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# A REVIEW OF EXISTING MODELLING FRAMEWORKS TO ASSESS CLIMATE CHANGE-DRIVEN SHORELINE CHANGES

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## Summary

A major challenge to the development of long-term projections of shoreline changes is to identify, address and model the coastal processes responsible for them. Future coastal processes, either longshore or cross-shore, are primarily induced by coastal drivers such as mean sea level, waves, storm surges and tides, will be affected by global and regional climate change, and hence are uncertain. This contribution aims at identifying best practices in the assessment of climate chance-induced shoreline change including uncertainty estimates. For this purpose, we (1) describe the drivers and processes shaping the shoreline and how climate change will affect them; (2) analyse uncertainty sources, their propagation and management options; (3) review existing modelling frameworks developed over the last decade to predict future impacts on shoreline change due to climate change and variability, emphasizing how climate change is considered and the way uncertainties are addressed; and (4) discuss whether a best approach can be identified and provide a set of recommendations.

# 1. Introduction

Sandy areas are extraordinary complex and highly dynamic systems that may undergo changes over a wide range of temporal and spatial scales (Stive et al., 2002). These changes entail from small-scale fluctuations due to the formation of beach cusps; to large-scale changes produced by episodic extreme weather events, storm grouping, seasonal weather patterns and long-term natural- and human-induced forcing (Miller and Dean, 2004). The effects of nearshore winds, water levels, breaking waves and turbulence within the surf zone add therefore a level of complexity greater than in hydrodynamics (Dean and Dalrymple, 2001), and, unfortunately, our capacity to understand and model this variability remains still limited (Stive et al., 2002).

Furthermore, the increasing need for risk-based informed decisions and climate-change adaptation planning requires long-term (i.e., multidecadal to centennial timescales) shoreline change projections to be more reliable than ever before. For example, they can be used to define setback lines and plan relocation of coastal assets, or to anticipate costs associated to adaptation options such as sand nourishment. However, modelling shoreline changes at these timescales is not easy for at least three reasons. First, long-term shoreline migration involves short-and long-term processes interaction and coupling beyond a few decades. Although this has been recognised in literature (Ranasinghe, 2016; Toimil et al., 2017), there is still no consensus on how best to model these complex interplays. Second, climate change-induced variations in these short- and long-term forcings are likely to have significant effects on shoreline change. While assuming a rise in mean sea level and no changes storminess is common practice (e.g., Ranasinghe et al., 2012), little efforts have been undertaken to include future waves, storm surge and river flow projections, although they are known important evolution factors at decadal timescales (e.g., Barnard et al., 2015; Castelle et al., 2018). Finally, the uncertainty in long-term shoreline change estimates is high.

Within this context, the present report seeks to provide an insight into the existing modelling frameworks conceived to assess long-term shoreline change driven by climate change and variability, emphasizing how climate change effects are incorporated and the way uncertainties are addressed. A secondary target of this research is to determine if we can identify a best approach to estimate climate change impacts on shoreline changes. The scope of this review is limited to mainland sandy beaches in temperate environments (i.e., excluding polar and tropical coasts, affected by seasonal ice and coral-related processes), considering both uninterrupted and inlet-interrupted coasts which are unaffected by human interventions. Inlet-related effects are limited to the impacts these systems can have on the adjacent beaches, disregarding any other morphodynamic interaction among the elements involved. Our focus is on holistic modelling strategies attempting to represent physical processes explicitly, therefore excluding multicriteria approaches addressing the need to identify the most vulnerable locations in the context of sea level rise (Gornitz, 1991). We consider the most relevant studies developed over the last decade that implement appropriate complexity modelling frameworks, using simplified surrogate models to quantify the contribution of each coastal process to the sedimentary budget (French et al., 2015).

The remaining of the report is structured as follows. Section 2 examine the main drivers and processes responsible for shoreline change. Section 3 describes uncertainty as well as its origin, propagation, accumulation and management options. Section 4 reviews existing frameworks to assess climate-change effects on shoreline changes. Finally, Section 5 discusses whether a best approach is likely to be identified and provides a set of recommendations.

## 2. Climate change-driven shoreline changes

### *2.1 A framework for the assessment of climate change-driven shoreline changes*

To respond to climate change efficiently, we need to anticipate its impacts. Since some of these impacts are expected to have occurred in the past, detection and attribution offer a form of validating and refining our projections about future changes (Cramer et al., 2014), allowing to reduce uncertainty (Karl and Trenberth, 2003). Although such sort of extrapolation faces many limitations due to the complex and non-linear behaviour of the systems and because the absence of past impacts cannot constitute evidence against the possibility of future impacts, it can provide a valuable contribution to risk assessments (Stone et al., 2013). However, even whether it is possible to detect the impact of climate change on a system, more detailed understanding is required to assess attribution, which indicates the magnitude of this impact in relation to the influences of additional factors and natural variability. This is particularly challenging for coastal erosion due to the lack of high-resolution, continuous and long-term observations (i.e. more than 50-year records) of shoreline change, and because isolating the erosion induced by climate change involves a precise evaluation of the effects of all other external factors (e.g., natural variability and human-related activities) (Le Cozannet et al., 2014). The latter has in turn a double constraint – climate change in conjunction with other drivers can be non-linear and non-local in both space and time, implying lagged responses and trans-regional effects hard to be understood, disentangled and quantified; and the ability of many beaches to self-adapt to climate change further aggravates the problem (Nicholls et al., 2016; Stone et al., 2013; Cramer et al., 2014). Given these limitations, it may well take several years for attribution to make significant advance. Consequently, the prospective modelling frameworks available today still lack a proper validation.

For immediate needs, however, prospective modelling still remains needed to guide decision. Hence, a reference modelling framework displaying all the components required to assess shoreline changes may provide useful guidance on the use of data concerning climate change-driven shoreline changes and the strategic development and application of numerical schemes most appropriate for their modelling. Fig. 1 shows a conceptual scheme containing key components that may be involved in the assessment of shoreline changes induced by climate change. The first challenge when it comes to develop future projections of coastal erosion – namely future shoreline evolution, storm erosion or their combined effect in the short-, mid- or long-term (box 4 in Fig. 1) – is to identify, address and model the coastal processes responsible for them (box 2 in Fig. 1). These coastal processes are triggered by coastal drivers (e.g., mean sea level, waves, storm surges, tides, river flow) which may well be affected, whether directly or indirectly, by global and regional climate change (box 1 in Fig. 1). Modelling coastal processes is of great complexity, and depending on the characteristics of the coast, the data available and the models used, certain physical processes (e.g., shoreline recovery, storm grouping, geomorphic/human constraints, inlet-induced effects) may be considered (box 3 in Fig. 1). Uncertainty arises from different sources and is introduced at each step, propagating through the whole process. There are many approaches to address uncertainty (box 5 Fig. 1), and their robustness differs, but depending on the impact of each source of uncertainty on the final model outcome, the most complex approach may not be necessary.

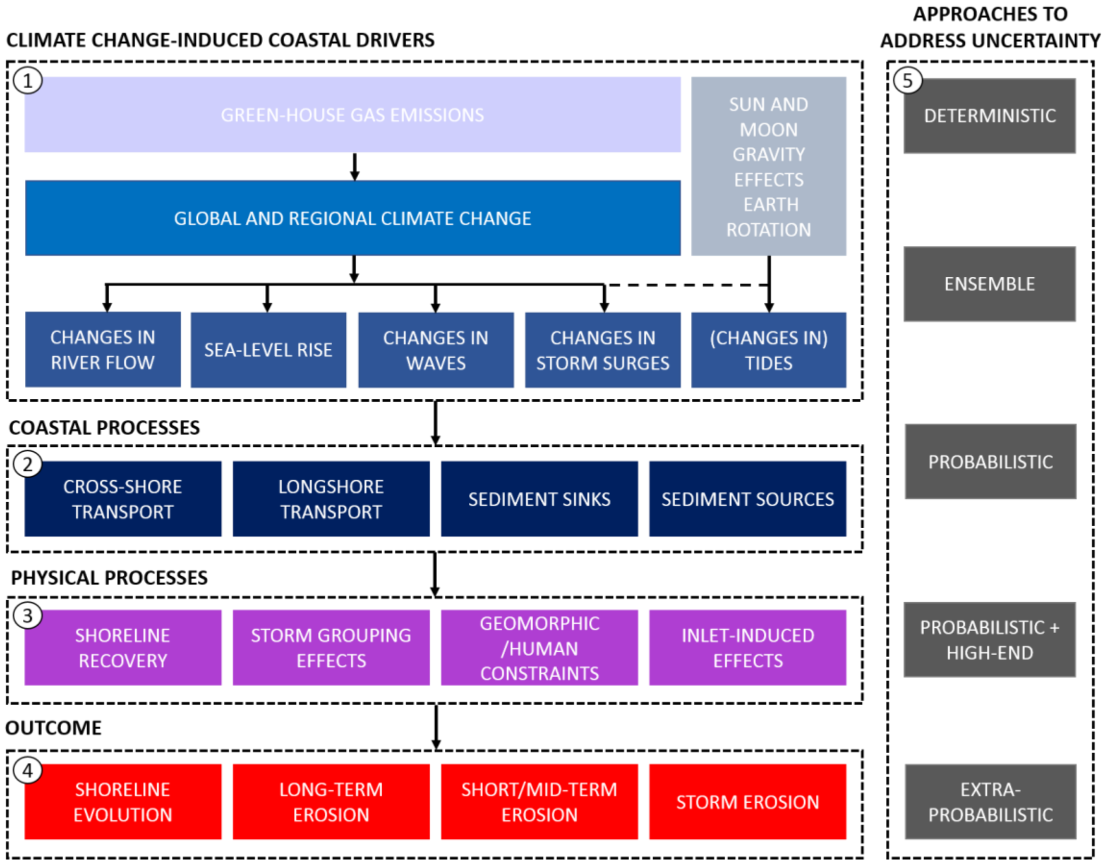


FIGURE 1 COMPONENTS OF A CLIMATE CHANGE-DRIVEN SHORELINE CHANGE FRAMEWORK.

Coastal processes responsible for shoreline change (box 2 in Fig. 1) and climate change-driven coastal drivers and their effects on shoreline changes (box 1 in Fig. 1) are discussed below.

## *2.2 Coastal processes responsible for shoreline change*

Both planform and beach profile shapes are mainly due but not limited to the combined action of mean sea level, storm surges, tides and wave conditions in the profile active zone (Dean and Dalrymple, 2001; Ranasinghe, 2016). In overall terms, waves set in motion the sediment and give rise to nearshore currents that carry that sediment, known as littoral transport, alongshore and/or cross-shore. Longshore sediment transport mostly results from longshore currents driven by waves breaking obliquely to the shoreline, but also from other longshore currents such as tidal currents in constrained areas (e.g., along the English Channel). These currents can carry sediment offshore if they turn seaward and become rip currents. Cross-shore sediment transport is primarily caused by wave- or wind-induced mean cross-shore flows and undertow and is largely responsible for the existence of sandbars and other beach profile changes (Dean and Dalrymple, 2001), which are more prevalent during coastal storms. Extreme weather events are often accompanied by a temporary increase in local mean sea level due to storm surges so that waves are able to reach higher elevations of the foreshore (Zang et al., 2004). In regions with high tidal range, storm surges may represent a great threat when they coincide with high spring tides (Toimil et al., 2017).

The processes shaping shorelines occur across many different time scales. While beaches change constantly under the action of individual waves that set in motion sediment and move it about, it is the erosion on the scale of hours and days that is responsible for the (cumulative) damage of extreme events (i.e., storm scale) (Dean and Dalrymple, 2001). The continued erosion or accretion due to the combined effect of storm surges, tides and waves over months and years allowing or not beaches to recover determines the mid-term shoreline erosion or accretion (i.e., seasonal to multiannual scale) (Miller and Dean, 2004; Dodet et al., 2018). Finally, long-term processes such as relative sea-level change, aeolian transport, soil erodibility, chronic fluvial sediment supply and gradients in longshore transport are often responsible for long-term shoreline changes (i.e., decadal to centennial scale) (Vitousek et al., 2017).

Therefore, spatial and temporal scales are somewhat related: nearshore cross-shore drivers (e.g., waves, storm surges, tides) mainly producing changes in beach profile and tending to operate on short- and mid-time scales; and long-term processes largely responsible for long-term changes and generally occurring with longer time scales (Miller and Dean, 2004). An exception to such generalization is the shoreline change driven by long-term sea-level change, which results in a readjustment of the beach profile to the new water levels and is a cross-shore response (Miller and Dean, 2004; Toimil et al., 2017). Other exceptions include the work developed by Harley et al. (2011), who show how the Narrabeen (Australia) pocket beach rotation is driven by longshore variations of cross-shore sediment transport.

### *2.3 Climate change-driven coastal drivers and their effects on shoreline changes*

Climate change-driven variations in mean sea level, waves, storm surges, tides, rainfall and river flows are expected to influence coastal processes, and hence shoreline changes, in many significant ways (Stive et al., 2002; Ranasinghe, 2016). One of the most certain impacts of climate change is global sea-level rise (SLR). However, when assessing SLR impacts, it is fundamental to consider local SLR rather than global. Local or relative SLR comprises both global and regional ocean changes, and local uplift or subsidence components induced by both natural and anthropogenic processes. Relative SLR may cause the long-term chronic recession of many coasts around the world, either directly (i.e., landward and upward displacement of the coast) or indirectly (e.g., inducing sand volume being borrowed from inlet systems) (Ranasinghe et al., 2013; Toimil et al., 2017). Under the debatable assumption that the nearshore bathymetry will not change, it will also have effects on nearshore hydrodynamics, resulting in more instances of extreme level thresholds being reached at the shorefront, and the likely amplification of waves, storm surges and tides due to changing non-linear interactions (Arns et al., 2017; Idier et al., 2017). Even moderate relative SLR can lead to a significant increase in the number of episodic extreme weather-related recession events (Wahl et al., 2018). In addition, climate change is expected to alter average wave conditions (Hemer et al., 2013; Camus et al., 2017) leading to increases or decreases in longshore drift (Idier et al., 2013), and changes in the magnitude and frequency of oscillation/rotation cycles in embayed beaches (Ranasinghe, 2016). This along with projected changes in storm surges (Vousdoukas et al., 2016) may be able to modify short- and mid-term erosion and accretion patterns. Furthermore, climate change may cause important variations in river flows (Nakaegawa et al., 2013). This is particularly relevant for inlet-interrupted coasts, where increases or decreases in river discharge may produce decreases or increases of shoreline recession, respectively (Ranasinghe et al., 2013). Also relevant for coasts adjacent to inlets are climate change-driven variations in rainfall/runoff and land use (affecting soil erodibility). These will result in increases or decreases in fluvial sediment supply and hence, in decreases or increases, respectively, in shoreline retreat (Ranasinghe et al., 2013).

## 3. Uncertainty cascading and management

Projections of driven coastal hazards for the 21st century in response to different socio-economic and demographic pathways are necessary to assess climate change shoreline changes. A sequence of steps is usually undertaken to produce a climate change projection at global and regional scales (top-down or scenario-led approaches, Wilby and Dessai, 2010). The first step consists in the generation into scenarios of atmospheric greenhouse gas (GHG) emissions based on hypothetical socio-economic and demographic pathways. Biogeochemical models are used to translate emission scenarios into GHG and aerosol concentration scenarios, which are the fundamental input to coupled Atmosphere-Ocean Global Climate Models (AOGCMs) to produce global climate projections. These global projections can be downscaled to the regional/local scale with the use of dynamical downscaling (Regional Climate Models, RCMs) or statistical downscaling methods. For example, climate variable relevant for temperate sandy shoreline change assessments that have been downscaled so far include sea level projections (Slangen et al., 2014; Kopp et al., 2014), waves (Hemer et al., 2013), surges (Vousdoukas et al., 2016) and river runoffs (Dayon et al., 2018). Bias correction is required before forcing impact models. Uncertainty associated to each step of a top-down climate change impact analysis is introduced (see Fig. 1), expanding the range of uncertainty through the whole process (cascade process). Two sources of uncertainty can be identified: Knowledge Uncertainty due to our poor knowledge of the climate change problem, and Intrinsic Uncertainty inherent to the problem (Giorgi, 2010). Emission scenarios and internal variability of climate system can be considered as Intrinsic Uncertainty and a full range of possible outcomes, particular low-probability-high impact outcomes, should be provided. The IPCC in the last AR5 provides likely range and median values for SLR conditional to four Representative Concentration Pathways (RCP2.6, RCP4.5, RCP6.0 and RCP8.5) corresponding to different trajectories of GHG emissions. RCPs include implied policy actions to achieve mitigation and were selected to have different targets in terms of radiative forcing at 2100. Internal climate variability uncertainty is characterized by performing ensembles of transient simulations starting at different times in the control period. Concentration scenario uncertainty due to an approximate representation of relevant processes in biogeochemical models, AOGCM configuration uncertainty due to a different representation of dynamical and physical processes, bias uncertainty related to systematic model errors, downscaling approach to produce climate information at a scale resolution demanded by impact models and shoreline evolution modelling approaches (Le Cozannet et al., 2019), categorized as the "bad" (knowledge) uncertainty should be reduced as much as possible advancing in science research. Paradoxically, increased knowledge might lead to an increase in uncertainty (Giorgi, 2010).

Probabilistic frameworks (rather than deterministic, single value) are necessary to consider the different uncertainty sources. However, an unmanageable number of simulations is required to sample the full uncertainty space to cover multiple scenarios, model configurations, internal variability, bias and downscaling methods. Generally, studies have limited the exploration of the uncertainty space to individual dimension (e.g., the quantification of model configuration using a reduced number of GCMs or RCMs for a particular scenario). As mention previously, climate-driven coastal drivers such as waves, storm surges, tides, currents, fluvial discharges, and sea level anomalies cause episodic beach and dune erosion on timescales of hours to days during storm events while relative sea level changes will result in chronic coastline recession on long-term time scale (Ranasinghe, 2016). Shoreline changes result from the combination of multiple drivers and/or hazards in the weather and climate domain spanned over multiple temporal scales (compound weather and climate events, Zscheischler et al., 2018). Top-down approaches are difficult to be implemented to asses climate change impacts associated with multiple interacting drivers. For this reason, the effect of climate change has been analysed for each driver or hazard independently. For example, in the case of shoreline retreat considering only SLR (Le Cozannet et al., 2015; Toimil et al., 2017) as the main climate change driver, or the assessment of future sediment transport due to waves changes derived from five RCMs under A1B scenario (Casas-Prat el al., 2016).

The importance of these sources of uncertainty depends on different factors such as the time horizon of the projection, the variable under consideration and the scale of interest (Giorgi, 2010). In general, scenario and model configuration uncertainty dominate for long term climate change (Clark et al., 2016), especially at global scale. The internal variability becomes of primary importance for short- and near-term 21st century projections and higher order climate statistics. For instance, the uncertainty associated to downscaling methods dominates over climate scenario and model uncertainties in global wave climate projections (Morim et al., 2018; Hemer et al., 2013).

SLR can amplify the episodic erosion from storms and drive chronic erosion on sandy shorelines (Ranasinghe, 2016). AR5 IPCC sea-level rise projections are obtained by summing different contributions as thermal expansion of ocean water, the melting of glaciers, ice caps and ice-sheets and changes in land water storage. Sampling the uncertainty of these contributions, SLR for the RCPs will "likely" (medium confidence which corresponds to a 67% probability) be in the 5 to 95% ranges derived from the Coupled Model Intercomparison Project Phase 5 (CMIP5) climate projections in combination with process-based models of glacier and ice sheet sur-face mass balance, with possible ice sheet dynamical changes assessed from the published literature.

However, AR5 only projects SLR likely ranges excluding higher magnitudes of ice loss which are only implied if less likely outcomes are included. Future impacts on coastal shoreline would be underestimated if only SLR projections that characterize just likely sea-level changes. Upper limits for global SLR by 2100 have been published (Horton et al., 2014; Jevrejeva et al., 2014) which combines modelling outcomes with expert knowledge, mainly regarding future ice-sheet contributions (Bamber and Aspinall, 2013). Recent studies highlight larger inherent uncertainties associated with the potential rapid disintegration of the Antarctic Ice Sheet (DeConto and Pollard, 2016). These results have been incorporated in updated probabilistic SLR projections (Le Bars et al., 2017; Kopp et al., 2017) and can be integrated with other results within a single framework using extra-probabilistic theories of uncertainty (Le Cozannet et al., 2017a).

Local SLR is critical for impact assessment. The spatial variability of local SLR arises from regional ocean steric and ocean dynamics effects and non-climatic effects such as glacio-isostatic adjustment, tectonics and sediment compaction (Wöppelmann and Marcos, 2016). Probabilistic local SLR projections are obtained combining a joint probability distribution for global mean thermal expansion and regional ocean dynamics derived from a CMIP5 ensemble, with glacier mass-balance changes, anthropogenic changes in land-water storage, ice sheet contributions (expert elicitation in Bamber and Aspinall, 2013, or physical model results including ice-shelf hydrofracturing and ice-cliff collapse in DeConto and Pollard, 2016) and regional non-climatic effects based upon a spatiotemporal statistical model of tide-gauge observations (Kopp et al., 2014; Kopp et al., 2017). Uncertainty associated with SLR contributions for each of the individual component has been sampled using each time-dependent probability distributions of cumulative contribution.

The generic approaches identified in literature to address uncertainty in climate change-driven shoreline change modelling are summarized in Fig. 1 and described in Table 1. They include deterministic methods that rely on a single input parameter, model parameterization and/or model providing highly uncertain results; ensembles that consider a limited number of input parameters, model parametrizations and/or models; probabilistic methods that use the probabilistic distribution of input parameters and/or model parametrizations requiring multiple model simulations; probabilistic methods plus high-end scenarios (e.g., H++ scenarios, Nicholls et al., 2014), which combine probabilistic approaches and deterministic values to compute an unlikely outcome with potentially high impacts; and extra-probabilistic or possibility methods that seek to assign imprecision to probabilistic measures, which can be achieved, for example, by integrating the probabilistic information given in the form of confidence intervals and expert judgement (e.g., Ben Abdallah et al., 2014; Le Cozannet et al., 2017a).

| Approaches to address uncertainty | Definitions adopted in this report |
|---|---|
| Deterministic | Results are presented in a deterministic way (single value), relying on a single input parameter, model parametrization and/or model. For example, a single sea level scenario, or a single model for computing the effects of longshore or cross-shore transports. |
| Ensemble | A limited number of input parameters, model parametrizations and/or models are used to compute an aggregate of outcomes. |
| Probabilistic | The uncertainties of the outcome are presented in the form of a probabilistic distribution, which relies on probabilistic descriptions of input parameters, model parametrizations and/or model. |
| Probabilistic plus high-end | In addition to the previous probabilistic approach, a single deterministic value is used to compute an unlikely outcome with potentially high impacts (e.g., H++ scenarios, Nicholls et al., 2014). |
| Extra-probabilistic | The uncertainties in the outcome are presented in the form of several credible probability functions conveying aleatory uncertainties as well as uncertainties on the shape of the distribution itself (e.g., Ben Abdallah et al., 2014; Le Cozannet et al., 2017a). |

**Table 1 Different approaches toward uncertainties that can be applied at each step of the analysis (see also Fig. 1).**

# 4. Frameworks to assess climate change-driven shoreline changes

One major challenge for coastal engineering and science is to develop models for the reliable prediction of long-term shoreline change that includes the effects of climate change and uncertainty estimates. At present, there is no full satisfactory shoreline-change model that allows coupling hydrodynamics, sediment transport and morphology (e.g., as in physics-based 2D/3D models); reproducing short-, mid- and long-term shoreline changes accurately; and that is not prohibitively expensive, enabling a robust quantification of uncertainty. Our still poor understanding of littoral sediment transport, our inability to represent fully the hydrodynamics of the surf zone, our current (limited) computational resources and the large uncertainties in projected shoreline-change drivers are good reasons to think that such “ideal” model may well be several years in the making. However, significant progress has been made over the last decade to develop, based on our present state of knowledge and resources, a wide range of possible frameworks for the assessment of long-term shoreline change within the context of climate change (Ranasinghe et al., 2012; Toimil et al., 2018; Vitousek et al., 2017). Modelling strategies composed of different process-based (or empirical) models responding each of them to cross-shore or long-shore processes, and to other sinks or sources that contribute to sediment budget hold much promise in this regard. Some of them have proven reliable on reproducing shoreline changes over a broad spectrum of relevant time scales to a fair degree of accuracy, while allowing addressing uncertainty.

In what follows, we provide a review of existing frameworks specifically focused on the assessment of climate change-driven shoreline changes, for both uninterrupted and inlet-interrupted coasts, identifying the elements displayed in Fig. 1. The criterion for classification is to include the works in the category (or categories) we consider they may be relevant for the community.

## 4.1 Uninterrupted coasts

For review purposes, we consider distinguishing between small pocket beaches, where longshore transport gradients are often neglected within the sediment budget; long embayed beaches, which are subjected to oscillations and rotations caused by climate variability, although with small change to mean orientation in the long term (Ranasinghe, 2016); and open beaches, where both short-term transport and longshore drift play a fundamental role in shoreline change.

### 4.1.1 Small pocket beaches

Over the last five decades, the method most widely used to estimate coastal recession due to SLR has been the Bruun Rule (Bruun, 1962). The Bruun Rule predicts a landward and upward displacement of the cross-shore profile in response to a rise in mean seal level. However, determining whether this approach performs within acceptable limits today is very complex, as SLR is still a minor contributor to shoreline change on many of the world’s coasts. This has led numerous authors to argue against its efficacy, for instance, demonstrating its conservationism, recommending it be abandoned (Cooper and Pilkey, 2004; Ranasinghe and Stive, 2009), or even offering alternatives (Ranasinghe et al., 2012; Toimil et al., 2017). These alternatives often include more generalized versions that incorporate additional physical processes, which might be relevant for shoreline change over different time scales. For instance, Rosati et al. (2013) presented a modified form of the Bruun Rule that deems the full range of parsing cross-shore transport from seaward to landward, based on the prevailing storm and surge conditions (i.e., overwash and aeolian processes) and whether there is a deficit or surplus of sand in the profile with respect to the equilibrium beach profile. The authors illustrated the framework deterministically considering a rise in mean sea level of 0.5 m as the only climate-related driver.

However, as mentioned earlier, any future shoreline change will result from the combination of long-term SLR, and short-term waves and local water levels. Two different approaches have been identified in this regard in literature: The Probabilistic Coastline Recession (PCR) model first developed by Ranasinghe et al., (2012) for Narrabeen Beach (Sydney, Australia), and further applied to the same beach on different studies (Wainwright et al., 2015; Jongejan et al., 2016), as well as to other beaches (e.g., in the sandy coast of Aquitaine in southwestern France, Le Cozannet et al., 2019); and the methodology proposed by Toimil et al. (2017) to manage coastal erosion at the regional scale. The PCR model provides probabilistic estimates of net long-term coastal dune recession as a proxy for shoreline recession due to the combined effect of storm erosion and global SLR projections (Meehl et al., 2007). To that end, and assuming no changes in storminess over this century, 110-year time series of storms are generated using joint probability distributions of design storm characteristics within a Monte Carlo simulation (Callaghan et al., 2008), in which storm grouping is considered to be represented appropriately. For each storm, SLR is also occurring, and dune recession is estimated using the process-based dune impact model proposed by Larson et al. (2004), allowing for beach recovery between storms which is obtained empirically. According to the authors, the bootstrapping method employed in the model minimizes the uncertainty associated with predicted probabilistic estimates. Toimil et al. (2017) developed a methodology to predict shoreline changes acted upon waves, storm surges, astronomical tides, and SLR probabilistically. Based on the small changes provided by the statistical projections of waves and storm surges developed by the authors within this framework using 40 GCMs, the approach considers the use of historical data and a vector autoregressive VAR model (Solari and van Gelder, 2012) to generate thousands of 90-year multi-variate hourly time series of these dynamics. The time series are combined with the astronomical tide reconstructed over this century and regional SLR curves (RCP8.5 mean value and standard deviation, from Slangen et al., 2014) into a shoreline evolution model. This model is composed by two modules: cross-shore transport due to wave setup, storm surges and astronomical tides following the equilibrium model of Miller and Dean (Miller and Dean, 2004); and cross-short transport due to SLR following an equilibrium beach profile change model (Bruun, 1962). Data and model enable to obtain probabilistic estimates of extreme recessions and long-term shoreline changes, as well as to quantify uncertainty. The use of high-resolution time series of coastal drivers has the advantage of accounting for storm occurrence and grouping and beach recovery without the need of introducing additional variables into the stochastic simulation. Both Ranasinghe et al. (2012) and Toimil et al. (2017) probabilistic approaches are a step forward to comply with the new risk-based informed coastal planning frameworks that require robust uncertainty estimates.

### 4.1.2 Long embayed beaches

Climate change-driven changes in net longshore sediment transport caused by changes in average wave climate may lead to changes in the mean orientation of embayed beaches, resulting in their permanent re-alignment (Ranasinghe, 2016). Zacharioudaki and Reeve (2011) looked into what the evolution of the coast around Poole Bay (UK) could be under a range of variations in future wave characteristics. Changes in mean sea level, tidal range and the swell component of wave conditions, although very relevant to shoreline change, have been excluded from this study. In that work, the one-line model described in Zacharioudaki and Reeve (2010) is used to obtain monthly and seasonal statistics of shoreline change for the time-slice 2071-2100 with respect to 1961-1990. In order to simulate time series of monthly or seasonal shoreline positions, the model is performed for individual 30-year time series of projected waves using two combinations of RCMs and GCMs with different resolutions, and with the shoreline set back to its initial shape after each shoreline shape outputs are derived. The way authors address uncertainty is using nine climate-change scenarios.

Simpler assessments of shoreline recessions in long embayed beaches include the works developed by Snoussi et al (2009) and Alexandrakis et al. (2015). The first used the Bruun Rule to determine the upward and landward displacement of the Tangier coast (Morocco) associated to three SLR scenarios (global estimates based on Warrick et al., 1996) by 2050 and 2100. The second obtained shoreline retreats in the beach in front of Rethymnon city (Crete Island) for time periods of 10, 20 and 30 years and for three SLR values (IPCC, 2007) by applying the Dean (1991) formula.

### 4.1.3 Open beaches

The assessment of climate change-induced shoreline changes in open coasts is of greater complexity than in small pocket beaches, since both cross-shore and longshore transport need to be considered. Existing works that tackle this issue entail the analysis of future wave-driven coastal sediment transport developed by Casas-Prat et al. (2016), the assessment of the SLR-induced shoreline response carried out by Dean and Houston (2016), and the approach proposed by Vitousek et al. (2017) for predicting shoreline evolution due to longshore and cross-shore transport driven by projected waves and SLR. In addition, we include the frameworks presented by Le Cozannet et al. (2016, 2018) to address uncertainty in future shoreline change.

Casas-Prat et al. (2016) evaluated the impact on the longshore and cross-shore sediment transport along the Catalan coast (Spain) resulting from climate projections obtained from five combinations of RCMs and GCMs. Special emphasis is given to how inter-model variability translates from wave projections to wave-driven coastal impacts, in this case, through waves. The CERC formula and the SBEACH profile evolution model developed by Larson and Kraus (1989) are used to compute longshore and cross-shore sand transport rates, respectively. The use of non-computationally expensive modelling tools enables the assessment of the suitability of each RCM– GCM combination considered to forecast changes in coastal dynamics. The approach provides projected absolute change in median longshore transport and storm-basis time series of eroded volumes caused by the impact of a wave storm for the time slices 2071-2100 with respect to 1971-2000. The uncertainty added by the RCMs to the coastal sediment transport response is quantified by the authors through the analysis of the discrepancies in patterns of change of forcing wave parameters.

Dean and Houston (2016), similar to Stive et al. (1991) and then to Stive (2004), proposed a sediment budget with the terms representing all phenomena affecting shoreline change. These phenomena include the Bruun-Rule recession, onshore transport, sand sources (e.g., beach nourishment), sinks that take sand from the littoral system (e.g., ebb shoal growth, dredged material disposed outside the littoral zone), and longshore transport gradients. The application used the RCP SLR scenarios (Church et al., 2013) enhanced with land subsidence rates as the climate-related driver, and provide projected shoreline change rates from 2015 to 2100 assuming beach nourishment at the rate from 1972 to 2007. The authors address uncertainty using an ensemble of SLR scenarios and considering the mean values and standard deviations in both relative SLR scenarios and sediment transport rates.

Le Cozannet et al. (2016) developed a study to quantify uncertainty in the evolution of sandy shorelines under the Bruun Rule assumption. They use the sedimentary budget proposed by Stive (2004) and probabilistic SLR scenarios based on IPCC (Church et al., 2013) to provide future shoreline changes that account for all uncertain hydro-sedimentary processes in low- and high-energy coasts. The application considers the case of idealized wave-exposed sandy beaches with infinite sand availability and defines realistic probability functions for each parameter involved in the sand budget: Bruun-Rule recession, storm wave-induced retreat, aeolian transport, other cross-shore effects (e.g., wave-nonlinearity-driven onshore sand transport), and longshore sedimentary processes in the absence/presence of groins. Le Cozannet et al. (2016) constructed the probability functions constructed using ranges of typical values provided by Stive (2004) and based on observations in the Netherlands and Australia. Finally, the authors propagate the uncertainties through the model equation to obtain the shoreline change projections and quantify their relative importance by performing a sensitivity analysis.

Vitousek et al. (2017) proposed a modular approach that integrates longshore and cross-shore transport induced by GCM-projected waves and SLR (Church et al., 2013), which allows it to be applied to both long and small pocket sandy beaches (in the latter case, disabling longshore component). The model is composed by longshore transport due to waves following the one-line approach (Larson et al., 1997); cross-shore transport due to waves using an equilibrium shoreline change model (Yates et al., 2009; Long and Plant, 2012); and cross-shore transport due to SLR employing an equilibrium beach profile change model (Bruun, 1962). The application of the model to the forecast period (2010-2100) allows to obtain one instance of how shoreline evolution could be over 90 years driven by a single projected time series of wave conditions (one GCM-RCM) and an ensemble of seven SLR scenarios. The way the authors address uncertainty is by considering many SLR scenarios and with data assimilation based on seasonal wave activity. More recently, O'Neill et al. (2018) used this modelling framework to obtain projected 21st century coastal flooding in the Southern California Bight considering morphodynamic changes.

More recently, Le Cozannet et al. (2019) presented a research work focused on estimating the uncertainty of coastal impact models by considering the difference in shoreline change projections derived by applying the Bruun Rule and the PCR model (described in section 4.1.1) to the Aquitaine coast (France). The application consists of setting up a sediment budget in the absence of human interventions, inlets or other major sediment sources or sinks in which the future shoreline changes resulting from the application of the two coastal impact models combine with longshore gradients in sediment transport derived empirically (based on past records). The authors address uncertainties though using probabilistic regional sea-level rise projections (Kopp et al., 2014), incorporating the geodetic uncertainty associated to vertical ground motions and considering observed variability of longshore sediment trends and shoreface beach slopes.

## *4.2 Inlet-interrupted coasts*

Shorelines in the in the vicinity of inlets (e.g., tide-dominated estuaries, wave-dominated estuaries, barrier-island inlets, lagoons) are influenced not only by the climate change-driven drivers affecting uninterrupted coasts but also by the effects that inlets can have in their long-term evolution. This review only considers research works focused on assessing inlet-induced climate change impacts on adjacent beaches (mainland).

Ranasinghe et al. (2013) and Toimil et al. (2017) have focused on studying the climate change-driven effects that wave- and tide-dominated estuaries can have in adjacent coasts, respectively. Both research works have demonstrated that the no consideration of sediment demands and/or supplies in the sediment budget others than the Bruun effect (Bruun, 1962) may lead to misleading shoreline change estimates. Ranasinghe et al. (2013) addressed this issue by developing a scale-aggregated model for wave-dominated, micro-tidal environments, which have little or no intertidal flats, backwater marshes or ebb tidal deltas. In this work, the four physical processes considered to contribute to shoreline change are the SLR-driven Bruun effect (Bruun, 1962), basin infilling due to the SLR-induced increase in basin accommodation space, basing volume change due to climate change-driven increases or decreases in river flow, and increases or decreases in fluvial sediment supply. The model is applied deterministically to assess the shoreline change by 2100, and no uncertainty estimates are provided. The authors use global projections of SLR, rainfall and river flow (Alley et al., 2007). More recently, Toimil et al. (2017) proposed a scale-aggregated model for tide-dominated, macro-tidal environments in response to climate change-modified forcing. Based on the nature of the inlet concerned, the physical processes deemed as shoreline-change contributors are SLR-driven landward displacement of the coastline (Bruun, 1962), basin infilling due to the SLR-induced increase in basin accommodation space, and SLR-driven ebb tidal delta volume change. In this case, fluvial sediment supply was considered negligible as the estuaries included in the assessment were regulated by dams or permanently dredged. The authors couple the SLR-induced shoreline recession due to basin infilling and ebb tidal delta volume change (acting as longshore sinks) with the shoreline change model described in section 4.1.1 to obtain probabilistic estimates of hourly shoreline evolution from 2010 to 2100, and a robust quantification of uncertainty, also in coasts interrupted by tide-dominated estuaries. It should be noted that the use of the equilibrium formulation to describe the complex behavior of an inlet is based on simplifying assumptions. For example, considering that the estuary and its elements reach dynamic equilibrium state, since the formulation are not able to describe neither their temporal evolution nor their spatial distribution. There is also a lag between SLR and the system's morphological response. Ranasinghe et al. (2013) considered a linearized single-element version of ASMITA (only valid for small inlet-basin systems, van Goor et al., 2003), in which they showed that this lag effect could be represented by including a coefficient of about 0.5 in the basin-infilling equation.

ASMITA (Aggregated Scale Morphological Interaction between a Tidal-inlet system and the Adjacent coast) is a scale aggregated model originally developed by Stive et al. (1998) and based on the conservation of sediment within a three-element system (ebb delta, channel, and basin) and the adjacent nearshore area (beach). The model assumes that the morphological interaction between the three system elements are due to diffusive sediment transport and that the system is in morphological equilibrium if undisturbed. When the system is perturbed (e.g. due to SLR), the three system elements change their volume and evolve towards an empirically specified dynamic equilibrium state. Under this condition, the basin borrows sand from the adjacent beach to satisfy a demand that is proportional to the rate of SLR. Hinkel et al. (2013) applied an adapted version of the ASMITA model (Stive and Wang, 2003) to carry out a global analysis of erosion of sandy beaches due to SLR. The authors developed and applied a simple first-order erosion model in which SLR-induced shoreline recession results from the combination of the direct effect of profile translation (i.e., the Bruun effect) and the indirect effect of tidal inlets in about 200 major tidal basin complexes. Global-mean SLR scenarios were obtained with the climate model CLIMBER-2 (Petoukhov et al., 2000). Uncertainty in climate was considered by using three different climate sensitivities of 1.5 K (low), 3 K (medium) and 4.5 K (high).

# 5. Discussion and recommendations: can we identify a best approach?

The assessment of shoreline changes is a complex site-specific issue. The most influential factors comprise the physical characteristics of sediment, local wave and mean sea level conditions, the bathymetry, as well as the orientation, configuration and exposure of the coast. Climate change is modifying the oceans in many different ways, including changes in coastal drivers (e.g., mean sea level, waves, storm surges, tides, river flow) responsible for coastal processes, and hence for shoreline change. Depending on the local coastal settings, it may not be necessary to consider every option displayed in Fig. 1. None of the existing studies can be identified therefore the best approach to address all the casuistry that may arise, and a method that allow to select the most appropriate modelling framework for the different types of environment in a consistent and transparent way is lacking. Until this method is available, the following concluding remarks may be found good practice in this field.

First, we need to look upon the whole range of forcing conditions involved in shoreline recession, and any relevant sediment sink and/or source. For example, neglecting the effect of waves and storm surges and considering sea-level rise as the only driver for coastal erosion may underestimate the impact of climate change and mislead adaptation planning in the worst case.

Second, modelling frameworks should not only ensure consistence among the different coastal processes and drivers, but also address physical processes (e.g., shoreline recovery) and/or constraints accordingly. For instance, reliable predictions of storm erosion require to consider the possibility of storm grouping and beach recovery between storms.

Third, the progression from event to multidecadal and centennial timescales demands increasing generalization of modelling approaches, but a solid understanding of processes is still required to support the simplifying assumptions. In addition, we need to strive for this generalization not to entail a low resolution of the outcome.

Finally, the weakest link is the lack of consistency in the management of uncertainty across all components of the modelling framework. Some reviewed works address uncertainty due to the random nature of waves, storm surges or storm events, but none of them includes sea-level rise in probabilistic terms. When working with sea-level rise, uncertainty can be addressed to some extent by using the mean value plus/minus the standard deviation. However, a similar approach combining likely and high-end scenarios has not been explored yet for other important variables such as waves and storminess. All these key aspects in relation to the most relevant reviewed papers are provided in Table 2.

| | Coastal processes | Climate change-driven coastal hazards | Physical processes | Outcome | Resolution of the outcome | Approach towards uncertainty |
|---|---|---|---|---|---|---|
| | Uninterrupted coasts | | | | | |
| | Small pocket beaches | | | | | |
| Rosati et al. (2013) | Cross-shore (seaward and landward) transport | SLR projections | Seaward transport and landward transport due to overwash and aeolian transport | Shoreline recession, volumetric transport and profile changes for a given horizon | Single value estimate | Deterministic |
| Ranasinghe et al. (2012) | Cross-shore transport | SLR projections (scenarios) and design storms | Storm events, storm duration, dune recovery, storm grouping | Storm-basis time series of dune erosion volumes and recession over the 21st century | Storm-basis dune recession. Extreme events and long-term analysis | Probabilistic. Joint Probability Method, bootstrapping technique (storm events) |
| Toimil et al. (2017) | Cross-shore transport and longshore sinks | Local waves, storm surges, and astronomical tides and regional SLR projections | Extreme events, beach recovery, events duration, events grouping, SLR-driven Bruun | Time series of shoreline change over the 21st century. Extreme events and long-term analysis | Hourly shoreline changes | Probabilistic. Stochastic generation of waves and storm surges and SLR standard deviation confidence levels |
| | Long embayed beaches | | | | | |
| Zacharioudaki and Reeve (2011) | Longshore transport | Wave projections (2 RCM-GCM with different resolutions) | Shoreline response to the spatial gradients of the alongshore component of sediment transport | Time series of monthly or seasonal shoreline positions. One-line simulations are performed for each individual 30-year time-series of waves but with the shoreline set back to its initial shape after each shoreline shape outputs | Monthly and seasonal shoreline change statistics relative to the present | Ensemble of 9 scenarios and statistical analysis of significance of changes (t-test, ks-test) over wave characteristics and shoreline changes |
| | Open beaches | | | | | |
| Casas-Prat et al. (2016) | Cross-shore and longshore transport | Wave projections (5 RCM-GCM) | Long-shore wave energy flux, storm events | Projected absolute change in median longshore transport and storm-basis time series of eroded volumes caused by the impact of a wave storm | Annual longshore transport and storm-basis eroded volumes | Ensemble of 5 RCM-GCM |
| Dean and Houston (2016) | Cross-shore (seaward and landward) and longshore transport, sand sinks and sources | Relative SLR projections | SLR-driven Bruun, erosion rates due to SLR-driven ebb shoal growth, nourishment rates, longshore drift rates | Averaged shoreline change rates (m/yr) for a period | Annual mean and standard deviation shoreline changes | Ensemble of 4 RCPs plus standard deviation confidence levels for each RCP |
| Le Cozannet et al. (2016) | Cross-shore and longshore transport | SLR projections | SLR-driven Bruun, Aeolian processes, cross-shore effects (wave-nonlinearity-driven onshore sediment transport), storm waves-induced retreat, longshore processes | Time series of shoreline change over the 21st century. | Annual mean shoreline change | Fully probabilistic |
| Vitousek et al. (2017) | Cross-shore and longshore transport and long-term trend (sinks/sources) | Wave projections (dynamic downscaling 1 GCM-RCM) and SLR projections | Wave energy, beach recovery, storm grouping, SLR-driven Bruun | Time series of shoreline change over the 21st century | Daily shoreline changes | Deterministic (waves) and ensemble of 7 SLR scenarios |
| Le Cozannet et al. (2019) | Cross-shore and longshore transport | SLR projections (scenarios) and design storms | Storm events, storm duration, dune recovery, storm grouping, longshore sediment transport gradients | Time series of shoreline change over the 21st century. | Annual mean shoreline change | Probabilistic. Joint Probability Method, bootstrapping technique (storm events) and probabilistic SLR projections |
| | Inlet-interrupted coasts | | | | | |
| Ranasinghe et al. (2013) | Cross-shore transport and longshore sinks | IPCC AR4 projections of SLR, rainfall and river flow | SLR-driven Bruun and estuary effects (basin infilling, river flow-driven basin volume change and rainfall/runoff-driven changes in fluvial sediment supply) | Total potential worst-case CC-driven coastline change by 2100 | Single value estimate | Deterministic |
| Toimil et al. (2017) | Cross-shore transport and longshore sinks | Local waves, storm surges, and astronomical tides and regional SLR projections | Extreme events, beach recovery, events duration, events grouping, SLR-driven Bruun and estuary effects (ebb tidal delta rise and basin infilling) | Time series of shoreline change over the 21st century. Extreme events and long-term analysis | Hourly shoreline changes | Probabilistic. Stochastic generation of waves and storm surges and SLR standard deviation confidence levels |
| Hinkel et al. (2013) | Cross-shore transport and longshore sinks | Global-mean SLR projections | SLR-driven Bruun and estuary effects (basin infilling) Nourishment | Land loss rates ($km^2$/yr) over the 21st century | Global annual shoreline recession | Ensemble of 6 global SRL scenarios and three different climate sensitivities |

**TABLE 2 SUMMARY OF THE KEY ELEMENTS OF THE MOST RELEVANT EXISTING MODELLING FRAMEWORKS TO ASSESS CLIMATE CHANGE-DRIVEN SHORELINE CHANGES THAT HAVE DEVELOPED OVER THE LAST DECADE (IN THE ORDER OF THEIR APPEARANCE IN THE TEXT).**

Future shoreline changes are uncertain and will probably remain so over the coming decades. Stakeholder's priorities and needs are crucial and ultimately the key factor in determining the approach toward uncertainty more appropriate in every particular case. A promising way forward in this regard may well consist in reversing current shoreline change-modelling procedures. This involves shifting from predicting top-down approaches that use climate change scenarios for the assessment of impacts (e.g., shoreline changes) to resilience bottom-up approaches focused on identifying stakeholder's needs and preferences (e.g., risk aversion) and applying the appropriate modelling and uncertainty frameworks according to these needs. The bottom-up approach is central to the concept of climate services supported by ERA4CS (Hewitt et al., 2012; Brasseur and Gallardo, 2016; Monfray and Bley, 2016; Le Cozannet et al., 2017b). As an illustration, Table 3 provides questions identified as relevant to stakeholders (e.g., adaptation practitioners) and information needs. These research needs raise in turn the following issues to coastal modelers when coming to develop future projections of shoreline change: (1) Is it necessary to consider the uncertainty associated to all possible scenarios, including those with high impacts, which have low probabilities or whose probability is difficult to quantify? (2) Is it necessary to disentangle the uncertainty associated to each of the drivers deemed? (3) Which modelling and uncertainty frameworks best satisfy stakeholder's preferences and risk aversion?

| Question from adaptation practitioners | Reasons for information needs | Research area |
|---|---|---|
| Can we quantify the impacts of climate change or sea level rise in current shoreline changes? | As adaptation is a slow process (decades for relocation), there is a need for early detection of climate induced shifts toward erosion for a timely implementation of actions | Detection or attribution of climate change impacts (Cramer et al., 2014) |
| Can we identify when climate change will modify current sedimentary processes? | Identify when and where current adaptation strategies (e.g., nourishment) may fail and new approaches (e.g., relocation) will be required. | Times of emergence of climate-induced shifts toward erosion (Le Cozannet et al., 2016) |
| Can we quantify future shoreline positions and rates at specific time steps in the future? | Planning adaptation, establishing adaptation pathways. | Coastal impact studies (see Table 2) |
| Can we quantify the impacts of different adaptation options? | Evaluate which adaptation option may best satisfy stakeholder's preferences. | Evaluation of adaptation (Hallegatte, 2009) |

**TABLE 3 INFORMATION NEEDS REGARDING SHORELINE CHANGE PROJECTIONS AND KEY CHALLENGES FOR COASTAL MODELLING**

Uncertainty is not only related to sea level rise but also to other coastal processes affecting mean sea level (e.g., vertical land motion) and sediment dynamics (e.g., effects of wave and currents, sediment holes and sources, or human impacts). Their characterization needs to consider specific needs, such as enabling local stakeholders and decision-makers to better position regulatory scenarios (if any) of sea level rise with respect to all possible shoreline and potentially define an acceptable level of risk loss that is more cautious than regulation, so as to make assets more secure. The choice of a framework for uncertainty analysis depends on the quantity, the quality and the relevance of the available data, as well as on the degree of risk aversion of decision-makers.

Among the needs listed in Table 3, those related to the detection and attribution of climate change impacts on shoreline changes and the identification of times of emergence are the most demanding in terms of precision and accuracy of modelling outcomes. In particular, a formal attribution of shoreline changes may not be attainable yet by means of a modelling approach (Le Cozannet et al., 2014). However, depending on the uncertainty framework implemented, one may reach different levels of confidence.

Since climate change and, in particular, sea-level rise is recognized to be a major threat for many coastlines around the world, stakeholders and decision-makers require full information on uncertainty, high-end estimates, future projections of shoreline change, and relevant adaptation options within the context of current practices and governance arrangements. This often results in strong heterogeneity in shoreline change assessments. Current challenges involving science-policy interactions require (1) the definition of applicable methods to include climate change impacts on sandy coasts under, and (2) the need to transfer research developments into the realm of operational applications and regulation. For example, in the Coastal Risks Prevention Plans in France, the Plan to Promote the Environment for Adaptation to Climate Change in Spain, the Shoreline Management Plans in UK, and the Coastline Management Manual in the Netherlands.

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