliable longshore drift gradients (see Qian et al., 1999).
2. truncation errors to accumulate in critical regions with high flow gradients (e.g. regions with high shear), which can destabilise the numerical solution (You et al., 2006; Tu et al., 2018). Truncation errors are the difference between the discrete and continuous governing equations (You et al., 2006; Jackson et al., 2020). These errors usually contain the diffusive terms (second-order derivatives) where the discretisation applied to such derivatives requires smooth changes between element sizes in the mesh (Jeng and Chen, 1992; Tu et al., 2018).
3. numerical instabilities to generate at the lateral (open) boundaries and propagate inside the domain when the resolution of the open boundary conditions specified is not in complete equilibrium with the mesh resolution range (Jones and Davies, 2005; Düben and Korn, 2014).
4. considerable mesh skewness, which can generate numerical instability and unreliable predictions (Bernard, 1993; Fabritius and Tabor, 2015; Nishikawa, 2020). MIKE21 process-driven modules are applied using a cell-centred finite volume approach (DHI, 2016c; DHI, 2016b; DHI, 2017b). As a result, the governing equations of MIKE21 process-driven modules are discretised using the distance between the centroids of adjacent mesh elements with the assumption that the vector joining these centroids is normal to the common face (Nishikawa, 2020). When this assumption is not met, the calculated flux accuracy at the common face reduces as its interpolated value lies at the intersection of the vector joining it to the element centroids. Flux errors at the common face of adjacent elements can prevent the numerical solution from converging and, in some cases, cause it to diverge (Fabritius and Tabor, 2015).

I maintain a maximum resolution of 70 m offshore in all meshes generated in this thesis but vary the nearshore resolution from 25 to 65 m to assess model sensitivity. The finest nearshore discretisations used are thus associated with the meshes having the largest growth rate and aspect ratio (and hence the most skewness), which may explain why these discretisations are not associated with the highest shoreline evolution prediction accuracy (Fig. 4.17). In the New York test site, for instance, there is a noticeable decline in net shoreline change prediction noise (errors) towards the open boundaries as the nearshore discretisation coarsens from 25 to 35 m (Fig. 4.3). This decline in prediction noise is likely due to a reduction in mesh skewness in response to decreasing mesh growth rate and aspect ratio, indirectly implying that the mesh construction criteria also significantly influence shoreline evolution predictions. Therefore, it is recommended that further research focus on identifying the optimal mesh growth rate, aspect ratio, and skewness for simulating shoreline evolution in different coastal morphologies. The outcomes of such research can help establish objective rules for guiding mesh generation to better apply mesoscale shoreline evolution models. As it stands, there are no set criteria for guiding mesh generation in shoreline evolution models (Williams and Esteves, 2017).

The second implication is that defining a nearshore spatial discretisation based on process length scales does not guarantee reliable shoreline evolution predictions, as assumed in related literature. This modelling insight is analogous to the findings of Hardy et al. (1999) and Williams and Esteves (2017). The range of nearshore spatial discretisations used to evaluate model sensitivity in each test site (25 to 65 m) corresponds to process length scales of primary shoreline evolution drivers (Table 1.1) (Cowell and Thom, 1994; Stive et al., 2002). Despite this, nearshore discretisations beyond 30 and 45 m generate considerable shoreline evolution prediction errors in the Southern California and New York test sites, respectively (Figs. 4.3; 4.14; Appendix A1). Along with the bathymetry data used for mesh interpolation, the nearshore discretisation determines how well the observed bathymetry gradients are represented in the model space (Kerr et al., 2013; Belibassakis and Karathanasi, 2017; Yeu et al., 2018). Errors accumulate in coupled processes simulations if the bathymetry gradients are not in equilibrium with the primary drivers of shoreline evolution forced in the model (e.g. wave climate, tides, and wind) (cf. Bloemendaal et al., 2018; Bilskie et al., 2020). Therefore, the most reliable nearshore spatial discretisation for simulating shoreline evolution is based on coastal system morphology, rather than the process length scales of shoreline evolution drivers, which we see clearly from MIKE21 sensitivity results in each test site (Table 4.4). These results show that the New York and Puerto Rico test sites have a coarser optimal nearshore discretisation than the Southern California test site even though their nearshore discretisation range is fine relative to the length scales of primary shoreline evolution drivers. As previously mentioned, this finding stems from the Southern California test site having a steeper profile than the New York and Puerto Rico test sites (Table 4.5).

Altogether, MIKE21 sensitivity results discussed here clearly show that nearshore discretisation (including its generation criteria) is as important as a typical calibration parameter (e.g. bed friction). Therefore, it is recommended that nearshore discretisation be included in model sensitivity evaluations to improve the reliability of shoreline change predictions for guiding coastal management.

8.2.2 Bathymetry data spatial resolution

Along with the nearshore discretisation, the spatial resolution of bathymetry data used for mesh interpolation determines how well the sea-floor gradients are represented in shoreline evolution models (Preston et al., 2018; Yeu et al., 2018). The sea-floor gradients directly affect wave-current interactions in process-driven shoreline evolution models, influencing the sediment transport gradients that drive shoreline evolution. In behaviour-oriented models, such as the Bruun Rule, the spatial resolution of bathymetry data affects the coastal profile morphology over which cross-shore sediment redistribution occurs to determine shoreline change. Related studies either use available bathymetry data without considering the effects on model solutions (Giardino et al., 2018; Le Cozannet et al., 2019; Parodi et al., 2020) or assume the highest bathymetry resolution produce the most accurate predictions (Splinter et al., 2013; Williams and Esteves, 2017). Contrary to these practices, model sensitivity results in each test site (Fig. 4.17) show that the accuracy of shoreline evolution predictions declines as bathymetry data coarsen beyond a specific resolution, depending on the underlying morphology. For instance, the New York and Puerto Rico test sites have a coarser optimal range of bathymetry data resolution than the Southern California test site because of their gentler sloping profile morphology (Fig. 4.17; Table 4.5). Steeper coastal profiles degenerate over a smaller range of bathymetry data resolution than gentler profiles (Figs. 4.5; 4.10) (Meng et al., 2017), hence these results. The degeneration of coastal profiles from coarsening bathymetry data can distort wave propagation and energy dissipation, generating unreliable sediment transport gradients that are not in equilibrium with observed coastal morphology (Poulter and Halpin, 2008; Kristensen, 2013; Roelvink et al., 2016). Altogether, the model sensitivity results mentioned here show that: (a) the bathymetry resolution used for mesh interpolation is important as a typical calibration parameter; (b) the optimal bathymetry resolution depends on coastal morphology; and (c) high bathymetry data resolution is not always needed to obtain reliable shoreline evolution predictions. These conclusions are consistent with those of Matsuyama et al. (1999), Ye et al. (2018), and Schweiger et al. (2020).

The bathymetry sensitivity results imply that we need relatively high bathymetry data resolution, which may be less than 10 m in some cases (see Fig. 4.17), to reliably simulate shoreline evolution in steep and complex planform morphologies. This finding presents a significant challenge for applying shoreline evolution models in data-poor vulnerable small islands of the Caribbean and Pacific where: (a) many sandy coastal systems have steep and complex morphologies; (b) there are minimal resources to obtain high-resolution data; and (c) coarse global terrain models are the primary source of bathymetry data (Giardino et al., 2018; Parodi et al., 2020). A potential solution for resolving this challenge is to establish combinations of mesh discretisation and bathymetry data resolution that effectively represent different spatial scales of sea-floor variability. Such information can help structure coastal monitoring campaigns, especially in data-poor vulnerable small islands of the Caribbean and Pacific, towards obtaining the minimal bathymetry data requirements needed to facilitate the use of shoreline evolution models as coastal management tools (Splinter et al., 2013).

Model sensitivity results indicate that bathymetry data resolutions up to 100 m may be appropriate for shoreline evolution simulations in simple morphologies with a relatively flat bed surface, such as the New York test site's morphology. This finding implicitly implies that coarse open-source bathymetry data, such as the Shuttle Radar Topography Mission (SRTM) (90 m resolution), may be sufficient for simulating shoreline evolution in relatively flat and gentle sloping morphologies. In this thesis, I evaluate model sensitivity to bathymetry data resolution in each test site by resampling their high-quality bathymetry data using the nearest neighbour approach, as outlined in section 3.6.2. The nearest neighbour resampling approach usually preserves the high-quality measurements of the original data (Li and Wong, 2010; Saksena and Merwade, 2015). The resampled (coarser) bathymetry used to assess model sensitivity in each test site may, therefore, contain higher precision measurements than open-source bathymetry data of the same spatial resolution (Seenath, 2018). Further research is needed to verify if open-source bathymetry data, such as SRTM, are appropriate for simulating shoreline evolution in simple planform morphologies before making such conclusions.

8.2.3 Coastal processes temporal resolution

Tide, wind, and wave climate data are the primary forcings driving MIKE21 coupled wave, flow, and sediment transport simulations, whereas sea-level rise is the only forcing in the Bruun Rule (Bruun, 1962; DHI, 2016c; DHI, 2016b). As sea-level rise rates are often derived from tide records, tides indirectly affect the Bruun Rule. To understand the relative influence of tides, wind, and wave climate on shoreline evolution predictions, I assess MIKE21 sensitivity to variations in their time series data resolution. I also consider the impact of tide time series data resolution on the Bruun Rule predictions by using varying sea-level rise estimations from different tide time series datasets. Chapter 4 model sensitivity results illustrate that MIKE21 shoreline evolution predictions are not sensitive to the range of coastal processes time series resolutions considered, whereas the Bruun Rule is sensitive to tide data resolution (Fig. 4.17). The following paragraphs discuss the wider implications of these results.

MIKE21 insensitivity to the temporal resolution of primary forcings may stem from limitations in the approach used to evaluate its sensitivity to tides, wind, and wave climate. As outlined in section 3.6.3, I assess MIKE21 sensitivity to tides, wind, and wave climate using coarsening time series data on these coastal variables in successive shoreline evolution simulations. The coarsening tide, wind, and wave climate data used for assessing model sensitivity are resampled from high-quality time series data on these coastal process variables using linear interpolation. Figs. 3.15 to 3.17 show that the linear interpolation resampling approach maintains the seasonality and trends of the original high-quality coastal processes time series data, likely masking MIKE21 sensitivity to tides, wind, and wave climate. MIKE21 insensitivity to the time series resolution of coastal processes data thus fails to address the uncertainties mentioned in section 3.6.3 regarding the: (a) optimal coastal processes data requirements for modelling shoreline evolution in different coastal morphologies, and (b) relative influence of tides, wind, and wave climate on shoreline evolution. The only insight gained from the MIKE21 sensitivity results discussed here is that coastal processes time series data resolutions that capture their general seasonality and trends are sufficient to simulate shoreline evolution. This finding is consistent with those of Kaergaard et al. (2017), Blanco et al. (2019), and Roelvink et al. (2020).

Contrary to MIKE21 insensitivity to the temporal resolution of coastal processes, Chapters 5 to 7 show that variations in nearshore wave heights calculated in the model domain largely govern the closure depth (Figs. 5.3; 7.1). The closure depth specifies the seaward extent of morphodynamics, directly influencing shoreline evolution predictions (Kraus and Harikai, 1983; Nicholls et al., 1998; Kaergaard and Fredsoe, 2013). Nearshore wave heights calculated in the model domain are determined from the interactions of wind, wave climate, and tide conditions forced and generated in the model domain (DHI, 2016c). With this in mind, the approach used to assess MIKE21 sensitivity to coastal processes may likely be ill-posed. Evaluating the effects of errors in tide, wind, and wave climate vector fields on the closure depth and associated shoreline evolution predictions may provide a more robust approach for testing the sensitivity of shoreline evolution models to coastal processes (Ashton and Murray, 2006b). Such an evaluation may give a better insight into the relative impact of tide, wind, and wave climate on shoreline evolution. As it stands, MIKE21 sensitivity results do not provide any definitive insight into the relative impact of these coastal variables on shoreline evolution.

The Bruun Rule shoreline evolution predictions in each test site, however, are sensitive to changes in tide level variations (Figs. 4.7; 4.12; 4.16). Differences in tide levels inevitably result in a different sea-level rise estimation, the primary forcing in the Bruun Rule (Bruun, 1962), hence these results. The Bruun Rule sensitivity results also do not reveal an optimal tidal resolution for simulating shoreline evolution in different coastal morphologies. Instead, it highlights the need to consider the impact of tide data on sea-level rise estimations when interpreting the Bruun Rule predictions. An optimal tidal resolution for modelling shoreline evolution cannot be identified from the Bruun Rule sensitivity results due to the micro timescales used for sensitivity testing. As the Bruun Rule is not designed for micro timescales, its shoreline change prediction magnitudes over the sensitivity testing period in each test site are negligible relative to corresponding observations (Tables 4.1 to 4.3). The Bruun Rule results over the sensitivity testing period in each test site thus do not allow an objective: (a) evaluation of its accuracy; and (b) identification of optimal tide resolutions for modelling shoreline change. Gauging the Bruun Rule sensitivity over meso timescales may address these uncertainties.

8.2.4 Free parameters

MIKE21 sensitivity results clearly demonstrate that free parameters in a shoreline evolution model do not have standard values that are optimal across all coastal systems (Fig. 4.17; Table 4.4). Instead, the optimal or most accurate values of free parameters depend on coastal system characteristics, including morphology and processes, as discussed in section 4.2.4. Apart from Manning's n and related friction parameters (e.g. Chezy number), there is a tendency in related literature to accept model default values of free parameters that broadly characterise coastal systems (Szmytkiewicz et al., 2000; Daghigh et al., 2017; Williams and Esteves, 2017; Preston et al., 2018). For example, related studies often accept default values of sediment porosity without considering the effects on resultant predictions (Drønen et al., 2011; Kristensen et al., 2013; Hendriyono et al., 2015). However, model sensitivity results show a linear relationship between declining model accuracy and increasing sand porosities in the New York and Puerto Rico test sites (Fig. 4.17). In contrast, model accuracy in the Southern California test site increases as sand porosity increases from 0.3 to 0.5 and then declines as porosity increases to 0.7 (Fig. 4.17). Therefore, while model default values of free parameters in shoreline evolution models may fall within the associated range of physically realistic values, it does not mean that these values are optimal or appropriate for modelling applications across all coastal systems (Williams and Esteves, 2017). In some cases, the default values of free parameters in shoreline evolution models can cause significant overprediction or underprediction of shoreline change magnitudes when default specifications are not in equilibrium with the hydrodynamics forced or operating in the model domain (Hanson and Kraus, 1991). Without calibrating and assessing the sensitivity of shoreline evolution models to all essential free parameters, we thus run the risk of introducing considerable errors in ensuing predictions. Significant shoreline change prediction errors can negatively affect coastal management decision-making and the success of resultant coastal defence initiatives (Vitousek et al., 2017; Tomasicchio et al., 2020).

Contrary to the above argument, Cunge (2003) argues that a model with parameter values based on engineering judgement should simulate reality correctly and generate results close to observed results without traditional calibration (i.e. tuning model inputs). Cunge's (2003) argument is based on the rationale that using accepted (or observed) values for model parameters and examining the error in model predictions provide a more robust account of a model's reliability. As Di Baldassarre et al. (2010) explains, Cunge's (2003) argument can only be valid if a model's input data and structure are perfect (error-free). As the structure of models and their input data are never error-free, calibration (and/or sensitivity testing) is needed to ensure accurate shoreline evolution predictions over time and space, particularly since these predictions normally inform coastal management decisions. Furthermore, it becomes problematic to identify the endogenous drivers of shoreline evolution in the absence of traditional model calibration and sensitivity testing (Roelvink et al., 2016; Williams and Esteves, 2017). Understanding the endogenous drivers of shoreline evolution is paramount to informing sound coastal management decisions and practices (Stive et al., 2002; Reeve et al., 2016; Van Maanen et al., 2016). On the need for such understanding, Splinter et al. (2013), Montano et al. (2020), and Payo et al. (2020) also recommend calibrating and assessing the sensitivity of shoreline evolution models contrary to Cunge's (2003) proposed model evaluation paradigm. The rationale for such recommendation is that traditional calibration and sensitivity testing allow us to identify the parameters and variables causing the largest errors in shoreline change predictions. This knowledge is fundamental for understanding (and refining) the intrinsic behaviour of shoreline evolution models.

8.3 Insights from the shoreline evolution modelling approaches applied

Advanced mesoscale shoreline evolution models assume an equilibrium coastal profile in their shoreline morphology update, which forces the coastal profile to maintain fixed vertical limits and a constant time-averaged form (Hurst et al., 2015; Van Maanen et al., 2016; Roelvink et al., 2020). These simplifying rules are needed to prevent the unrealistic breakdown of coastal profiles and the associated unstable morphology update that restricts process-driven models over meso timescales (Hanson et al., 2003; Karunarathna and Reeve, 2013; Kristensen et al., 2013). However, the equilibrium profile assumption does not allow advanced mesoscale shoreline evolution models to fully account for sea-level rise and complex planform morphologies. Sea-level rise will likely be an endogenous factor driving mesoscale shoreline evolution, whereas complex planform morphologies characterise coastal systems in many vulnerable Caribbean small islands (Stive et al., 2002; Mycoo and Donovan, 2017). The unrealistic breakdown of coastal profiles previously mentioned stems from the inability of advanced mesoscale shoreline evolution models to account for the vertical variability of undertow currents that drives coastal profile evolution (Kristensen et al., 2013; Franz et al., 2017; Albernaz et al., 2019). Acknowledging the need for a stable morphology update, my solution to account for sea-level rise and complex morphologies in mesoscale shoreline evolution models entails modifying their equilibrium profile assumption to include closure depth time and space variations (details in sections 3.8 to 3.10). The underlying rationale of these solutions are summarised below:

1. Sea-level rise causes wave breaking closer to the shoreline, potentially increasing the undertow mobilisation and offshore transport capacity of near-bed sediments (Guannel, 2010; Aagaard and Sørensen, 2012). Changes to the wave setup and associated undertow currents induced by sea-level rise can affect cross-shore sediment mass balance and modify the coastal profile shape, particularly the offshore part (Aagaard and Sørensen, 2012; Idier et al., 2019). Therefore, modifying the equilibrium coastal profile assumption to include temporal variations in the closure depth (the offshore extent of the active coastal profile) may offer an interim solution to account for sea-level rise in mesoscale shoreline evolution models morphology update until we can represent undertow currents in these models. The closure depth is a good index of sea-level change as it indicates the extent of morphodynamics offshore (Hallin et al., 2019). A time-varying closure depth will allow the offshore vertical limit

of the active coastal profile to vary over time, similar to what is expected under sea-level rise.

2. Complex planform morphologies are characterised by non-parallel contours, typical of coral reef systems in many Caribbean islands where shoreline evolution models are most needed to guide coastal management. Wave transformation over non-parallel depth contours generates spatial variations in wave heights reaching the shoreline, causing some areas to have a shallower closure depth than others (Bender and Dean, 2003; Sabatier et al., 2004; Keshtpoor et al., 2015). The equilibrium coastal profile assumption of mesoscale shoreline evolution models consequently prevents realistic longshore shoreline evolution simulations in complex morphologies as the closure depth influences the morphodynamics in these models. Until mesoscale shoreline evolution models can effectively represent the processes underlying coastal profile evolution (undertow currents), modifying their equilibrium profile assumption to handle a space-varying closure depth may offer an interim solution for mirroring the effects of wave transformation over non-parallel contours on the offshore part of coastal profiles longshore. A space-varying closure depth will allow the offshore vertical limit of the active profile to vary longshore, as observed in complex planform morphologies.

3. Considering the above reasonings, modifying the equilibrium coastal profile assumption of mesoscale shoreline evolution models to facilitate closure depth temporal and spatial variations will allow us to project the effects of sea-level rise and complex planform morphologies on shoreline evolution predictions. A time and space-varying closure depth will enable the offshore vertical limit of the active coastal profile to vary over time and space, similar to what we can expect under relative sea-level rise in complex planform morphologies.

Chapters 5 to 7 compare the above modelling approaches (time and space-varying closure depth) with MIKE21 current approach and the Bruun Rule over micro to meso timescales, the results of which are summarised in Tables 8.1 to 8.3. Altogether, three main findings are derived from these results. *First*, a time-varying closure depth in MIKE21 overpredicts shoreline erosion but provides a better approach than the Bruun Rule for simulating mesoscale shoreline evolution under relative sea-level rise. The overprediction of shoreline erosion is primarily due to mean closure depth overestimation (Fig. 5.3). The *second* main finding is that a space-varying closure depth enables acceptable shoreline evolution predictions in complex planform morphologies. The *third* main finding is that a time and space-varying closure depth facilitates *theoretically plausible* meso timescale shoreline evolution predictions in complex planform morphologies under sea-level rise. Sections 8.3.1 and 8.3.2 discuss the wider theoretical and practical implications of these findings, respectively.

8.3.1 Theoretical implications

Chapters 5 to 7 shoreline evolution modelling results have two theoretical implications for improving our current understanding of the drivers of shoreline evolution in managed sandy coastal systems:

First, 3D temporal changes in the coastal profile play a critical role in influencing shoreline evolution in managed sandy coastal systems. This insight stems from the significant effect closure depth changes have on MIKE21 shoreline evolution predictions in the New York and Puerto Rico test sites (Figs. 5.2, 6.2, 7.2; Tables 8.1 to 8.3). The closure depth is the vertical offshore limit of the active coastal profile, marking the seaward extent of significant sediment transport (Kraus and Harikai, 1983). Closure depth changes are a function of sea-level and wave climate variations (Nicholls et al., 1996). MIKE21 simulates shoreline evolution in response to littoral drift gradients based on the assumption of an equilibrium coastal profile, which means that changes in littoral drift gradients are uniformly distributed over the active coastal profile (Kristensen, 2013). A change in sediment balance over the profile causes it to move shore-normal, which gives a change in shoreline position whilst ensuring the shape and vertical limits of the active profile stay constant. While this 2D cross-shore mass balance approach is generally valid for simulating shoreline evolution in natural coastal systems with linear sloping profiles, it is almost never correct for simulating shoreline evolution in managed coastal systems (Pilkey et al., 1993; Cooper and Pilkey, 2004). This assertion is evident from a time and space-varying closure depth providing more realistic shoreline evolution predictions in the Puerto Rico test site relative to the traditional equilibrium profile assumption of a constant closure depth (Figs. 6.2, 7.2, 8.1). On the contrary, a time-varying closure depth causes MIKE21 to overpredict erosion in the New York test site, but this is due to net closure depth overestimation (Figs. 5.2; 8.2). 2D cross-shore mass balance principles are not always valid for modelling shoreline evolution in managed sandy coastal systems since these systems are often fixed by defences, which prevent coastal profiles from migrating to maintain an equilibrium form (Cooper et al., 2000). In these systems, offshore sediment transport generally causes a lowering of the upper beach at the offshore boundary of defences (Reeve et al., 2004). Upper beach lowering causes wave breaking closer to the shoreline, consequently changing the closure depth and ensuing shoreline dynamics (Aagaard and Sørensen, 2012). Hence, accounting for the vertical time variability of coastal profiles is needed to reliably simulate shoreline change in managed coastal systems (see Chapters 6 and 7). This conclusion aligns with those of Cooper et al. (2000), Cooper and Pilkey (2004), and Slott et al. (2010).

Second, the nearshore wave climate has a more dominant influence on micro and meso timescale shoreline evolution in managed sandy coastal systems than sea-level rise. This insight stems from:

1. MIKE21 predicting more accurate shoreline evolution trends, rates, and magnitudes than the Bruun Rule throughout this thesis (Tables 8.1 to 8.3) even though both models apply similar rules in their shoreline morphology update. Both models assume that the active coastal profile moves shore-normal from a change in sediment balance. Changes in sediment balance are driven by littoral drift gradients in MIKE21 and sea-level rise in the Bruun Rule. MIKE21 calculates littoral drift gradients in response to nearshore wave conditions in the model space.
2. The closure depths calculated in response to nearshore wave heights significantly affecting shoreline evolution predictions in the New York and Puerto Rico test sites (see Figs. 5.2; 7.2).
3. A space-varying closure depth calculated in response to longshore variations in nearshore wave climate conditions generating the most accurate shoreline evolution predictions in the Puerto Rico test site’s complex morphology relative to alternative approaches (see Fig. 6.2).

Nearshore wave climate affects the spatial variations in wave energy dissipation and the direction that waves approach the shoreline, determining the alongshore flux of sediment that influence accretion and erosion patterns (Tomasicchio et al., 2020). Sea-level rise can also directly influence shoreline evolution by forcing shorelines to retreat. However, sediments eroded due to shoreline retreat from sea-level rise typically become entrained in longshore transport, often getting trapped and deposited elsewhere along the shoreline, especially in managed coastal systems (Leatherman, 1990; Cooper and Pilkey, 2004; Cooper et al., 2020). Therefore, longshore drift can cause segments of managed shorelines to accrete under sea-level rise by increasing the sediment budget downdrift of defences (Anderson et al., 2015), as observed over meso timescales in the New York test site (Fig. 5.2). Slott et al. (2006) show that the longshore variation in shoreline change rates from littoral drift can be an order of magnitude higher than the shoreline change rate expected from sea-level rise alone, which is also evident from comparing the results of MIKE21 and the Bruun Rule in the preceding chapters. Nearshore wave climate generally changes over years to decades and are partly dependent on water depth due to shallow water effects on wave propagation (Townend, 1994). Water depths, on the other hand, will change under sea-level rise. Thus, sea-level rise indirectly affects the nearshore wave climate and associated littoral drift. In this regard, a good proxy of wave climate and sea-level change is the closure depth, which marks the depth limit of significant wave action (Slott et al., 2006; Nguyen et al., 2021). As advanced mesoscale shoreline evolution models assume a constant closure depth in line with equilibrium beach profile theory, their prediction accuracy will likely reduce as wave climate and sea-levels change over increasing timescales. For instance: (a) the BSS of the New York test site's calibrated MIKE21 model decreases from 0.46 to ~ 0.2 as timescales change from micro to meso; and (b) the accuracy of the Puerto Rico test site's calibrated MIKE21 model increases as the closure depth changes from constant (BSS ~ 0) to space-varying in response to nearshore wave climate variations (BSS 0.37). These results reaffirm the dominant influence of the nearshore wave climate on shoreline evolution in managed sandy coastal systems. Hence, we need to account for time and space variations in the nearshore wave climate to reliably simulate shoreline evolution over meso time and space scales in managed coastal systems. This conclusion is analogous to those of Nicholls et al. (1999), De Figueiredo et al. (2020), and Nguyen et al. (2021).

8.3.2 Practical implications

Chapters 5 to 7 shoreline evolution modelling results also have two practical implications for improving our ability to simulate mesoscale shoreline evolution in managed sandy coastal systems:

First, a time and space-varying closure depth provides a promising solution to account for nearshore wave-climate variations, sea-level rise, and complex morphologies in mesoscale shoreline evolution predictions without compromising the stability of the shoreline morphology update. This insight stems from the: (a) *theoretically plausible* meso timescale shoreline evolution predictions derived from applying a time and space-varying closure depth in the Puerto Rico test site's complex planform morphology (Table 8.3); and (b) expected meso timescale shoreline evolution predictions derived from using a time-varying closure depth in the New York test site (section 5.2.2; Figs. 5.2 and 5.3). Without considering the vertical variability of the coastal profile over time and space, we run the risk of obtaining unreliable mesoscale shoreline evolution predictions in managed coastal systems as the nearshore wave climate, which is indirectly influenced by sea-level rise, is often the dominant driver of shoreline evolution in these systems (Slott et al., 2006; Slott et al., 2010). A notable effect of nearshore wave climate variations is a change in the depth limit of significant wave action (the closure depth), which affects the shape of the coastal profile and ensuing shoreline dynamics (Coelho et al., 2013). Closure depth variations thus provide a plausible solution to mirror the effects of nearshore wave climate on mesoscale shoreline evolution predictions without comprising the equilibrium profile assumption underlying the morphology update in advanced mesoscale shoreline evolution models (Coelho et al., 2013; De Figueiredo et al., 2020). Further testing, however, is needed to verify whether a time and space-varying closure depth can facilitate *physically realistic* mesoscale shoreline evolution predictions. Such verification is necessary before we can accept a time and space-varying closure depth as a viable solution to more realistically simulate mesoscale shoreline evolution in managed coastal systems. After all, the reliability of mesoscale shoreline evolution predictions affect the credibility of associated coastal management decisions and solutions (Van Maanen et al., 2016).

Second, the one-line theory equilibrium profile concept can be extended to reliably simulate shoreline evolution in complex planform morphologies, subject to some modification. The one-line theory main assumption is that the active coastal profile keeps its shape while moving shore-normal from a change in the alongshore component of sediment transport (Pelnard-Considere, 1956; Roelvink et al., 2016). This assumption implies shore-parallel contours, meaning that the closure depth is considered constant and hence a single contour line can be used to describe changes in beach plan shape (Pelnard-Considere, 1956; Larson et al., 1987; Thomas and Frey, 2013). In theory, these assumptions are not valid for complex planform morphologies where depth contours are non-parallel (Hurst et al., 2015). Consequently, advanced mesoscale shoreline evolution models have limited applicability in such morphologies, as their morphology update is based on the one-line theory. Results in this thesis, however, show that we can simulate shoreline evolution to an acceptable level in complex planform morphologies by applying the one-line theory to smaller coastal segments with shore-parallel contours and the same closure depth (Figs. 6.1 to 6.3, 7.2, 8.1; Table 8.3). In other words, a workaround of getting mesoscale shoreline evolution models to work in complex planform morphologies is to: (a) divide the coast into segments conforming to the one-line theory morphology assumptions; (b) simulate shoreline change in each segment; and (c) piece together the simulated shoreline change from each segment to get a complete picture of shoreline evolution alongshore, as demonstrated in the Puerto Rico test site (Chapters 6 and 7). Such an approach indirectly allows the closure depth to vary 'freely' longshore in response to spatial variations in nearshore wave climate and sea-level, which characterise coastal systems with complex planform morphologies, and can easily be incorporated in other mesoscale shoreline evolution models based on the one-line theory, including CEM (Ashton and Murray, 2006a), CoastalME (Payo et al., 2017), COVE (Hurst et al., 2015), GENESIS (Hanson, 1989) and UnaLinea (Sutherland et al., 2015). The proven adaptability of the one-line theory to realistically simulate shoreline evolution in complex planform morphologies is a significant innovation of this thesis, since it has important practical implications for improving our capability to predict and better understand shoreline evolution beyond simple planform morphologies.

8.4 Thesis conclusions

This section summarises the key findings of the thesis relative to each governing research question:

Research question one: What are the key boundary conditions needed to model the mesoscale evolution of managed sandy shorelines?

Chapter 4 shows that nearshore discretisation, bathymetry spatial resolution, tides, friction, and sediment properties (grain diameter, sediment grading, and porosity) are the key boundary conditions for simulating the evolution of managed sandy shorelines. Chapters 5 to 7 subsequently show that shoreline evolution predictions in managed sandy coastal systems are also sensitive to the closure depth and wave climate. However, the optimal specifications of these key boundary conditions generally vary according to the underlying coastal morphology and processes. Model sensitivity results, summarised in Fig. 4.17, show that specifying boundary conditions beyond their optimal range, even if specifications fall within realistic ranges, can generate significant shoreline evolution predictions errors. Such errors can affect the credibility of ensuing coastal management decisions. Hence, it is strongly recommended to evaluate the sensitivity of shoreline evolution models to all potentially ‘crucial’ boundary conditions before applying them to support coastal management.

Research question two: How can sea-level rise be incorporated in shoreline evolution models for mesoscale application in managed sandy coastal systems?

I introduce a time-varying closure depth in MIKE21 as a solution to account for sea-level rise in the morphology update in mesoscale shoreline evolution models. Using the New York test site as a case in point, Chapter 5 demonstrates that a time-varying closure depth in MIKE21 provides an improved alternative to the Bruun Rule for simulating shoreline evolution under sea-level rise despite causing MIKE21 to overpredict shoreline erosion. MIKE21 overprediction of shoreline erosion in response to the time-varying closure depth specified in the New York test site, however, is attributed to net closure depth overestimation. Hence, a time-varying closure depth may improve mesoscale shoreline evolution predictions under sea-level rise if closure depth estimations can be accurately prescribed over time. Further work is needed to verify this assumption before a time-varying closure depth can be ruled out or accepted as a practical solution to include sea-level rise in shoreline evolution models.

Research question three: How can complex planform morphologies be accounted for in shoreline evolution predictions?

Chapter 6 shows that allowing a space-varying closure depth in MIKE21 offers a viable approach to account for complex planform morphologies in meso timescale shoreline evolution predictions. For instance, using a space-varying closure depth in MIKE21 replicates observed net shoreline change trends, patterns, and magnitudes to an acceptable level (BSS: 0.37) in the Puerto Rico test site’s complex planform morphology compared to using: (a) a constant closure depth in line with MIKE21 current approach (BSS: 0.03) and (b) the Bruun Rule (BSS: -0.03). This finding has implications for refining shoreline evolution models to: (a) better support coastal management in many vulnerable Caribbean small islands where coastal systems typically have considerable spatial variations in their active coastal area; and (b) improve our knowledge on coastal behaviour in complex morphologies.

Research question four: Can shoreline evolution models be developed to incorporate both sea-level rise and complex planform morphologies over meso timescales?

Chapter 7 shows that a time and space-varying closure depth allows MIKE21 to provide *theoretically* *plausible* meso timescale shoreline evolution predictions in complex morphologies under sea-level rise. This finding is evident in two instances. *First*, a time and space-varying closure depth allows MIKE21 to forecast meso timescale accretion in reef areas and erosion elsewhere in response to a 0.28 m sea-level rise in the Puerto Rico test site in line with historically associated meso timescale shoreline change trends (1936 to 2017) under past sea-level rise. *Second*, a time and space-varying closure depth enables MIKE21 to predict meso timescale accretion (mean: 0.36 m yr^{-1}) and erosion (mean: 0.3 m yr^{-1}) rates consistent with those observed from 1936 to 2017 (accretion: 0.3 to 0.5 m yr^{-1}; erosion: 0.2 to 1.21 my^{-1}) in Puerto Rico. These are all promising results, indicating that a time and space-varying closure depth in MIKE21 can allow us to account for sea-level rise and complex planform morphologies in mesoscale shoreline evolution predictions. Further work, however, is needed to verify if a time and space-varying closure depth in MIKE21 can provide *physically realistic* meso timescale shoreline evolution predictions in complex planform morphologies under sea-level rise. This validation is necessary before we can accept such an approach as a viable solution to account for sea-level rise and complex morphologies in mesoscale shoreline evolution simulations.

8.4.1 Future research suggestions

Modelling results discussed above present multiple avenues for further research, as outlined below:

Identifying main controls on shoreline evolution predictions

The model sensitivity results in Chapter 4 open up three pathways for further research, including:

1. Chapter 4 shows that nearshore spatial discretisation is as important as a typical calibration parameter, such as bed friction. Section 8.2.1 later explains that the criteria used for mesh generation determine the reliability of the nearshore spatial discretisation for simulating shoreline evolution. These criteria include the mesh growth rate, aspect ratio, and skewness. Further research should therefore establish the optimal mesh generation criteria for different coastal morphologies. The implications of such work can help refine the mesoscale development and application of shoreline evolution models to better guide coastal management decision-making.

2. Chapter 4 demonstrates that bathymetry data resolution is also at least as important as a typical calibration parameter in shoreline evolution models. Considering that vulnerable small islands are often data-poor, further work is needed to define a range of resolutions that can optimally capture different spatial scales of bathymetric variability in shoreline evolution models. The outcomes of such research will have practical implications for informing coastal monitoring programmes in data-poor regions towards facilitating the use of shoreline evolution models as decision-making tools to support coastal management (Splinter et al., 2013; Nicholls et al., 2016).

3. Incorporating open-source bathymetry data in model sensitivity testing to assess whether such data can be reliably used to simulate shoreline evolution in simple planform morphologies. This research pathway stems from the fact that bathymetry data resolutions ≤ 100 m appear suitable for simulating shoreline evolution in the New York test site's simple planform morphology. A likely reason for this finding may be the resampling method used to downgrade the high-quality

bathymetry data obtained for model sensitivity testing in the New York test site. Resampling high-quality bathymetry data typically preserves the high-quality measurements of the original data (Seenath, 2018). Therefore, the acceptable shoreline evolution predictions derived from the resampled bathymetry datasets in the New York test site may not be a good indicator of the likely outcomes that will be obtained from using open-source bathymetry data of equivalent resolution.

4. Evaluating the sensitivity of shoreline evolution predictions to the error in the wind and wave vector fields (magnitude and direction) used as boundary conditions. This research pathway stems from the fact that changes in wave climate largely govern the variations in closure depth, which significantly affect shoreline evolution predictions, as shown in Chapters 5 to 7. Extending model sensitivity studies to consider wind and wave magnitude and direction error will help us better understand the sensitivity of shoreline evolution predictions to coastal processes. Such knowledge can also help structure coastal monitoring campaigns in data-poor regions to facilitate the application of mesoscale shoreline evolution models as coastal management decision tools.

Incorporating sea-level rise in mesoscale shoreline evolution models

Future research should continue to determine if a time-varying closure depth can improve our ability to study meso timescale shoreline evolution under sea-level rise. As it stands, a time-varying closure depth offers the most plausible solution to account for sea-level rise in meso timescale shoreline evolution predictions (De Figueiredo et al., 2020). This assertion stems from the fact that closure depths change under sea-level rise (Nicholls et al., 1996; Udo et al., 2020), which is not accounted for in existing mesoscale shoreline evolution models as these models assume an equilibrium coastal profile (Roelvink et al., 2016). Hence, the following suggestions are made to guide future research:

1. Evaluate shoreline evolution prediction accuracy over varying timescales in response to a constant closure depth in different sandy coastal system morphologies. Doing so will allow us to verify whether the one-line theory assumption of a constant closure depth significantly reduces the achievable accuracy of shoreline evolution predictions over increasing timescales, as seen in the New York test site. This verification is necessary since drawing on net shoreline change prediction data in one test site alone does not allow for such definitive conclusions to be made.

2. Evaluate whether high-resolution wave climate data can improve the accuracy of the workflow used to allow a time-varying closure depth in MIKE21. The results of such evaluation can have important implications for: (a) refining shoreline evolution models to improve their application over meso timescales; and (b) informing coastal monitoring in data-poor regions to better enable the mesoscale application of shoreline evolution models as coastal management decision tools.

3. Evaluate if alternative closure depth estimation methods, such as those reviewed in Brutsche et al. (2016) and Valiente et al. (2019), can improve the accuracy of the workflow defined for time-varying the closure depth in MIKE21. Such research will also have implications for refining the meso timescale application of shoreline evolution models to better support coastal management.

Accounting for complex morphologies in mesoscale shoreline evolution predictions

Chapter 6 shows that a space-varying closure depth allows MIKE21 to hindcast micro timescale (2014 to 2016) shoreline evolution in the Puerto Rico test site's complex morphology reasonably well (BSS: 0.37). This promising result warrants further work to determine if a space-varying closure depth can improve mesoscale shoreline evolution predictions over much more complex morphologies than the Puerto Rico test site's morphology. Such research is necessary before we can accept a space-varying closure depth as a solution to account for complex morphologies in mesoscale shoreline evolution predictions. If the outcome is favourable, further work should develop a method that allows the closure depth to vary freely over space in shoreline evolution models. Doing so will: (a) address the high computational cost of having to focus the shoreline morphology update on smaller coastal segments to account for closure depth longshore variations; and (b) allow us to vary the closure depth at a fine spatial resolution to better study coastal behaviour in complex planform morphologies.

Handling both sea-level rise and complex morphologies in shoreline evolution models

Chapter 7 reveals that a time and space-varying closure depth allows *theoretically plausible* meso timescale shoreline evolution predictions under sea-level rise in a complex morphology. This promising finding requires additional research to establish if a time and space-varying closure depth enables *physically realistic* meso timescale shoreline evolution predictions under sea-level rise in complex morphologies. Such research will require applying a time and space-varying closure depth to hindcast observed meso timescale shoreline evolution in complex morphologies. As before, if the outcome is positive, further research should develop modelling approaches that allow the closure depth to vary freely over space and time in shoreline evolution models to: (a) reduce the high computational cost of manually forcing the shoreline morphology update to account for closure depth time and space variations; and (b) allow us to include closure depth time and space variations at a fine resolution to better study meso timescale coastal behaviour in complex planform morphologies.

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