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Using quantitative dynamic adaptive policy pathways to manage climate change-induced coastal erosion

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ABSTRACT

Adaptation requires planning strategies that consider the combined effect of climatic and non-climatic drivers, which are deeply uncertain. This uncertainty arises from many sources, cascades and accumulates in risk estimates. A prominent trend to incorporate this uncertainty in adaptation planning is through adaptive approaches such as the dynamic adaptive policy pathways (DAPP). We present a quantitative DAPP application for coastal erosion management to increase its utilisation in this field. We adopt an approach in which adaptation objectives and actions have continuous quantitative metrics that evolve over time as conditions change. The approach hinges on an adaptation information system that comprises hazard and impact modelling and systematic monitoring to assess changing risks and adaptation signals in the light of adaptation pathway choices. Using an elaborated case study, we force a shoreline evolution model with waves and storm surges generated by means of stochastic modelling from 2010 to 2100, considering uncertainty in extreme weather events, climate variability and mean sea-level rise. We produce a new type of adaptation pathways map showing a set of 90-year probabilistic trajectories that link changing objectives (e.g., no adaptation, limit risk increase, avoid risk increase) and nourishment placement over time. This DAPP approach could be applied to other domains of climate change adaptation bringing a new perspective in adaptive planning under deep uncertainty.

1. Introduction

Climate change is posing significant risks from rising temperatures, droughts, increasing flooding and storm damage, shoreline recession, and saltwater intrusion (IPCC, 2014). Although there is a need to understand these risks and address them with adaptation (Collins et al., 2019), this is challenged by the deep uncertainty in future climate change (Hallegatte, 2009; Lempert and Schlesinger, 2000; Wilby and Dessai, 2010). Thus, projections of impacts are highly influenced by uncertainties that arise from different sources (scenarios, climate models, downscaling, and impact models), cascade through the modelling process and accumulate in the outcome, as shown for coastal erosion for instance (Ranasinghe, 2016; Toimil et al., 2020, 2021).

In this context, it has been argued that the best way to incorporate uncertainty in adaptation decision making is through robust

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(Lempert, 2002; Kasprzyk et al., 2013; Hamarat et al., 2014; Trindade et al., 2017) and dynamic (Kwakkel et al., 2015, 2016; Zeff et al., 2016; Garner and Keller, 2018; Trindade et al., 2019) planning. More specifically, dynamic planning, which can also be robust, aims at identifying adaptation policies that respond to new observations over time (Herman et al., 2020), acknowledging that adaptation can be rarely solved with a single action but is a dynamic process of adjusting changes as they unfold through multiple actions managed over time (Barnett et al., 2014). This means to take the necessary actions now and monitor to see when further action is required to address a new situation (Dewar et al., 1993; Haasnoot et al., 2018). Adaptation pathways (AP) (Haasnoot et al., 2012), and their combination with adaptive policymaking (Kwakkel et al., 2010) that includes monitoring and contingency actions, namely dynamic adaptive policy pathways (DAPP) (Haasnoot et al., 2013; Walker et al., 2013), are decision-making tools that implement this idea.

AP consist of sequences of actions (also called policies, options or alternatives) linked by transfer stations analogous to a Metro map (Haasnoot et al., 2012). The shift from one action to another is triggered by adaptation tipping points (ATP), which are the points in time when an action no longer meets its specified objective (Kwadijk et al., 2010). After reaching an ATP, a new action is required. ATP can be triggered by changes in climate, biophysical and socio-economic conditions, with actions guided by the magnitude of change rather than by the time itself (Wise et al., 2014; Brown et al., 2014). Such analysis results in an AP map showing all identified actions together with their ATP and transfer stations to alternative actions. The map illustrates alternative actions and pathways as well as the conditions under which they may succeed or fail (Haasnoot et al., 2012; Rosenzweig and Solecki, 2014). Two key features of AP maps within the DAPP approach are adaptation signals and decision points (Haasnoot et al., 2018). The first signs that an ATP is approaching; the second indicates when a decision is required before reaching the ATP, provided that an adaptation signal is identified.

AP and DAPP approaches are prominent in the climate change adaptation literature. Either independently or in combination with other methods such as real options (Hertzler, 2007), risk-of-failure planning (Palmer and Characklis, 2009) or multi-objective optimisation (Hadka and Reed, 2015), they have proven potential in dynamic adaptation planning in flood risk and water resources management (Haasnoot et al., 2012, 2013; Ranger et al., 2013; Barnett et al., 2014; Rosenzweig and Solecki, 2014, Zeff et al., 2016; Kingsborough et al., 2016; Lawrence and Haasnoot, 2017; Manocha and Babovic, 2017; Bloemen et al., 2018; Ramm et al., 2018; Trindade et al., 2019), forest resilience management (Petr et al., 2015), urban heat-risk management (Kingsborough et al., 2017), and territorial archetypes adaptation to coastal hazards (Rocle et al., 2020). However, while there is a growing number of quantitative applications of AP and DAPP approaches (e.g., Petr et al., 2015; Kingsborough et al., 2016, 2017; Zeff et al., 2016; Manocha and Babovic, 2017; Trindade et al., 2019), considering monitoring and modelling systems and their ability to enable the timely detection of adaptation is still in need of more attention (Walker et al., 2001; Haasnoot et al., 2015, 2018; Lempert and Groves, 2010; Stephens et al., 2018; Raso et al., 2019)

In this paper, we present a quantitative DAPP application for coastal erosion management by means of an approach in which both

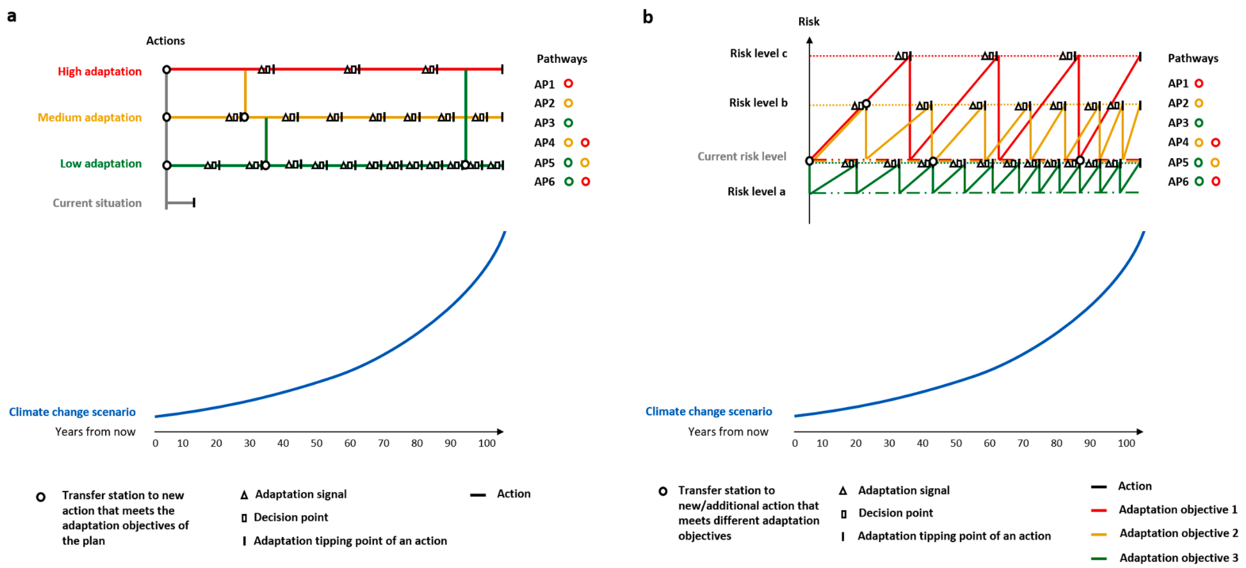

Fig. 1. Nomenclature comparison between a traditional adaptation pathways map (Panel a) and our reshaped adaptation pathways map (Panel b). Panel a shows a classical adaptation pathways (AP) map for an example similar to Haasnoot et al. (2020). In its ordinal scale, the map has generic discrete actions such as "low adaptation", "medium adaptation" and "high adaptation". In this approach, new actions are linked by transfer stations. Adaptation signals specify that an adaptation tipping point (ATP) is approaching and that an adaptation decision on adaptation actions needs to be made. Panel b shows the new type of AP map that would emerge from the proposed dynamic adaptative policy pathways application. In its ordinal scale, the AP map has risk levels, which is a continuous variable upon which adaptation objectives (AO) are formulated. AO can change over time, and actions that meet different AO are linked through transfer stations. Adaptation signals specify that an ATP is approaching and that an adaptation decision on AO and actions needs to be made. AP display information about actions and their intensity, but also about AO, which are measured quantitatively and are expressed using risk terms. As can be observed in both panels, increasing climate change-modified hazards (e.g., mean sea-level rise) lead to increasing action.

adaptation objectives and actions have continuous quantitative metrics and vary in time as conditions change. The approach relies on an adaptation information system that couple monitoring and modelling, allowing linking quantified risk analysis over time, timely detection of adaption signals and AP. In order to illustrate an application of our approach, we model the shoreline evolution probabilistically from 2010 to 2100, incorporating uncertainty in extreme weather events and climate variability (through exploring different multivariate chronologies of waves and storm surges), and in mean sea-level rise (by means of considering the representative concentration pathway of high radiative forcing, RCP8.5, and three alternative trajectories). As each simulation progresses, nourishment actions are applied following distinct narratives governed by transient objectives and adaptation signals that hinge on beach functions (i.e., flood protection and recreation), and additional considerations related to climate and environmental, resource and financial constraints. We provide a new type of AP map showing a subset of probabilistic pathways of linked adaptation objectives and actions of different intensity.

2. Methods

2.1. Dynamic adaptive policy pathways approach

The quantitative DAPP approach we apply herein revolve around three fundamental components. The first two primarily relate to the way the AP map displays the results. On the one hand, the AP map itself shows the performance of a continuous variable on the Y-axis; on the other, each pathway provides graphical information on the dynamic change of both adaptation objectives (AO) and actions over time along the X-axis. The third component is an adaptation information system that combines monitoring and modelling to facilitate the timely detection of adaptation needs.

Considering discrete actions in traditional AP maps has demonstrated to be well suited in many contexts, such as for the Thames Estuary 2100 Project on flood risk management (e.g., over-rotate or improve the barrier, build a new barrier, build a new barrage, as described in Ranger et al., 2013). However, adaptation domains where actions are better characterised by continuous variables (e.g., amount of sand nourished for fighting beach erosion) could benefit from representing these variables on a continuous scale. This has been acknowledged in the literature of dynamic planning (e.g., as risk of failure in Zeff et al., 2016; volume of water saved or gained in Kingsborough et al., 2016; and dike heightening in Garner and Keller, 2018) but, to our knowledge, has never been shown on an AP map before. Hence, we replace the typical nominal or ordinal scale of the AP map diagram (i.e., the Y-axis that usually lists different discrete actions, Fig. 1a, as for instance in Haasnoot et al., 2012, 2013; Buurman and Babovic, 2016) by a continuously scaled axis representing an outcome variable. This variable can be expressed using quantitative risk levels associated with the implementation of adaptation measures (Y-axis, Fig. 1b). Here, risk levels refer to the risk decision-makers are willing to take, also called acceptable or tolerable risk level (Losada et al., 2019), and the residual risks that follow the implementation of an action, which are mainly given by the intensity of the action (i.e., decision variable). In this DAPP application, decision and outcome variables are continuous.

AP approaches do not necessarily consider actions that include changing AO over time. Implicitly, each AP map has a static set of underlying AO (e.g., Haasnoot et al., 2012, 2013; Kingsborough et al., 2016, 2017) and the AP approach aims to explore alternative pathways of actions that meet these AO (the classical “all roads lead to Rome”) (Fig. 1a). While Haasnoot et al. (2013) include the idea of changing AO within the iterative adaptive policy cycle, they do not represent nor analyse this possibility in the AP map. However, under deep uncertainty, the AO may change if an ATP is reached (IPCC, 2019). Hence, an important policy question for adaptation practitioners is whether and when to change AO. In the context of coastal erosion management, an increase in the frequency of ATP derived from rising mean and extreme sea levels may require switching from hold the line to retreat, accepting the decline in beach services due to unaffordable costs (Toimil et al., 2018). Thus, we allow AO to change over time as the future unfolds due to non-stationarities in climate, biophysical, and socio-economic conditions. In this way, when an ATP is approaching and an adaptation signal is identified, decisions on both actions and AO are needed, resulting in the choice between taking more action to achieve the given AO (AP1, AP2 and AP3, Fig. 1b) or changing AO (AP4, AP5 and AP6, Fig. 1b). Here, our AP consist of actions meeting the same or different AO over a given time period. Along an AP, ATP connect actions with the same AO, and transfer stations link actions with distinct AO. AO can be fulfilled by applying different types of actions and different quantitative intensities of the same type of action.

The efficacy of adaptive policies depends on detecting on-going change and ensuring that actions are taken if and when necessary (Raso et al., 2019). A fundamental component of DAPP is to identify and monitor strategic indicators of change (signposts, Dewar et al., 1993) and to watch out for the exceedance of critical values (triggers, Walker et al., 2001) that may jeopardise the continued fulfilment of the AO, and hence the success of the policy. In the broad literature of adaptive planning, the need to design monitoring systems specific for the decision-making problem to be addressed has been long recognised (Lempert and Groves, 2010; Hamarat et al., 2014; Zeff et al., 2016; Haasnoot et al., 2018). Additionally, models can support the analysis of signpost variables, provided that they are capable of exploring beyond the present behaviour of the system and accounting for the uncertainty left after observations (Raso et al., 2019). This can be of key importance in the context of climate change (Haasnoot et al., 2015; Stephens et al., 2018), as adaption decisions solely triggered by observations may not suffice given the late emergence of mean sea-level rise signals (Haigh et al., 2014; Lyu et al., 2014) and the long planning and implementation times for some adaptation measures (Lavery and Donovan, 2005). We set out an adaptation information system that incorporates a monitoring system composed of relevant signposts and associated triggers, and a coastal erosion modelling system that allows simulating potential shoreline evolutions whose forcing conditions are derived stochastically.

Fig. 2 summarises the steps of the proposed approach. The first step involves selecting climate scenarios, climate-related hazard and impact models, AO, adaptation measures, signposts to be tracked (Dewar et al., 1993) and quantitative critical values of the signposts (triggers, Kwakkel et al., 2010) (orange boxes) that lead to adaptation signals. The modelling and monitoring systems (blue boxes) are the fundamental features of the adaptation information system, comprising climate hazard and impact models, and signposts and triggers, respectively. The impact model is forced with probabilistic forcing conditions that incorporate the uncertainty associated with extreme weather events, climate variability, and mean sea-level rise. When an adaptation signal indicates an ATP will be reached, decisions on changing AO and/or implementing actions are needed (green box). All decisions translate into model constraints that condition impact estimates over time (purple box).

2.2. Adaptation objectives

We model the future response of the shoreline to coupled short-term waves, storm surges and astronomical tides, and long-term mean sea-level rise over 90 years. Short-term drivers make the shoreline oscillate around a mean position, shaping changes at time scales from years to decades and leading to episodic storm erosion events, which usually persist over hours and days. However, large erosion can accumulate and grow if clusters of storms reach the coast, slowing down or even hampering the process of beach self-recovery (the natural recovery of beaches, without human intervention). Slow onset mean sea-level rise will increase the number of storm erosion events and, at the same time, will cause chronic shoreline retreat.

We formulate acceptable risk levels (outcome variable) in terms of acceptable beach widths associated with flood protection and recreation services, considering coastal extreme events and mean sea-level rise as key erosion drivers. For the sake of simplicity, we consider the single adaptation measure of nourishment, which is a flexible option (Neufville and Stefan, 2011) that is widely applied (de Schipper et al., 2021). Nourishment actions are herein expressed as placing variable amounts of sand (decision variable) on the beach, resulting in shoreline advances seawards, and hence increasing beach width (Y-axis, Fig. 3). During the simulation, as erosion forcing conditions evolve, changes in the shoreline position together with other factors may lead to changes in AO and actions intensity needs. Table 1 describes five possible incremental strengthened AO that thoroughly sample the space of acceptable beach widths: (a) no adaptation; (b) limit risk increase to maintain recreation services; (c) limit risk increase to maintain flood protection and recreation services; (d) avoid risk increase reactively; and (e) avoid risk increase proactively. In a sense, there is a certain similarity with the idea of water utilities' risk of failure proposed by Zeff et al. (2016) in the Research Triangle region, where objectives and decision are regulated using time-varying risk-related metrics and objectives that change across simulations. Hence, this idea had been used as a decision support mechanism to identify optimal regional pathways in the literature but had not been yet incorporated into an AP map.

Besides, Table 1 presents the indicators and targets that we use to formulate the AO, which are about maintaining defined beach widths associated with specific flood protection and recreation levels. The consequences of following the AO and the required monitoring and modelling needs are also displayed. For instance, AO (a), (b) and (c) involve shoreline retreat, but only AO (b) and (c) are managed retreat, which imply the strategic abandonment of land to address natural hazard risk (Hino et al., 2017). AO (d) means a protection response and AO (e) represents coast advancement seawards (Oppenheimer et al., 2019). In terms of the monitoring and modelling requirements, a key signpost is thus the beach width. The Y-axis in Fig. 3 shows the beach widths that constraint the

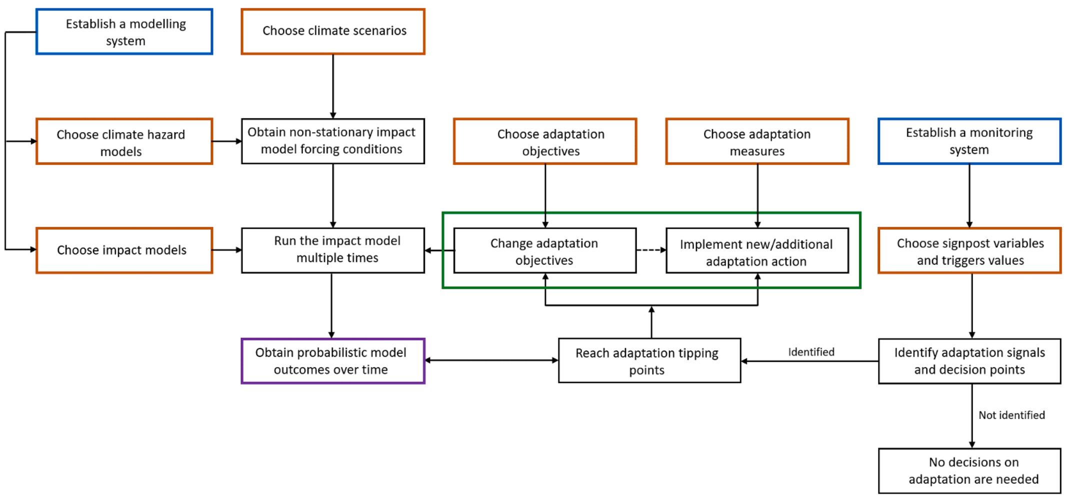

Fig. 2. Flowchart summarising the steps of the proposed dynamic adaptive pathways application. Entry points are climate scenarios on which the forcing conditions of the impact models are projected, climate hazard and impact models, adaptation objectives (AO), adaptation measures, and signpost variables and triggers (orange boxes). Climate hazard and impact models, and signpost variables and triggers compose the modelling and monitoring systems, respectively (blue boxes), as key features of the adaptation information system required. Using accurate but fast impact models allows sampling the uncertainty associated with concentration scenarios, climate models ensembles and multiple realisations. Monitoring signpost variables and modelling probabilistic impact estimates over time enable the timely identification of adaptation signals and decision points, and thus adaptation tipping points (ATP). Once an ATP is reached, decisions either on changing AO or implementing new/additional actions are necessary (green boxes). Finally, new actions and AO are implemented in the impact model (e.g., in the form of new boundary conditions or model constraints), which in turn are then applied to simulate the adaptation pathways considering uncertainty over the time period considered (purple box). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

proposed AO and the intensity of the actions required to fulfil the AO. By way of example, in AP3, if beach width is reduced up to self-recovery width (third width in the Y-axis from the bottom) at least once during the monitoring period, an ATP is reached, and nourishment is applied. The amount of sand nourished (namely nourishment intensity) is such that allows the shoreline to advance until the current beach width is restored.

Fig. 3 illustrates seven examples from the large possible set of AP that can emerge from the proposed AO. The narratives underlying them are as follows. If there is no adaptation (AP1), the shoreline will retreat with increasing coastal hazards. Nourishment action may either anticipate CC impacts by advancing the shoreline seawards (AP2) or react to small changes by keeping beach width between current width and the self-recovery width. The self-recovery width is defined by a shoreline landward position (recession) likely to be recovered naturally (AP3). As mean sea-level rise-driven erosion becomes apparent, a new ATP may arise and a decision on changing AO may be required. In AP6, shoreline retreat due to mean sea-level rise is accepted (e.g., due to a financial constraint) and nourishment is meant to provide certain beach width for summer recreation. Beyond mid-century, mean sea-level rise is more uncertain and it will almost certainly accelerate if emissions are not in accordance with the Paris Agreement to limit global warming below 2 °C (Oppenheimer et al., 2019). This may lead to a new ATP in AP2 or AP3 triggered by harsh environmental effects, high nourishment costs, or financial constraints. Alternative actions may include changing AO and accepting larger although limited shoreline retreat (AP5) or allowing progressive width loss (AP7). Under beach decline, a new ATP may arise in case width is reduced beyond the minimum width that guarantees flood protection. In that situation, changing AO and starting nourishment may avoid waterfront property and infrastructure damage (AP4). Rather than optimising policy design, these AP seek to explore plausible sequences of both AO and actions over time triggered by the dynamic interplays between the system and surrounding conditions.

2.3. Adaptation information system

We establish an adaptation information system with two complementary components: a monitoring system that identifies relevant

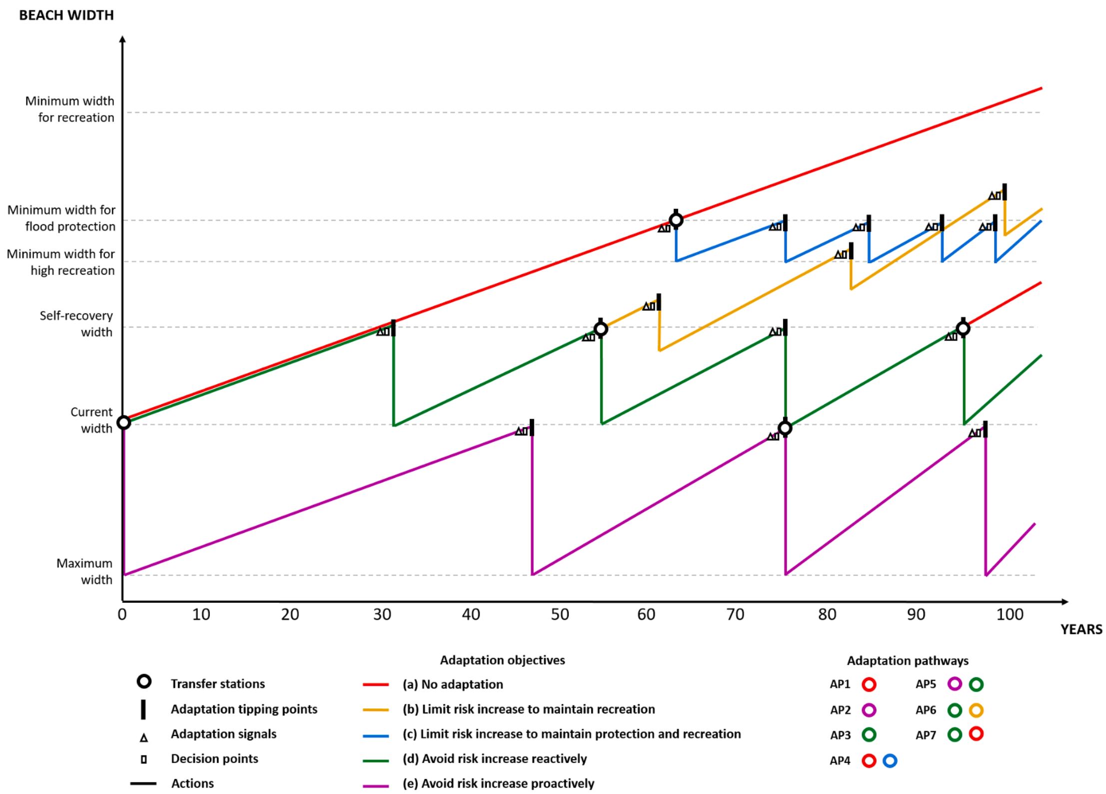

Fig. 3. Conceptual representation of seven illustrative adaptation pathways (AP, 1–8) that use nourishment as action and combine the adaptation objectives (AO, a-e). The AO described in Table 1 are formulated in terms of acceptable beach widths ("Y-axis"). Adaptation signals specify that an adaptation tipping point (ATP) is approaching and that an adaptation decision will be required. Adaptation signals are triggered by critical values of signpost variables that can be of climate, biophysical or socioeconomic nature. ATP may result in the choice between taking more action to achieve the AO given (e.g., AP2, AP3) or changing the AO (e.g., AP4 to AP8). Actions that address different AO are linked by transfer stations. If no action is implemented (e.g., AP1, AP4), the shoreline will continue to retreat. In this case, for illustrative purposes, we assume that coastal hazards increase linearly, but they can follow any path. Another simplifying assumption is that nourishment occurs immediately after reaching an ATP. In reality, nourishment is usually applied following the winter season, when extreme coastal events are rare. During the winter, the shoreline can reach or exceed the thresholds more than once depending on local conditions.

Table 1
Proposed adaptation objectives (AO), indicators and targets. AO are related to the beach services at risk and expressed in terms of acceptable beach widths. Consequences of following the AO and required shoreline monitoring and modelling are also displayed. AO (b) pursues to guarantee the minimum width for recreation, disregarding flood protection. AO (c), (d) and (e) seek to limit beach width over time between two acceptable beach widths that guarantee flood protection or flood protection and recreation. AO (c) seeks to maintain beach width between the minimum width that guarantees flood protection (i.e., if the shoreline recedes behind the minimum position for flood protection, inland flooding can occur) and the width that provides recreation although not at a high level. AO (d) seeks to maintain beach width between the current width and the self-recovery width (i.e., the self-recovery shoreline position is the maximum retreat that is likely to be naturally recovered). AO (e) pursues to maintain beach width between the maximum width (i.e., the maximum feasible advance that the shoreline can experience) and the current width. (*) Here, we assume that whenever there is dry beach, there can be certain level of recreation. Otherwise, target beach width >= max (minimum beach width for recreation, minimum beach for flood protection). (**): note that hold the line with nourishment does maintain a fixed shoreline (unlike hard structures) due to short-term variability (erosion and accretion due to varying wave, storm surge and tide conditions) and the same rationale applies to advance the line or other shoreline responses associated with different AO.

Adaptation objective	Indicator and target	Consequences of following the adaptation objectives	Required shoreline monitoring and modelling
(a) No adaptation	None	Shoreline retreat and risk increase over time.	None
(b) Limit risk increase to maintain recreation services	target beach width $\geq$minimum beach width for recreation	Shoreline retreat and risk increase but less than in (a), as nourishment against beach loss due to coastal extreme events is conducted to maintain certain level of recreation.	Monitoring of shoreline evolution to identify erosion thresholds.
(c) Limit risk increase to maintain flood protection and recreation services	target beach width $\geq$minimum beach width for flood protection (*)	Shoreline retreat and risk increase but less than in (b), as additionally some nourishment against beach loss due to sea-level rise is conducted to maintain flood protection and guarantee recreation.	Monitoring of shoreline evolution and modelling of short- and mid-term projected shoreline evolution to design actions not allowing retreat beyond a certain level during the lifetime of the action.
(d) Avoid risk increase reactively	current beach width $\geq$target beach width > self-recovery beach width	The shoreline is held (**), and retreat is kept below the beach self-recovery threshold, and risk increases accordingly.	
(e) Avoid risk increase proactively	maximum beach width $\geq$target beach width > current beach width	The shoreline advances, and risk is reduced compared to the present following nourishment.	

signpost variables and provides guidance on how to determine triggers; and a coastal erosion modelling system, which in turn combines stochastic and exploratory features in the simulations.

The design of an effective monitoring system involves identifying the signposts or variables that should be tracked (Walker et al., 2001), long robust and homogeneous time-series of these signposts, and sufficient spatial coverage and temporal resolution to understand the system analysed. We could extrapolate observed trends into the near future using simple statistic methods, but for time spans no longer than the observation period. Instead, modelling allows extension of the number of observed parameters, the length of time series, and the spatial coverage and time resolution of measurements, as well as to generate multiple scenarios to inform AP analysis. An adaptation information system that combines these two components can thus help understand, manage and reduce uncertainty (e.g., through assimilation, calibration and validation), enable early warning, and extend adaptation planning times.

As highlighted by Raso et al. (2019), stochastic and exploratory modelling are also complementary features. Exploratory models such as coastal erosion models are used to explore potential coastline changes resulting from physical processes driven by forcing conditions that are uncertain (Toimil et al., 2020). Stochastic models are statistical models that can provide random samples of the forcing variables to account for their uncertainty. For example, since the chronology of extreme weather events highly influences the timing and magnitude of storm erosion, a weather generator could be used to derive multiple possible chronologies of waves and storm surges in order to consider climate variability uncertainty. The combination of these two features requires the exploratory or impact model to be run multiple times with all possible combinations of forcing variables to sufficiently account for the associated uncertainty. In this regard, it is important to distinguish between deeply uncertain factors (e.g., mean sea-level rise) that can be represented through alternative scenarios without probability measure, and aleatory variables (e.g., waves and storm surges), which require stochastic characterisation.

2.3.1. Coastal erosion modelling system

We propose simulating the set of seven AP illustrated in Fig. 3 following the probabilistic methodology developed by Toimil et al. (2017) in San Lorenzo Beach (Supplementary Fig. S1), a urban pocket beach in Asturias (northern Spain), where the methodology has already been validated. It integrates the explicit application of statistical models and multiple realisations of the coastal erosion model. Climate uncertainty is considered by means of the stochastic characterisation of waves and storm surges combined with three deeply uncertain mean sea-level rise trajectories for one radiative forcing scenario.

The shoreline evolution model proposed by Toimil et al. (2017) is forced with hourly time series of waves (DOW, Camus et al., 2013) and storm surges (GOS, Cid et al., 2014), astronomical tides, and mean sea-level rise (Oppenheimer et al., 2019). Given that the statistical projections of waves and storm surges developed by the authors using 40 global climate models show very little change, a vector autoregressive model is applied to stochastically generate hundreds of synthetic multi-variate time series of waves and storm surges from 2010 to 2100 based on DOW and GOS hindcasts. These time series are combined with three mean-sea level rise trajectories derived from the local mean and standard deviation of the RCP8.5 scenario and the reconstruction of the astronomical tide using the harmonic constituents of the TPXO 7.2 global tides model (Egbert et al., 1994). Considering all the possible combinations of forcing variables, the model is run 300 times for each AP. This dovetails well with the idea of using transient scenarios based on boundary conditions to identify ATP proposed by Haasnoot et al. (2015) for a case on water management in the Netherlands.

This shoreline evolution model is particularly suitable for beaches where alongshore gradients in longshore sediment transport are negligible and allows accounting for storm occurrence and grouping and beach recovery without the need of introducing additional variables into the simulation. Since the model has been slightly modified for this DAPP analysis, we provide a brief summary of its components as follows.

The model combines a cross-shore equilibrium shoreline evolution component that considers the effect of water level variations on shoreline change (first term on the right side of Eq. (1)) and an alongshore sediment sink component. Herein, we have turned this sediment sink into a sediment source representing nourishment actions (second term on the right side of Eq. (2)) according to:

$$\frac{dS(t)}{dt} = k\left(y_{eq}(t) - y(t)\right) + \frac{V(t)}{(B + h^{*})L} \tag{1}$$

where $S(t)$ is the resulting shoreline position at time t; $y(t)$ is the shoreline position in response to water level variations at time t; $y_{eq}(t)$ is the equilibrium shoreline position determined by the forcing at time t; k is a constant governing the rate at which the shoreline approaches the equilibrium; $V(t)$ is the volume of sediment supply; B is the berm height; h^{*} is the depth of closure; and L is the length of the beach. Note that the term $\frac{V(t)}{(B+h^{*})L}$ represents a shoreline advance towards the sea when applicable, and that $V(t)$ is a continuous variable.

The cross-shore equilibrium shoreline evolution component follows a modified version of the Miller and Dean's (2004) dynamic equilibrium model, which assumes that the shoreline approaches the equilibrium position at an exponential rate when it is subject to constant forcing conditions:

$$y_{eq}(t) = \Delta y_0 + \Delta y_{eq}(t) \tag{2}$$

where $\Delta \boldsymbol{y}_0$ is an empirical parameter; and $\Delta \boldsymbol{y}_{\boldsymbol{eq}}$is the change in the equilibrium position due to wave setup, storm surges and astronomical tides.

$$\Delta \boldsymbol{y}_{\boldsymbol{eq}}(\boldsymbol{t}) = -\boldsymbol{W}_{\boldsymbol{b}}^{*}(t)\left(\frac{0.106\boldsymbol{H}_{\boldsymbol{b}}(\boldsymbol{t}) + \boldsymbol{SS}(\boldsymbol{t}) + \boldsymbol{AT}(\boldsymbol{t})}{\boldsymbol{B} + 2\boldsymbol{H}_{\boldsymbol{b}}(\boldsymbol{t})}\right) \tag{3}$$

where $\boldsymbol{W}_{\boldsymbol{b}}^{*}$ is the active surf zone width determined from the break point by $\boldsymbol{W}^{*} = \left(\frac{H_b}{\gamma A}\right)^{1.5}$, in which $\boldsymbol{A}$ is the profile scale parameter (Dean, 1991); $\boldsymbol{H}_{\boldsymbol{b}}$ is the breaking significant wave height obtained using $\boldsymbol{\gamma} = 0.55$ spectral breaking criteria; $\boldsymbol{SS}$ is the storm surge; $\boldsymbol{AT}$ is the astronomical tide; and $\boldsymbol{W}^{*}$ is the active beach profile width.

Toimil et al. (2017) modified Eq. (3) to include the SLR-driven landward displacement of the coast using an equilibrium beach profile change model based on Bruun-type conservation volume (Bruun, 1962). Herein, we incorporated an additional term that allow adjusting the equilibrium position to sediment inputs (Δy_s). Therefore, Eq. (2) can be rewritten as:

$$\boldsymbol{y}_{\boldsymbol{eq}}(\boldsymbol{t}) = \Delta \boldsymbol{y}_0 + \Delta \boldsymbol{y}_{\boldsymbol{eq}}(\boldsymbol{t}) - \boldsymbol{W}^{*}(\boldsymbol{t})\frac{\boldsymbol{SLR}(\boldsymbol{t})}{\boldsymbol{B} + \boldsymbol{h}^{*}} + \Delta \boldsymbol{y}_s(\boldsymbol{t}) \tag{4}$$

2.3.2. Monitoring system

Table 2 provides a summary of the key features of the seven AP illustrated in Fig. 3. These features include the sequence of AO, the associated signpost variables to be tracked, the triggers or threshold values of these signposts that activate an adaptation signal, and hence a change in AO or additional action, and the intensity of the actions applied following these triggers in accordance with the pursued AO. Dashes represent AO changes, which are the equivalent of transfer stations in the AP map (Fig. 3).

For the decision-making problem of coastal erosion management, and for this application, we identify five different signposts the most relevant of which is the loss of beach width. We obtain this variable by applying the shoreline evolution model described in Section 2.3.1. For each AP considered and, in every simulation, we track shoreline positions and compute the associated beach width changes at each time step. If over the monitoring period (here, from November to March) the shoreline exceeds a predefined threshold position, an adaptation signal is identified, resulting in AO change and/or nourishment placement. Nourishment actions are always taken at the beginning of the bathing season (i.e., April 1), as in Spain nourishment is usually implemented in spring, when winter has finished and extreme coastal events are rare, and summer has not started yet. These threshold positions are associated with the beach widths represented in the Y-axis of Fig. 3, which limit actions intensity and the AO in place (Table 1) and can be set by coastal managers according to different criteria. For this particular case, the maximum beach width (defined by the maximum shoreline position seawards) is reached when current width increases by 50%; the self-recovery width is reached when current width decreases by 20%; and the minimum beach width for high recreation and flood protection is reached when current width decreases by 30% and 35%, respectively. In practical terms, any additional action to fulfil certain AO or to change to different AO, regardless of the trigger, always results in an advance of the shoreline position, and hence in an increase in beach width. The magnitude of such advance is governed by the intensity of the action (i.e., amount of sand nourished).

Since actual policy decisions must be linked to monitoring of environmental and social tolerance indicators (Stephens et al., 2018), we also consider social preferences in terms of unacceptable flood risks (translated into the minimum beach width to ensure flood protection and thus avoid potential waterfront damages) and constraints based on environmental externalities, resources and financial issues (translated into nourishment protocols that regulate nourishment frequency). In addition, we consider mean sea-level rise as a signpost variable itself for its potential effect on shoreline change. Importantly, our identification of both signposts and triggers is based on observations in San Lorenzo and on its potential policy context. For other beaches and coastal erosion management contexts, the monitoring system could be designed using Supplementary Table S1, which provides further signposts and suggestions on how to determine potential triggers.

3. Results

To reproduce in San Lorenzo the seven conceptual AP shown in Fig. 3, and following the steps illustrated in Fig. 2, we introduced the restrictions on the shoreline evolution model considering the signpost variables and triggers described in Table 2. For each AP, we obtained 300 possible shoreline evolutions in San Lorenzo from 2010 to 2100 on an hourly basis, which consider extreme weather events, climate variability and mean sea-level rise uncertainty and that already incorporate nourishment actions in response to distinct AO (Supplementary Fig. S2). We derived annual beach changes by subtracting the average position of the coastline during the bathing season (from April to October, both inclusive) between two consecutive years (Toimil et al., 2018). The accumulation of these annual changes over time results in cumulative annual beach changes. As a risk indicator we use the expected cumulative change in beach surface (ECCBS), where positive and negative values are gains and losses relative to the present, respectively. ECCBS is directly related to beach services such as protection and recreation (Toimil et al., 2018).

Fig. 4 shows the probability density functions of the ECCBS with respect to the present beach surface. The first three AP do not change the AO. In AP1, inaction leads to a steady decrease in ECCB. In AP2, as the AO is to avoid risk increase proactively, nourishment is applied to increase the present beach width by 50% (the maximum feasible widening allowing for San Lorenzo's physical boundaries). The trigger activating additional action is reaching present beach width. AP3 shows the AO of avoiding risk increase reactively. The trigger activating nourishment is the loss of 20% of beach width (based on San Lorenzo's capacity of self-recovery) and action intensity is such that current beach width is reached. We obtained San Lorenzo's self-recovery capacity by looking at historical annual

Table 2
Summary of key features of the simulated adaptation pathways. (*): lost at least once during the monitoring period (herein from November to March, both included). Note that during this period of time, erosions greater than the threshold can occur, as the shoreline evolves naturally in response to the forcing conditions. (**): see Fig. 3 for a conceptual illustration of the intensity of the actions associated with the adaptation objectives described in Table 1.

Adaptation Pathway	Actions	Adaptation objectives (AO)	Signpost variables	Triggers	Intensity of the actions (**)
1 Red	Nourishment	No adaptation	–	–	–
2 Magenta	Nourishment	Avoid risk increase proactively	Physical constraint (loss of beach width).	Nourishment is activated if current beach width is reached.	Nourish up to increase 50% current beach width.
3 Green	Nourishment	Avoid risk increase reactively	Physical constraint (loss of beach width based on self-recovery capacity).	Nourishment is activated if 20% of beach width is lost (*).	Nourish up to reach current beach width.
4 Red-blue	Nourishment	No adaptation - Limit risk increase to maintain flood protection and recreation services	Social preferences in terms of unacceptable flood risks (flood protection to avoid damages to the waterfront).	AO changes when 35% of beach width is lost*. In what follows, nourishment is activated if 35% of beach width is lost (*).	Nourish up to increase 5% beach width (losses between the 30% and 35% of current beach width are accepted).
5 Magenta-green	Nourishment	Avoid risk increase proactively - Avoid risk increase reactively	Environmental externality constraints (nourishment protocol based on nourishment frequency) - physical constraint (width loss that the beach is able to self-recover).	Nourishment activates if current beach width is reached. AO changes when nourishment is required for a third time. In what follows, nourishment is activated if 20% of beach width is lost (*).	Nourish up to increase 50% current beach width. Once the AO has changed, nourish up to reach current beach width.
6 Green-yellow	Nourishment	Avoid risk increase reactively - Limit risk increase to maintain recreation services	Physical constraint (loss of beach width based on self-recovery capacity) - Changes in climate-related erosion drivers (magnitude of SLR).	Nourishment activates if 20% of beach width is lost*. AO changes when SLR reaches 15 cm. In what follows, nourishment is activated if 20% of beach width minus the SLR magnitude is lost (*).	Nourish up to reach current beach width. Once the AO has changed, nourish up to reach current beach width minus the magnitude of SLR (losses due to SLR are accepted).
7 Green-red	Nourishment	Avoid risk increase reactively – No adaptation	Physical constraint (loss of beach width based on self-recovery capacity) - Environmental externality, resource and financial constrains (nourishment protocol)	Nourishment is activated if 20% of beach width is lost (*). AO changes when nourishment is required for a second time. In what follows, no more nourishments are considered.	Nourish up to reach current beach width. Once the AO has changed, abandon the beach.

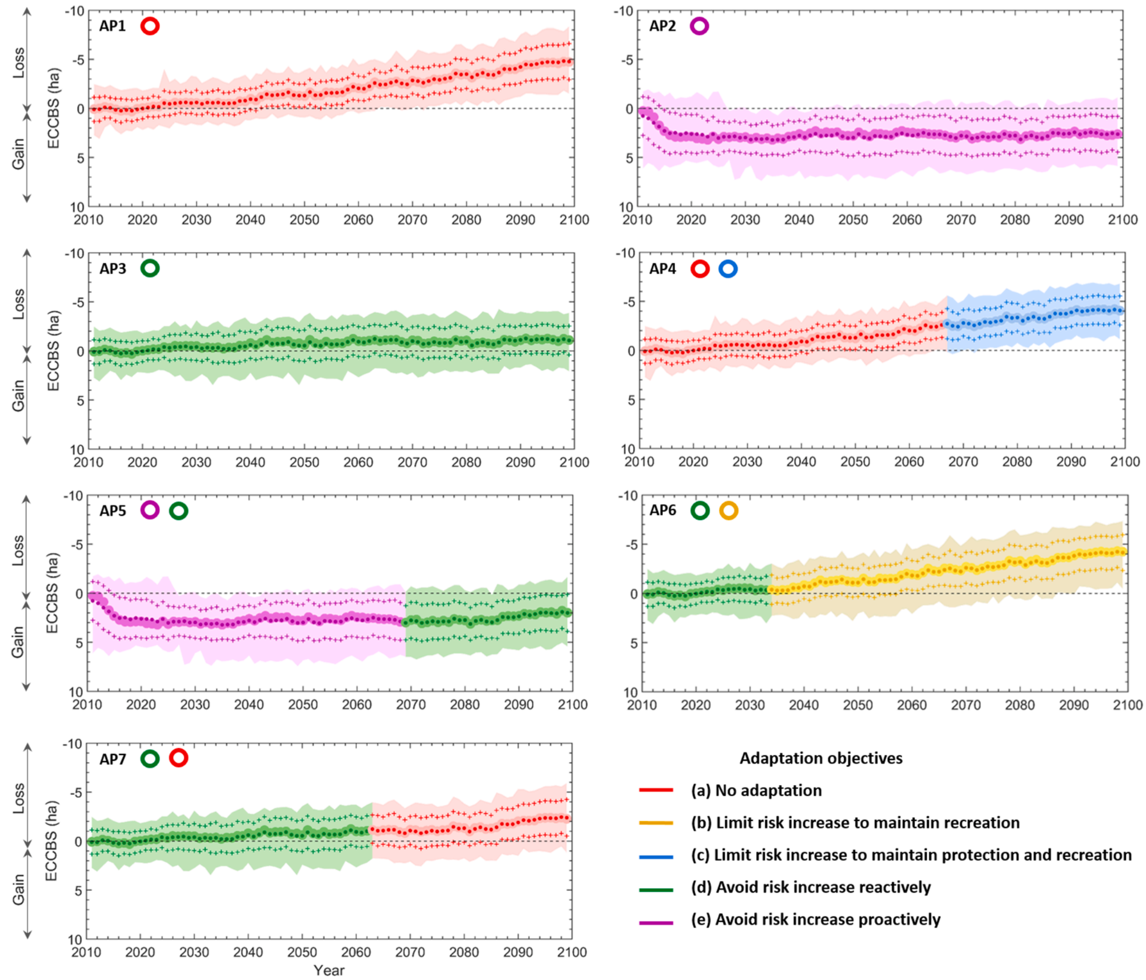

Fig. 4. Simulated probability density functions of expected cumulative change of beach surface (ECCBS in hectares, with positive and negative values representing gains and losses, respectively). The seven panels correspond to the seven probabilistic pathways we developed based three hundred potential hourly shoreline evolutions simulated from 2010 to 2100 that consider uncertainty in climate variability and extreme events (stochastic characterisation), and mean sea-level rise (three deeply uncertain trajectories associated with the RCP8.5), which already incorporate nourishment actions in response to distinct adaptation objectives (AO). Shaded bands represent the 95% confidence levels of ECCBS; big circles are medians; small circles are mean values; and crosses are mean values plus/minus standard deviations. It is important to note that colour changes when the mean value of the ECCBS considering all the simulations changes from one AO to the next. However, this does not mean that at such moment in time, AO have changed in all the modelled shoreline evolutions.

recovery rates, which were computed by subtracting the average beach position during the non-bathing season (from November to March, both inclusive) from the average beach position over the bathing season. Results indicated that San Lorenzo's annual mean recovery capacity is 14.3 ± 6.8% of the current beach width, and that it is able to recover from the loss 20% of its width less than the 20% of the years.

In this context of coastal erosion and nourishment, avoid risk increase (reactively or proactively) means that actions are oriented to maintain the shoreline between two positions, either near the current mean position or advanced seawards, respectively. The shoreline may recede without reaching an ATP, and such recession accumulates over time. Since the shoreline shows variability to storms and recovery, it does not necessarily imply that erosion risk does not increase at all. For example, AP3 shows that by 2100 the ECCBS mean value loses 1 ha with respect to the present (i.e., 6% of current beach surface). This implies, however, that ECCBS mean value losses are reduced by 80% with respect to AP1 for the same time slice.

The other panels in Fig. 4 show AP with changing the AO. In AP4, the AO switches from no adaptation to limit risk increase to provide flood protection and recreation. The trigger for changing the AO and activating nourishment is the loss of 35% of beach width, which is the minimum width that guarantees flood protection for waterfront building and infrastructure, based on historical large erosion events (e.g., those that occurred in March 2014). In AP5, the AO switches from avoiding risk increase proactively to doing so reactively in 2069, when increasingly frequent nourishments would be required to continue following the objective to proactively avoiding risk (Supplementary Fig. S3). This implies reducing ECCBS mean value gains by 23% with respect to AP2 in 2100. In AP6, beach decline due to mean sea-level rise is accepted from 2034 onwards. The trigger to change the AO is a rise in mean sea level of 15 cm, assuming that induced recession becomes apparent and that there are relevant financial constraints. In AP7, the AO change to no adaptation in 2063, when nourishment needs increase and sand is likely to be scarce and costly.

The loss of beach width (or ECCBS) is a relevant signpost that needs to be monitored through combining observations with modelling. Although observations with sufficient spatial and temporal resolution could inform on the self-recovery capacity of beaches, complementing such observations with future projections can provide coastal managers and decision makers with key information for planning purposes (e.g., the probability of exceedance of a given beach width loss over the next 5 or 10 years).

Fig. 5 shows for this case study the practical implementation of Fig. 1. Fig. 5a illustrates the evolution of ECCBS mean values for the seven AP from 2010 to 2100. Overall, the greater the difference in the AO, the sharper the change of the slope of the risk curve. One notable result is that risk levels only differ slightly between AP4 and AP6 by 2100. This shows that, following the pathway of nourishing beaches and allowing mean sea-level rise-driven recession (AP6 second phase) may maintain recreation over decades, but ultimately lead to flood protection losses. In Fig. 5b the AP are represented based on the classical AP map, although with different colours representing the different AO. As can be seen, the pathways themselves do not provide information about the intensity of actions nor residual risk following adaptation.

Once built, the AP map provides an overview of sequences of actions aligned with their corresponding AO that could be used by decisionmakers for the development and implementation of dynamic adaptive plans. These plans provide useful information on which actions and decisions to take now, which can be deferred, and how the preferred AP can be followed (Haasnoot et al., 2013). While the aim of this application is to illustrate the proposed DAPP approach rather than to design an adaptive plan, we acknowledge that the best alternatives do not necessarily entail the lowest risk levels as cost and benefit streams vary between paths. By way of example, Table S2 presents a qualitative multi-criteria analysis for the seven AP considering six criteria. In terms of *dynamic robustness* (that attempts to adapt systems over time in order to maintain the required level of reliability; Babovic et al., 2018), AP2, AP3 and AP5 maintain or increase current ECCBS mean values irrespective of climate and other conditions. Since beach nourishment is per se a flexible and low regret measure, the lowest *flexibility* could be given by the highest intensity of action needed to follow a pathway (i.e., AP2 and AP5). In the literature of coastal adaptation, dynamic robustness and flexibility have been related to the concept of anti-fragility (Babovic et al., 2018), which is a property that results in systems become increasingly resistant to external shocks by being exposed to them (Taleb, 2012). In our application, robustness contributes to preserving the shoreline behind its self-recovery (or fragility) threshold from which there could be chronic coastal recession; and flexibility enhances the opportunity to learn from shocks and the beach response.

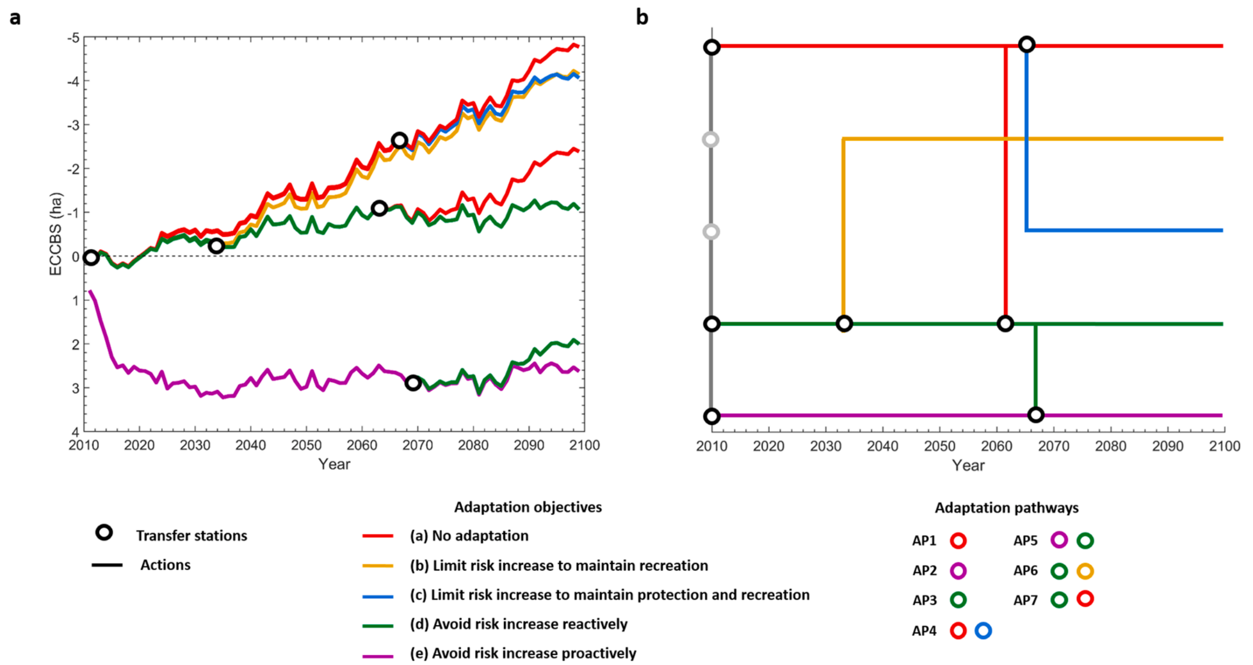

Fig. 5. Comparison between the new type of AP map (Panel a) and a traditional AP map (Panel b). Panel a shows the evolution of the expected cumulative change in beach surface (ECCBS in hectares, with positive and negative values representing gains and losses, respectively) mean values from 2010 to 2100 for the seven adaptation pathways (AP) considered. Grey circles represent transfer stations that link nourishment actions that meet different adaptation objectives (AO, a-e). For simplicity, other statistical parameter such as 95% confidence levels, adaptation tipping points, adaptation signals and decision points are not shown. Panel b shows the way in which the same seven AP would be depicted following the classical AP approach. As can be observed, no information about the actions intensity nor residual risk is provided. A scoreboard with some indicators of the performance of the AP developed is provided in Table S2.

In order to rank AP based on *costs* and *negative environmental impact* we used as proxies the average amount of sand nourished and the average number of times that nourishment is applied, respectively. Considering these two criteria, AP4 and AP7 are the best positioned, followed by AP3 and AP6. AP2, AP3 and AP5 provides *flood protection* along the entire pathway, while AP4, AP6 and AP7 cannot guarantee it continuously over time. Finally, AP3 maintains current level of *recreation*, while AP2 and AP5 increase, and AP1, AP4, AP6 and AP7 decrease recreational services, respectively. Although the overall picture may suggest that AP3 offers the best trade-off between the criteria set, decisionmakers may have different views and risk perceptions, and hence their preferred AP may be different.

4. Discussion and conclusion

The quantitative dynamic adaptive policy pathways application presented herein has demonstrated potential to support decisions in the context of coastal erosion management under deep uncertainty. The approach we adopt considers changing objectives and implementing actions over time within the erosion modelling itself, providing probabilistic shoreline evolutions over the twenty-first century, which consider uncertainty in climate forcing conditions (i.e., waves, storm surges and mean sea-level rise) and incorporate adaptation. We combine this modelling system with the systematic monitoring of signpost variables relevant for coastal erosion management that allow the timely detection of adaptation signals, an essential feature given the late emergence of a low or high mean sea-level rise pathway, and the long planning and implementation times for some adaptation measures (e.g., here, the interplay between the nourishment and the town to landward). As a result, we provide a new type of adaptation pathways map showing a continuous outcome variable on the Y-axis (risk levels) and pathways composed of time-varying sequences of objectives and actions. Our approach thus builds upon the traditional adaptation pathways within the dynamic adaptive policy pathways although raises some methodological and presentational novelties that are summarised in Supplementary Table S3.

Another key contribution of the paper is the fully elaborated case study of coastal erosion, showing how contrasting adaptation pathways developed by changing objectives and implementing actions characterised by a continuous decision variable over time (amount of sand applied) lead to different evolution of residual risk, expressed through probability density functions. We set five incremental strengthened adaptation objectives based on flood protection and beach recreation criteria and establish an illustrative modelling system to support adaptive coastal management by combining the stochastic generation of relevant forcing conditions and the exploratory modelling of shoreline changes. However, other geomorphic models could also have been used to consider uncertainty and assess shoreline evolution and risk estimates. The robustness of our results would benefit from the application of models that incorporate data assimilation in combination with long-term observations of human decisions and their effects on shoreline change. We limit this application to beach nourishment, although new infrastructure, ecosystem-based solutions, and/or planned retreat could be simultaneously incorporated to the analysis in future developments of this approach. The consideration of other adaptation measures would change the timing and location of adaptation tipping points (e.g., following the construction of a groyne), for which it could be appropriate to extend the study area to the scale required for decision making. Finally, while for the sake of simplicity we consider a single radiative forcing scenario (RCP8.5), it is important to recognise that different emission scenarios could bring forward or more likely delay decision points, but they would not affect the pathways themselves.

We argue that this quantitative dynamic adaptive policy pathways approach applied to coastal erosion could be extended to other domains of climate change adaptation, especially where continuous decision variables and quantifiable objectives changing over time are important aspects. By way of example, Supplementary Table S4 displays some recommendations on the way the criteria we applied to define adaptation objectives for coastal erosion management could be brought to adaptation decisions concerning water scarcity, food security and human health. These extensions would require establishing an adaptation information system with stochastic and exploratory modelling that allow considering uncertainty and reproducing the physics of the decision-making problem while systematically monitoring relevant signpost variables. Representing these features in the new type of adaptation map that gives information about actions and following residual risk could bring a new perspective in the field of adaptive planning in deep uncertain environments.

As a next step to further this agenda, additional research on the quantitative analysis of the trade-off between costs and benefits in this dynamic adaptive policy pathways approach would be useful for policy analysis (e.g., using real options). Besides, the approach could be extended to situations where adaptation objectives incorporate multiple criteria and metrics (e.g., combining risk levels and overall cost), allowing considering the economic and other dimensions relevant to decision making. The application of optimisation algorithms to identify pathways according to stakeholders' preferences is also worthy exploring.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.crm.2021.100342.

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