ARTICLE TITLE:

Describing adaptation tipping points in coastal flood risk management

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Abstract

Assessing changing coastal flood risk becomes increasingly uncertain across multi-decadal timeframes. This uncertainty is a fundamental complexity faced in vulnerability assessments and adaptation planning. Robust decision making (RDM) and dynamic adaptive policy pathways (DAPP) are two state-of-the-art decision support methods that are useful in such situations. In this study we use RDM to identify a small set of conditions that cause unacceptable impacts from coastal flooding, signifying that an adaptation tipping point is reached. Flexible adaptation pathways can then be designed using the DAPP framework. The methodology is illustrated using a case study in Australia and underpinned by a geographic information system model. The results suggest that conditions identified in scenario discovery direct the attention of decision-makers towards a small number of uncertainties most influential on the vulnerability of a community to changing flood patterns. This can facilitate targeted data collection and coastal monitoring activities when resources are scarce. Importantly, it can also be employed to illustrate more broadly how uncontrolled societal development, land use and historic building regulations might exacerbate flood impacts in low-lying urban areas. Notwithstanding the challenges that remain around simulation modelling and detection of environmental change, the results from our study suggest that RDM can be embedded within a DAPP framework to better plan for changing coastal flood risks.

Keywords

Adaptation, climate change, inundation, tipping point, uncertainty, vulnerability

Highlights

- GIS software, open source data and programming languages can support coastal flood risk management activities
- Scenario discovery helps simplify complex environmental changes for use in vulnerability assessment and adaptation planning
- Scenario discovery can be used to describe conditions leading to adaptation tipping points
- The timing of adaptation responses can be better informed by knowledge of key sensitivities in existing management controls
- Insights from scenario discovery can facilitate targeted data collection and coastal monitoring activities

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1 Introduction

Increasing rates of sea-level rise have the potential to alter coastal flooding regimes around the world (Hunter 2010; McInnes et al. 2015; Nicholls and Cazenave 2010), placing increasing pressure on decision-makers to minimise physical, environmental and social impacts. However, understanding what changes could lead to unacceptable impacts within the community and when such changes might occur is challenged by ambiguity (Dewulf et al. 2005), different risk perceptions (Jones et al. 2014), multi-decadal climate variability (Hallegatte 2009) and long-term uncertainty associated with varying regional responses to climate change.

Various decision support tools have been proposed to guide decision-makers through climate risk assessments and to evaluate adaptation responses under conditions of uncertainty (e.g. Dittrich et al. 2016; Watkiss and Hunt 2013). When deep uncertainty exists, dynamic adaptive policy pathways (DAPP) (Haasnoot et al. 2013) and robust decision making (RDM) (Lempert et al. 2003) have emerged as two state-of-the-art decision support tools (Kwakkel et al. 2016a). Deep uncertainty describes dynamic conditions where there is limited knowledge and agreement on the use of models, description of parameters in those models and what impacts are considered (Lempert et al. 2003; Kwakkel et al. 2016a). Decision-makers are likely to encounter deep uncertainty when assessing the vulnerability of a community to changing coastal inundation patterns that may be experienced decades from now, or through coastal development and land use planning whereby near-term investments will influence urbanisation patterns over the coming decades.

RDM is a decision support method that evaluates the robustness of *new* policy options such as a flood alleviation scheme. DAPP is an adaptive management framework that begins by considering what future scenarios will cause *existing* management controls to fail, before evaluating the suitability and timing of new policy options. Both methods use hundreds to thousands of non-probabilistic ‘what-if’ scenarios to explore the impact of the uncertain future on the performance of new (or existing) adaptation policies, allowing key sensitivities of the policy to be identified. When external changes cause the existing system or future adaptation plans to no longer meet decision-maker objectives, an adaptation tipping point is reached and new actions should be implemented (Kwadijk et al. 2010). Adaptation tipping points provide a practical way to communicate risks to the community associated with a changing built and natural environment (Werners et al. 2013). This focuses coastal flood risk management towards understanding the sensitivity of an urban area to change and assessing when management responses might be needed to keep impacts at a tolerable level (Kwadijk et al. 2010).

RDM and DAPP aim to design robust policies, and they achieve this in different ways. RDM identifies adaptation policies that perform satisfactorily under many different future scenarios, whilst DAPP provides an adaptive management framework within which flexibility is created, allowing progressive review and update of policy options as more information becomes available (see Appendix A in the Online Resource for a comparison of RDM and DAPP). Importantly both approaches have the potential to provide complementary information to decision-makers under conditions of deep uncertainty (Kwakkel et al. 2016b).

There are few examples from local government that use RDM or DAPP to assess the vulnerability of low-lying areas to coastal inundation and design adaptation pathways. This could be due to many factors including unclear adaptation responsibilities in government (Nalau et al. 2015), limited awareness of new decision support tools (Lawrence and Haasnoot 2017), limited availability of relevant data to undertake such an analysis (Bhave et al. 2016) and technological or financial constraints. Simplified applications of RDM (e.g. Daron 2015) and adaptation pathways (e.g. Barnett et al. 2014) have been demonstrated for resource-constrained decision-makers. However, the growing global repository of spatial data and open source programming code (e.g. the exploratory modelling workbench; Kwakkel, 2017) means that local governments, business and individuals have an opportunity to use more sophisticated techniques to analyse climate risks, quantify thresholds and evaluate adaptation responses (Ramm et al. 2017a).

Many of the adaptation pathway examples to date in coastal flood risk management describe conditions that lead to an adaptation tipping point with a single parameter like sea-level rise (Reeder and Ranger 2011) or storm surge height (Kwadijk et al. 2010). This conceptualisation of risk suggests that flood impacts could be treated by controlling the single hazard with a sea wall or levee (Klijn et al. 2015). However, important factors that relate to land use or property design are often omitted, which can overlook broader risks in urbanised areas that may exacerbate coastal inundation impacts.

We contribute to adaptation pathways planning research by exploring whether RDM and DAPP methods can be integrated to support coastal adaptation planning under conditions of uncertainty. We propose that RDM is well suited to describe a set of conditions where existing or future plans would no longer satisfy adaptation objectives in low-lying urban areas, signifying that an adaptation tipping point is reached. Knowledge of conditions that lead to adaptation tipping points can be used to further develop adaptation pathways using the DAPP framework, whereby each pathway represents a different set of adaptation options sequenced over time. A more comprehensive understanding of an area's sensitivity to coastal inundation allows questions such as *'what change in the built and natural environmental is important?'* and *'when might such change occur?'* to be explored. A similar philosophy was used by Kalra et al. (2015) to manage water resources in Lima. However, we are not aware of any literature that proposes the integration of RDM and DAPP for use in coastal flood risk management and adaptation planning. The methodology presented herein uses open source spatial datasets and programming languages for the benefit of resource constrained decision-makers. However, it relies on commonly used commercial software (ArcGIS) and flood modelling capability. We illustrate the potential for the approach on a case study site in Kingston Beach, Australia, to identify what future change might lead to unacceptable coastal flood impacts to people, property and lifestyle objectives.

With over $200 billion of infrastructure in Australia exposed to a 1.1 m sea-level rise (Commonwealth of Australia 2011), strategic investment in coastal adaptation responses is important to avoid an increasing burden on the nation's resources. A greater upfront investment in risk identification and adaptation planning using state-of-the-art decision support methods could generate sizable budget savings to all levels of government and the community. Section 2 of this paper presents an overview of the methodology. The approach is demonstrated with a case study in Section 3. The implications and prospects of the method are discussed in Section 4, with conclusions drawn in Section 5.

2 Methods

We present a methodology that draws on the strengths of RDM to describe conditions leading to adaptation tipping points that can be used in a DAPP framework to map adaptation pathways. The basis of the presented methodology overlaps with the XLRM framework used in RDM to organise exogenous uncertainties (X), policy levers (L), relationships and models (R) and metrics (M) (for more details see Lempert et al. 2013). The key steps in the methodology are summarised in Fig. 1. Details about each step are provided in Sections 2.1 to 2.7.

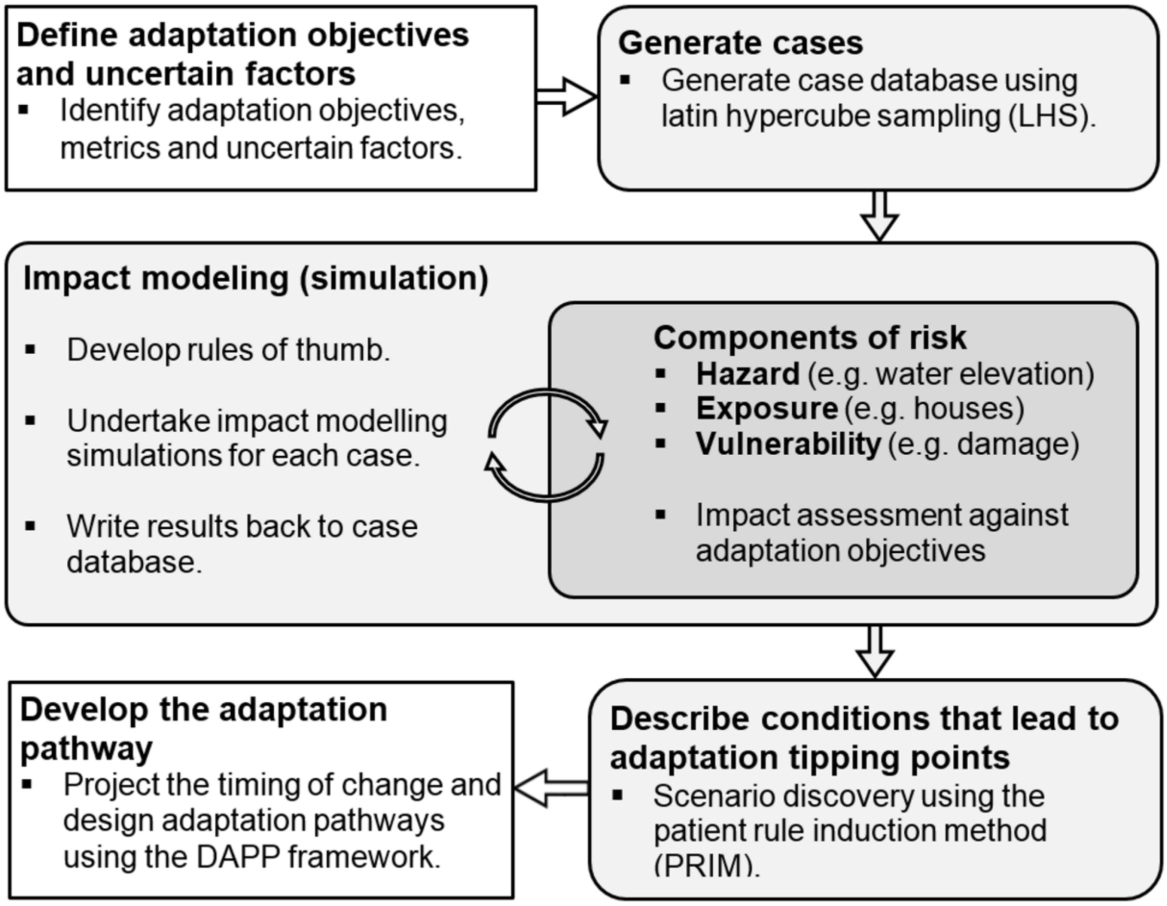

Fig. 1 Summary of methodological steps to describe conditions leading to adaptation tipping points for use in adaptation pathways planning. These steps are expanded on in Sections 2.1 to 2.7.

2.1 Define adaptation objectives

Adaptation objectives describe what coastal decision-makers are trying to achieve by managing coastal inundation impacts. The objectives can be guided by organisational requirements or through stakeholder engagement. An example of an adaptation objective that accounts for physical impacts might be *minimising the length of critical access roads inundated during a flood*, whilst an environmental adaptation objective might be *minimising the loss of beach and dune area* (e.g. Ward et al. 1998). Both of these objectives could also relate to intangible social values held by local residents, such as ensuring recreational opportunities, aesthetic value and an ongoing feeling of safety.

2.2 Define uncertain factors

Uncertain factors are those that cannot be influenced by decision-makers, are relevant to the adaptation objectives, and whose future state is unknown. They can be exogenous (X) to the system and outside the decision-makers control, or influence relationships inside the system (R) itself. An example of an uncertainty in the context of coastal adaptation is relative sea-level rise. The range of values that uncertain factors might take in the future is specified *a priori* and can be based upon stakeholder participation or guided by scientific evidence.

2.3 Generate cases

A case is a future realisation that represents a combination of randomly sampled uncertain factors (analogous to a single ‘what if’ scenario). Each case captures a single set of assumptions about the future state of uncertain factors. The generation of numerous cases allows future realisations to be explored in a process of exploratory modelling (Bankes 1993). Cases are generated by selecting values for uncertain factors using latin hypercube sampling (LHS) (‘lhs’ package[1]), which then become inputs to the computational experiments.

2.4 Develop rules of thumb

Rules of thumb are simple principles that relate the value of an uncertain external factor (X) to a change in the model (R) (Section 2.5). For example, sea-level rise may affect the depth and extent of coastal flooding, which is used to assess impacts to the adaptation objectives for the case being explored. Rules of thumb can be derived from expert judgement, prior knowledge, or from a set of detailed scientific models.

2.5 Impact modelling (simulation)

The ability to simulate many cases to assess coastal inundation impacts in a reasonable timeframe requires a trade-off with the precision of the model (Bhave et al. 2016; Walker

[1] LHS is a sampling technique and the package is implemented in the free open-source R environment. See Carnell (2016) for details.

et al. 2013). Proxy models are often useful in such instances (also referred to as metamodels or surrogate models) (Haasnoot et al. 2012; Teng et al. 2017).

A simulation model was developed in Python 2.7 using geoprocessing tools from the ArcPy module (ArcMap 10.4) and incorporating the 'spatial' and '3D analysis' ArcMap extensions. Risk was conceptualised as the product of a hazard, an exposed element and the associated vulnerability (de Moel et al. 2015; Klijn et al. 2015; IPCC 2012), which was a useful way to organise various components of the simulation model. For example, a floodwater elevation map reflects a hazard, property reflects an exposed element, and the vulnerability of that element is described by monetary damage based upon flood depth.

2.6 Describe conditions that lead to adaptation tipping points

Scenario discovery searches through results in the case database and aims to identify a small number of 'candidate scenarios' (Fig. 2) that best identify 'cases of interest' (Lempert 2013). Cases of interest are those cases that result in acceptable impacts to adaptation objectives. A candidate scenario describes a cluster of cases and resembles a subspace of the uncertainty space that is explored in the computational experiments. It is defined by a small set of factors and intervals (i.e. conditions) that capture a high concentration of cases of interest. Should the small set of identified conditions occur simultaneously in the future, an adaptation tipping point is likely to be reached and an adaptation response would be needed to maintain impacts to the adaptation objectives at or below the desired tolerance. Identifying a small number of candidate scenarios through scenario discovery helps to keep the result interpretable for decision-makers.

The 'sdtoolkit' R package[2] was used to undertake scenario discovery, applying the Patient Rule Induction Method (PRIM) algorithm (Friedman and Fisher 1999) to identify clusters of the cases of interest. Whilst Classification And Regression Trees (CART) offer an alternate data mining algorithm to PRIM (Breiman et al. 1993), neither algorithm currently

[2] See Bryant (2016) for package details.

has a strong advantage over the other (Lempert et al. 2008; Kwakkel and Jaxa-Rozen 2016).

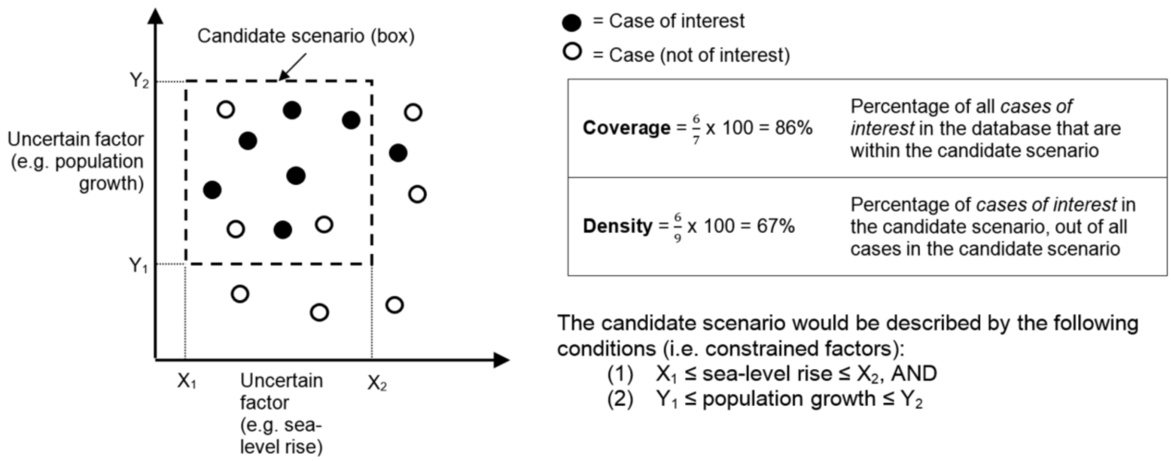

Fig. 2 Key concepts used in scenario discovery. Filled circles represent cases of interest. The candidate scenario is defined as a box (dashed line) that constrains key input factors. Coverage and density describe the quality of the candidate scenario.

The quality of the candidate scenario is measured by its ‘coverage’ and ‘density’ (Fig. 2). Coverage describes the cases of interest captured by the candidate scenario as a proportion of all cases of interest in the entire results database. Density describes the percentage of the cases of interest captured by the candidate scenario out of all cases captured by the candidate scenario (Bryant and Lempert 2010; Lempert et al. 2013). Other diagnostic measures, such as the quasi p-value and reproducibility statistics, are useful for understanding the significance of the constrained factors in the candidate scenarios (for more details see Bryant and Lempert 2010).

2.7 Develop the adaptation pathway

Once conditions under which adaptation objectives are no longer achieved have been identified through scenario discovery, scientific trends and projections can be considered to understand 1) the potential for such conditions to occur in the future based upon available evidence, and 2) over what timeframe such changes are projected to occur. This information can then be used to develop adaptation pathways using the DAPP framework (for more details see Haasnoot et al. 2013).

3 Case study: Kingston Beach, Tasmania

The method presented in Section 2 is illustrated for the case of the coastal suburb of Kingston Beach, Tasmania (Australia). The study area is located approximately 13 km south of the capital city of Hobart (Fig. 3). A unique aspect of the study area is that approximately 86% of the housing stock located in low-lying areas were built before 1980 (Dunford et al. 2014). Thus, they were built prior to the introduction of higher building standards. The suburb is predominantly residential, with approximately 20-40 small businesses in low-lying areas and many natural landscapes including beaches, grassland, saltmarshes and forests. Whilst new dwellings will be subject to more stringent building regulations and land use planning controls, the characteristics (e.g. floor level, building materials) of many existing houses in the study area could remain unchanged for decades. Therefore these houses may have increasing exposure and vulnerability to changing flood hazards in the future. Extreme sea-levels from storm tides are considered to be a lower threat to people and property in the study area compared to the inundation threat of riverine flooding from Browns River. However, sea-level rise will threaten low-lying coastal landscapes of significant social and cultural value, such as the Kingston Main Beach (Ramm et al. 2017b).

Fig. 3 Study location in the suburb of Kingston Beach, Tasmania. The topographical terrain is shown with 10 m contours relative to Australian Height Datum (AHD), to highlight low-lying areas. The existing sea-wall is identified (white dashed line) from which beach width is estimated.

3.1 Define adaptation objectives

Three adaptation objectives were chosen to manage impacts to people, property and lifestyle, and these were grouped into key results areas (KRA) as might be done in a strategic coastal management plan (Table 1). This number of objectives is consistent with other RDM applications (e.g. three objectives were studied by Lempert et al. 2013; two were used in Bonzanigo and Kalra 2014). The average beach width objective was selected on the basis that: 1) the beach is a highly valued coastal landscape by residents, and 2) there are many social values associated with the beach, including recreational use, being free of access restrictions, and providing residents with a sense of identity (Ramm et al. 2017b). The tolerable impacts signify whether an adaptation tipping point is reached.

Table 1. Adaptation objectives selected for illustrating the methodology, grouped into key result areas (KRA). Acceptable (tolerable) impacts to people (AAPE) and property (AAD) reflect an increase of 10% from the current-day baseline risk. Arriving at the tolerable impact threshold signifies that an adaptation tipping point is reached. Baseline risk is determined by modelling impacts with current-day best estimates for the uncertain factors (see Table 2).

ID	KRA	Adaptation objective	Metric	Tolerable impact
1	**People:** Minimise exposure	Maintain people exposed to within 10% of current baseline	AAPE	AAPE < 23.5 people / year
2	**Property:** Minimise damage	Maintain dwelling damage to within 10% of current baseline	AAD	AAD < $650,000 / year
3	**Lifestyle:** Preserve social values	Maintain a minimum average beach width of 5 m from sea wall to MHWS level [a.]	Average width of Kingston Main Beach	Average beach width > 5m

[a.] Mean high spring water level (MHWS) is 0.623 m above the Australian Height Datum (Kingborough Council 2017, p.47) and reflects the average of spring tide high water observations over a 19 year period (Woodroffe 2003).

3.2 Define uncertain factors

A total of seven exogenous uncertainties (X) were identified in our case study illustration (Table 2). Three of the uncertainties related to the hazard component of risk and four characterised the vulnerability. The Bruun factor in Table 2 represents a simplified relationship between coastal recession and increasing sea-levels.

Table 2. Uncertain factors used for the study site, showing their range and the adaptation objective(s) to which they apply.

		Adaptation objective			Range [a]			
Risk dimension	**Uncertain factor**	**(1) AAPE**	**(2) AAD**	**(3) Beach width**	**Min**	**Baseline (current-day best estimate)**	**Max**	**Basis for selected range**
Hazard	Sea-level rise (increase from 2010 levels)	✓	✓	✓	0m	0m	+1 m	User defined, guided by McInnes et al. (2016)
	Changing 9-hour rainfall intensity (relative to present) [b]	✓	✓		-10%	0%	+30%	White et al. (2010; 2013)
	Bruun Factor			✓	10	*N/A*	100	Carley et al. (2008); Mariani et al. (2012)
Vulnerability	Maximum structural damage (per 4 m^2) [c]		✓		\$4,000/4 m^2	\$5757/4 m^2	\$10,000/4 m^2	Dunford et al. (2014) [c]
	Maximum contents damage (per 4 m^2)		✓		\$500/4 m^2	\$1058/4 m^2	\$2,500/4 m^2	Dunford et al. (2014) [c]
	Damage index at 10 cm inundation		✓		-0.1	*N/A*	+0.1	Approximate deviation from the vulnerability curve (Geosciences Australia 2012)
	Average people per house	✓			2	2.2	3	Value is 2.15 for low-lying statistical area, 2.3 for Kingston Beach and 2.6 for Australia (ABS 2013)

[a] The range is not limited to scientific consensus (e.g. IPCC) and can be inclusive of resident perceptions.

[b] 9-hour rainfall intensity is the critical duration for the study area (Kingborough Council 2017, p.22)

[c] The raster cell size is 4 m^2 in the impact model. The damage in *real* dollars for 2016 was obtained from the NEXIS building exposure database (Dunford et al. 2014) by dividing the 'resident structural value' by the 'residential building footprint' for low-lying houses. House reconstruction cost estimates could alternatively be obtained from insurance providers using representative dwelling details (e.g. 3-bedroom; pre-1980's; slab on ground; weatherboard) or industry publications such as Rawlinsons (2017).

3.3 Generate cases

A total of 1,000 cases were generated using Latin Hypercube Sampling (LHS). The results were stored in a simple flat file database (ASCII csv).

3.4 Develop rules of thumb

Three ‘rules of thumb’ were determined for this study to incorporate the effect of uncertain factors on the simulation model: 1) the change in floodwater elevation for each meter of sea-level rise, 2) the change in the floodwater elevation for each percentage increase in the 9-hour critical rainfall intensity, and 3) the horizontal beach recession for each meter of sea-level rise.

Peak floodwater elevation maps were developed by Kingborough Council using SWMM 2D hydrodynamic modelling software for 11 different scenarios (see Appendix B in the Online Resource for details). This allowed the current-day baseline risk to people and property in Table 1 to be established. The 11 scenarios also allowed the relationship between sea-level rise and peak floodwater elevation to be investigated, revealing that a 1 m rise in sea-level only increases the peak floodwater elevation by 1 cm. The relationship between rainfall intensity and floodwater elevation was based upon prior flood study work by Kingborough Council, which suggested that the peak floodwater elevation of Browns River changed by about 0.1 m per 10% increase in the 9-hour rainfall intensity (Kingborough Council 2017, p.40). The baseline scenarios from the hydrodynamic modelling were converted into peak floodwater elevation raster grids. These grids could then be adjusted using the rule of thumb relationships in the simulation model, depending on the change to sea-level and 9-hour rainfall intensity.

The relationship between horizontal beach recession and sea-level rise was underpinned by the Bruun rule (Bruun 1962). Notwithstanding the dynamic nature of sandy beaches and the difficulty in modelling coastal processes, Kingston Main Beach is understood to be threatened by inundation from long-term sea-level rise (Sharples 2016), regardless of its historic ability to recover from erosion events (CoastAdapt 2016). Although there are many simplifications of the Bruun rule (e.g. Cooper and Pilkey 2004), there are currently few scientifically recognised alternatives for policy design (Mariani et al. 2012). Prior studies of nearby beaches in the Derwent Estuary suggest that the Bruun factor could be in the range of 15-37 (Carley et al. 2008), whilst Mariani et al. (2012) suggest that a Bruun factor of 50 be used for Tasmania (and a factor of 100 for a conservative estimate). The presence of a sea wall in the study area makes application of the Bruun rule further problematic. We therefore only apply it to generate indicative beach loss seaward of the existing sea-wall at Kingston Main Beach.

3.5 Impact modelling (simulation)

A schematic diagram of the model used to simulate impacts against the three adaptation objectives is shown in Fig. 4. Spatial datasets were sourced online from the Tasmanian State mapping authority (DPIPWE 2015). Low-lying houses were digitised into polygon shapefiles using georectified aerial imagery, and a 2 m x 2 m raster grid was specified for all geoprocessing analysis. This provided adequate model resolution whilst improving the processing speed, which was important when raster grids were converted into NumPy arrays to evaluate coastal flood impacts. Looping through each row in the case database and applying the rules of thumb allowed different proxy flood depth rasters to be generated (peak floodwater levels). These rasters could then be overlayed above the land use raster to identify exposed dwellings and to determine the vulnerability of those dwelling in terms of damage costs (see Appendix C in the Online Resource for details on the data and geoprocessing tools used in the simulation model).

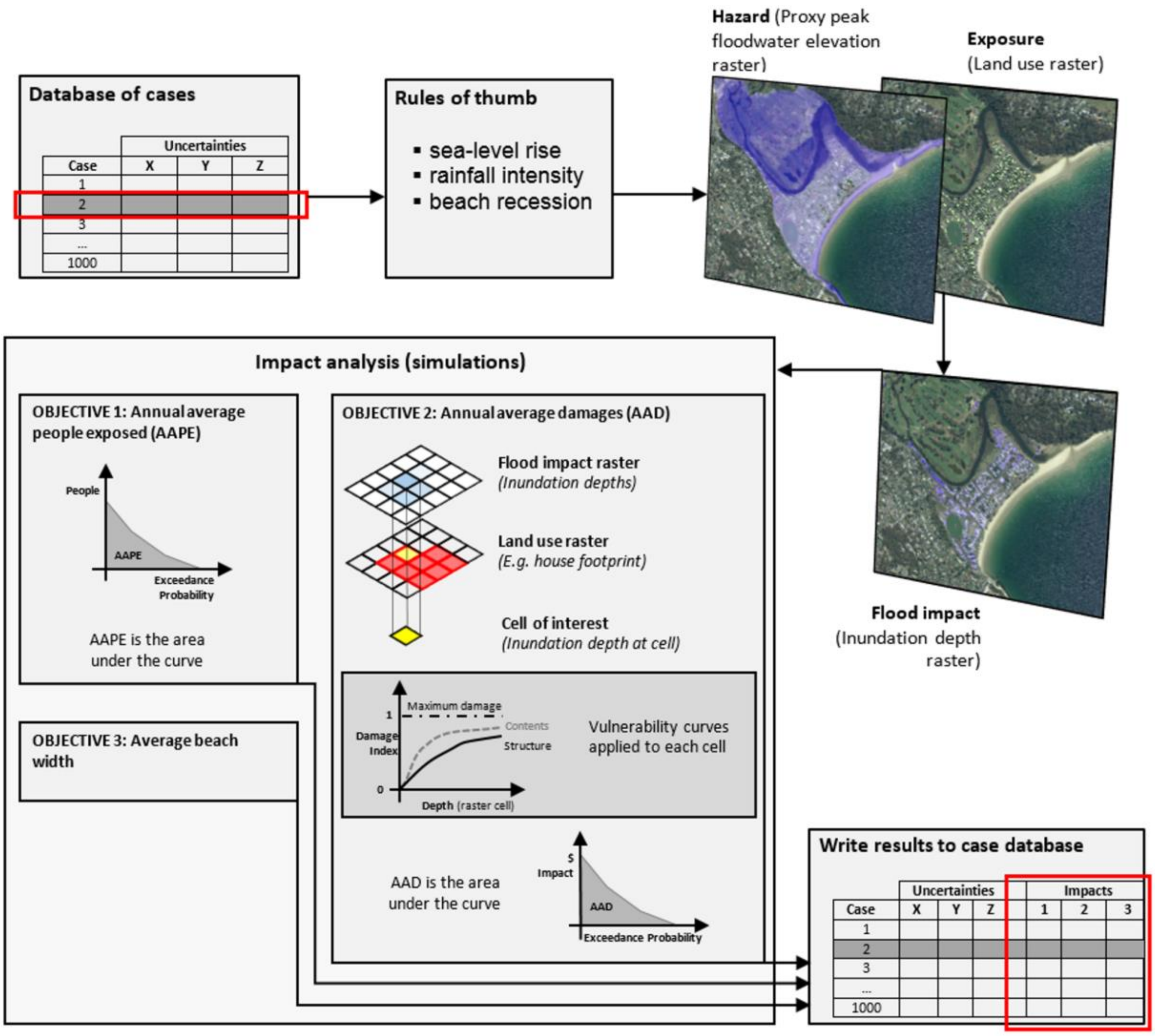

Fig. 4 Schematic diagram of the main activities undertaken to assess impacts to AAPE, AAD and average beach width. The case database was generated using the R programming language, before being imported into Python. Impacts on the adaptation objectives for each case were assessed in Python using geoprocessing tools (ArcPy module).

3.5.1 Calculating AAPE

The number of people exposed to hazards was estimated for 1%, 2%, 5% and 20% AEP events by multiplying the average number of people per dwelling by the number of houses inundated. AAPE was then determined by applying the trapezoidal rule to calculate the area under a plot of AEP against the number of people exposed. A similar measure to AAPE was used by Lempert et al. (2013).

3.5.2 Calculating AAD

Calculation of the AAD to dwellings was based upon established practice used to assess monetary flood impacts (de Moel et al. 2015; Egorova et al. 2008). The proxy peak floodwater surface was used to determine an inundation depth at each 2 m x 2 m raster cell, from which vulnerability curves were applied to exposed dwellings to determine a damage index. The damage index reflects the percentage of damage relative to the full replacement cost. A separate vulnerability curve was used to assess damages to the house structure (i.e. fixed elements) and contents (i.e. movable assets), and vulnerability curves were guided by empirical data from Geosciences Australia (2012) (see Appendix D in the Online Resource for details). The monetary impact to all dwellings in each case was calculated by summing the damage across all raster cells for the 1%, 2%, 5% and 20% AEP events, allowing the AAD to be determined using the trapezoidal rule (Ramm et al. 2015).

3.5.3 Calculating average beach width

The average beach width was determined by creating a transect line at five distinguishable locations along Kingston Main Beach, corresponding to beach access points. A buffer distance based on the Bruun factor was created around the sea-level rise polygon (at MHSW) based upon the amount of sea-level rise in the case being considered. The transect length was then calculated as the horizontal distance from the fixed sea wall to the adjusted sea-level polygon. The average width across the five locations was then calculated.

3.5.4 Simulation results

The impact model took 85 hours to analyse 1,000 cases on a standard 16GB RAM machine with a 3.4 GHz Intel processor. Plotting the cases against the adaptation objectives (Fig. 5) suggests that although the majority of case realisations resulted in unacceptable impacts to the adaptation objectives (i.e. Q3 in Fig. 5a and Q2 in Fig. 5b), there are cases that lead to reduced impacts on adaptation objectives (i.e. Q1 in Fig. 5a and Q4 in Fig. 5b). Scatter plots were used as an initial diagnostic tool to visualise the sensitivity of the individual input factors on the adaptation objectives (Pianosi et al. 2016).

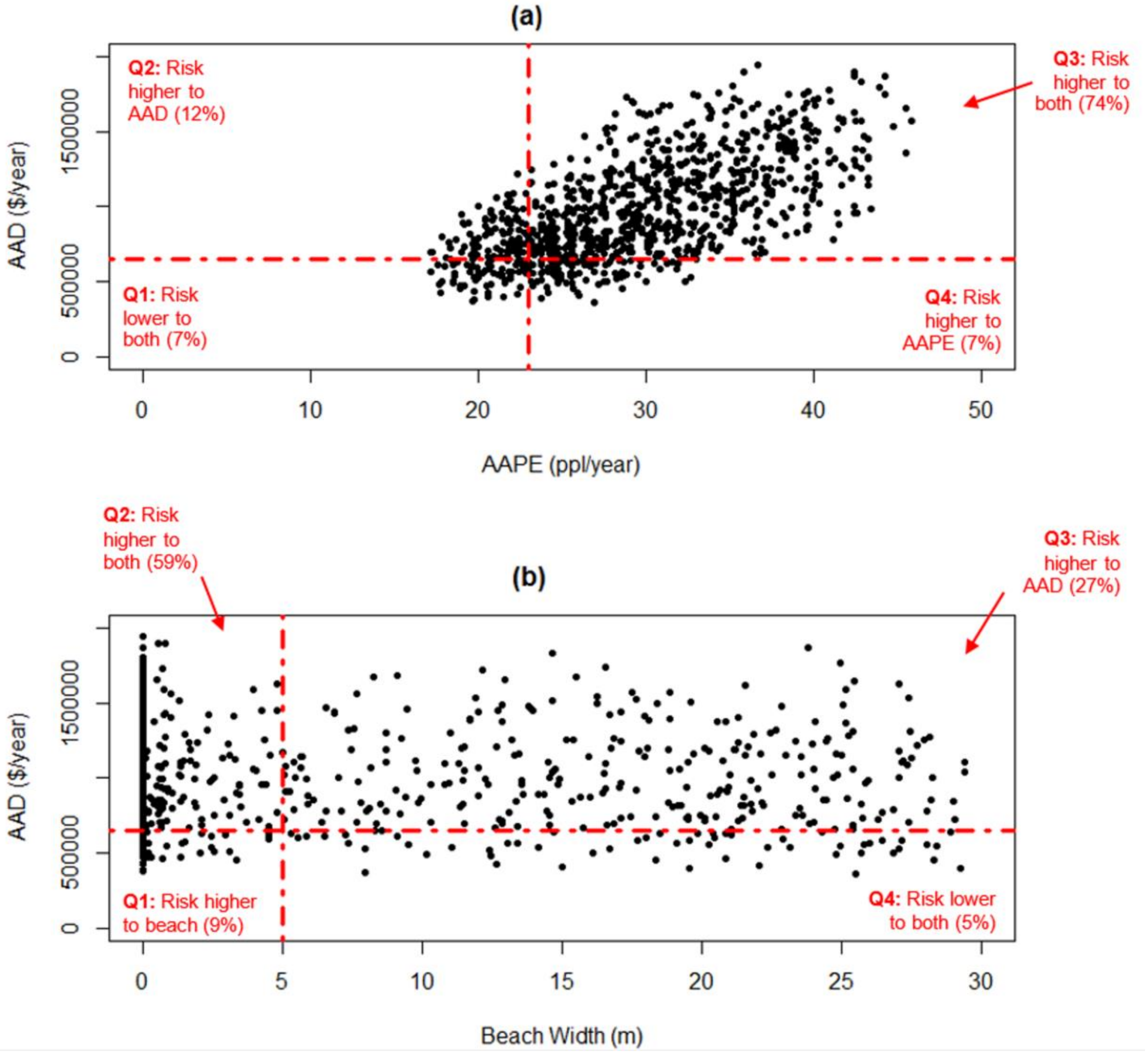

Fig. 5 Plot of impacts to (a) AAPE and AAD objectives and (b) average beach width and AAD objectives, for the 1,000 cases. The upper bound of tolerable impacts to the objectives (see Table 1) are defined by red dashed lines. The percentage of cases in each quadrant of the plot is also shown (denoted Q1-Q4).

3.6 Describe conditions that lead to adaptation tipping points

Scenario discovery validated observations made from the scatter plots that rainfall intensity and maximum structural damage costs were the most important uncertainties in defining the candidate scenario for the AAD adaptation objective. The significance of these variables was confirmed by the reproducibility statistics and p-values at the 0.05 level. Coverage and density trade-offs were further investigated for a range of candidate scenarios (see Appendix E in the Online Resource for further details). The strongest candidate scenarios for the three adaptation objectives are summarised in Table 3. These candidate scenarios describe the conditions beyond which coastal inundation impacts related to the adaptation objectives are unacceptable (i.e. signify adaptation tipping points are reached).

Table 3: Scenario discovery results showing candidate scenarios beyond which impacts related to the adaptation objectives become unacceptable.

	Candidate scenario		
Adaptation objective	**Conditions (factor and values)**	**Cases of interest**	**Coverage / Density**
1: AAPE	9-hour rainfall intensity < 4.8%, *AND* Average people per house < 2.4	194 / 1000	73% / 88%
2: AAD	9-hour rainfall intensity < 6.3% *AND* Maximum structural damage < $1,536/m^2	167 / 1000	75% / 76%
3: Beach width	Sea-level rise < 0.3m *AND* Bruun factor < 83	320 / 1000	70% / 97%

Key factors in the selected candidate scenarios are shown in Table 4, along with projected trends and associated timeframes. The timing is not intended to be exact. Rather it focuses on identifying an indicative time period at which conditions describing adaptation tipping points could be reached, thereby indicating a use-by year (Haasnoot et al. 2013).

For the environmental factors, projections for lower (RCP4.5) and higher (RCP8.5) emissions scenarios are useful to understand timeframes for a range of potential changes (Bates et al. 2016). Time-series were available for projected mean sea-level rise in coastal council areas (McInnes et al. 2016), providing an indication of when the conditions associated with this uncertain factor might be exceeded. Additionally, guidance was sought from the Australian Rainfall and Runoff guide for projecting changes to rainfall intensity. This relates future rainfall intensity changes to temperature change using a scaling estimate of 5 % per °C of warming, based on the Clausius-Clapeyron vapour pressure relationship (Bates et al. 2016). However, uncertainty remains with this approach, with research suggesting that extreme rainfall intensities could increase by more than 15 % per °C in Tasmania by the end of the century (Mantegna et al. 2017). Projected temperature change was obtained from the Climate Change in Australia web portal (CSIRO and Bureau of Meteorology 2015), which guided the indicative timeframes for changes to rainfall intensity based on the relationship used by Bates et al. (2016).

The projections suggest that changing rainfall intensity is likely to cause unacceptable impacts to AAPE between the years 2040-2060, if the average people per house exceeds 2.4. The impacts to AAD are projected to remain acceptable for a longer timeframe, until years 2050-2070, if the maximum replacement cost of dwellings exceeds \$1,536/m^2 in *real* dollars. The impacts to average beach width may become unacceptable between the years 2060-2070, which is conditional on the Bruun factor exceeding 83 (a conservative value for the study area). Ongoing monitoring of each key factor at local, regional and national scales is necessary to confirm the adequacy of the presently projected trends and to update the projected time periods at which adaptation tipping points may be reached.

Table 4. Projected timeframe for changing factors. The selected factors are those identified in the candidate scenarios.

Condition		Projected change		Adaptation objective		
Factor	**Value**	**Indicative timeframe**	**Scientific basis**	**(1) AAPE**	**(2) AAD**	**(3) Beach width**
Sea-level rise increase (*relative to 2010 levels*)	0.3m	2060 (RCP4.5) – 2070 (RCP8.5)	McInnes et al. (2016)			✓
Changing 9-hour rainfall intensity (*relative to present*)	4.8% 6.3%	2040 (RCP4.5) – 2060 (RCP8.5) 2050 (RCP4.5) – 2070 (RCP8.5)	Bates et al. (2016); CSIRO and Bureau of Meteorology (2015)	✓	 ✓	
Bruun factor	83	-	Nil [a.]			✓
Max. structural damage per m^2 (*real dollars in 2016*)	$1,536/$m^2$	-	Dunford et al. (2014) [b.]		✓	
Average people per house	2.4	Minimal change [c.]	ABS (2010)	✓		

[a.] No data is available on the Bruun factor for Kingston Beach. Estimates from nearby areas are lower than the value shown.

[b.] No projections available. Periodic updates to the structural value are necessary (e.g. NEXIS building exposure database; Dunford et al. 2014), which are then adjusted from *nominal* to *real* dollars using the ‘average weekly earnings’ figures (Department of Environment and Climate Change 2007) that are tracked by the Australian Bureau of Statistics (e.g. ABS 2017).

[c.] The average household size is estimated to fall to between 2.2-2.3 by 2031 in Tasmania (ABS 2010).

3.7 Develop the adaptation pathway

The key conditions that lead to adaptation tipping points and time projections identified in Section 3.6 can be brought together within a DAPP framework to begin developing an adaptation pathway. The steps in the DAPP framework require identifying possible adaptation responses, evaluating the responses, assembling the pathways, identifying preferred pathways, contingency planning, and creating a dynamic adaptive plan (Haasnoot et al. 2013). The key factors identified through scenario discovery can also support the definition of technical signposts in the DAPP process. The first part of the adaptation pathways mapping process for the study area is shown in Fig. 6, which indicates when an adaptation response would be needed to manage the different adaptation objectives in the case where no adaptation measures are taken. Planning and implementation timeframes for each adaptation response needs to consider the lead time as the option progresses through project/policy governance systems. Each subsequent adaptation option identified in the pathway can be assessed for robustness by repeating the steps in Section 2.2 through to Section 2.6, or evaluated using other decision support tools (e.g. Dittrich et al. 2016). Furthermore, some options may impact on multiple adaptation objectives (e.g. a levee could provide benefits to both the AAD and AAPE objectives). Therefore the evaluation of the costs and benefits of each adaptation option would need to consider the implications to multiple objectives.

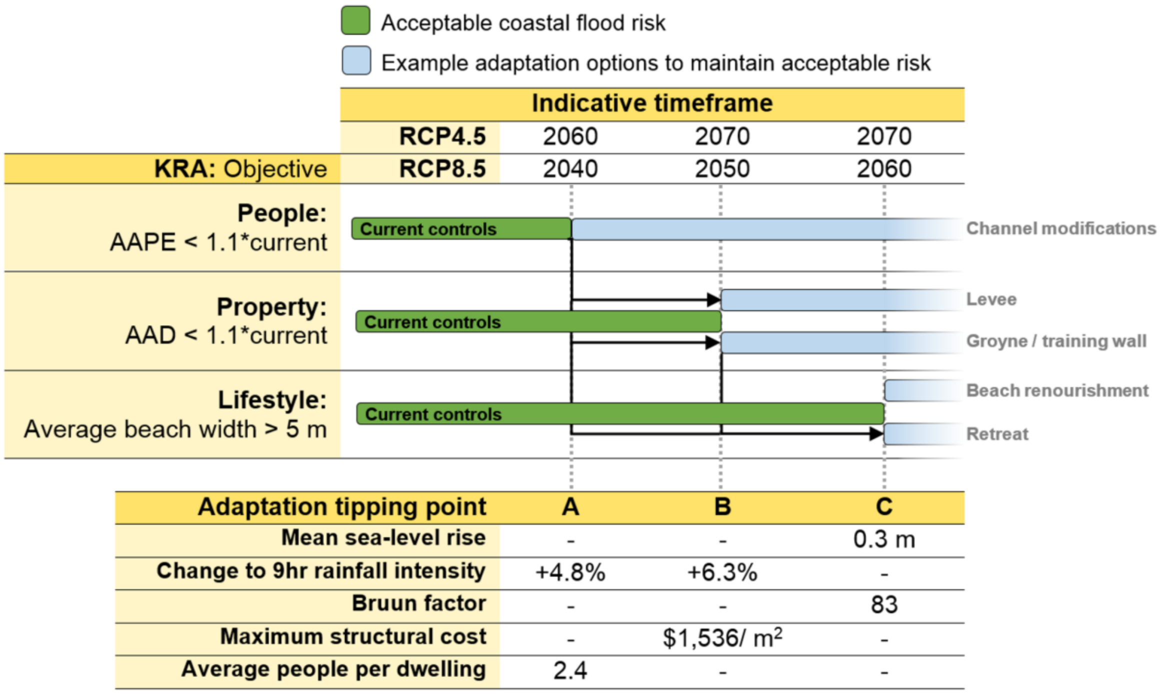

Fig. 6 Development of the adaptation pathway using adaptation tipping points and the projected timeframe of change. Adaptation objectives and future options to be explored are organised into key result areas (KRAs) to guide long-term planning. Options shown are mutually exclusive and black arrows indicate options that can improve outcomes for correlated objectives. Timeframes are indicative and require ongoing monitoring and reassessment as part of iterative risk management.

4 Discussion

4.1 Greater insights for coastal flood risk management

The ability to simulate coastal flood impacts across many future scenarios better equips decision-makers to address questions such as *'what change leads to unacceptable impacts?'* and *'when are adaptation responses needed?'*. The case study illustrates that open source spatial data and programming, combined with commercial GIS software, can be used to address these questions by uncovering key risk management considerations in communities that face uncertain long-term change. There is an opportunity for local government and other coastal authorities to replicate the illustrated method whilst customising it for their local needs.

The use of scenario discovery to identify conditions whereby existing plans no longer meet the adaptation objectives can simplify complex changes to the built and natural environment in a meaningful format for stakeholders to understand. As demonstrated in the case study, RDM offers the potential to explore the interaction between a broad set of uncertain hazard, exposure, and vulnerability factors and how they influence coastal inundation impacts. This recognises that societal development, building codes, and other land use policies can exacerbate flood impacts in low-lying communities, especially when coupled with changing flood patterns. This approach is an improvement on seminal adaptation pathway methods that focus on changes to a single hazard parameter (Kwadijk et al. 2010; Reeder and Ranger 2011). However, using multiple uncertain factors to describe conditions leading to adaptation tipping points adds further complexity to the risk monitoring process. Each variable may change in different directions and with varying rates. Therefore a vulnerability assessment to coastal inundation, including periodic monitoring, needs to be done routinely as part of the managing authorities' iterative risk management process.

The key factors uncovered with scenario discovery can support the selection of signposts that are identified in the later stages of the DAPP process. They can also allow causal factors to be further explored to better understand leading indicators that signify changing risk (Bonzanigo and Kalra 2014). For example, population growth and housing density is driven by land use and development decisions, which influences the average number of people per dwelling exposed and therefore achievement of the AAPE objective. Techniques like root cause analysis, systems thinking, or hazard chains (Downing 2012) can be undertaken at this stage of the assessment to identify (and treat) causal risk factors that are interconnected but less apparent. These insights can build a case for targeted data collection and monitoring activities in urbanised coastal areas, which is important when financial resources are limited. In further developing adaptation pathways, technical signposts such as those noted above would need to be considered alongside political signposts to be inclusive of different stakeholder needs (Hermans et al. 2017).

The methodology illustrated in the case study takes a different approach to traditional risk management methods, such as the ISO31000 process that is recognised worldwide. Our methodology requires tolerable risks to be defined at the outset and baseline impacts to be assessed, before the sensitivities of the site to coastal inundation are uncovered. Conversely, the ISO31000 process begins with a risk assessment, then prioritises risks based on likelihood and consequence matrices before evaluating whether risks are acceptable, tolerable, or intolerable. Identification of a baseline risk acknowledges that there is already a certain coastal inundation threat that the community has accepted, knowingly or not. This allows analysts to focus their efforts on searching for what changes to the current built and natural environment will cause unacceptable inundation impacts. This makes the process of communicating risks more straightforward and salient to concerned parties, since they can consider how environmental change might affect them relative to what they are experiencing today. An important strength of the ISO31000 process over our method is that it considers a much broader set of impacts. For example the National Emergency Risk Assessment Guidelines used in Australian emergency management considers consequences to people, environment, economy, public administration, social setting and infrastructure (National Emergency Management Committee 2010). Our approach was limited to a quantitative assessment of impacts to people, property, and lifestyle objectives. Therefore there is scope for the presented method to increase the number of adaptation objectives and include a qualitative assessment of intangible consequences.

4.2 Making change salient in the community

A characteristic of the key factors identified by scenario discovery in the case study was that they change slowly over time. However, detecting such environmental changes can be problematic due to natural variability, sparse data records, and non-stationarity (Milly et al. 2008). Detecting a modest 4-7% increase to 9-hour rainfall intensity – as identified in our case study – is difficult in practice, and a coastal authority asserting that such change has occurred is likely to be challenged by residents with different views.

Translating changes to key variables into observable impacts can provide an evidence-based approach to substantiate claims within the community that they may be approaching a threshold or adaptation tipping point. For example, a 4.8% increase in rainfall intensity in the study area suggests that inundation of the Windsor Street / Balmoral Road intersection may occur once every 7 years, instead of 9 years (Fig. 7). Consequently, flooding of this intersection twice in a 7-year timeframe could signal that the rainfall intensity is approaching its adaptation tipping point limit. Although this does not account for changing catchment characteristics (e.g. upstream development) and changing extreme rainfall frequencies that can affect the recurrence interval of peak floodwaters, it does serve to convert an otherwise meaningless number into demonstrable evidence that change may be occurring.

A similar philosophy was used by Barnett et al. (2014) in their case study at Lakes Entrance, whereby an adaptation response was planned in the event that the esplanade flooded for 5 or more days in a year. Importantly, observed changes to rainfall intensity and/or flood frequency at a local scale requires robust assessment against expected variability. In this regard, local agencies require input from national agencies (e.g. CSIRO, Bureau of Meteorology and Geosciences Australia) who are concerned with the scientific assessment of changes across various spatial and temporal scales. This ensures decision are based on robust scientific understanding of changes that are occurring, reducing the chance of reactive decisions being made by coastal authorities in the face of chance events or natural variability.

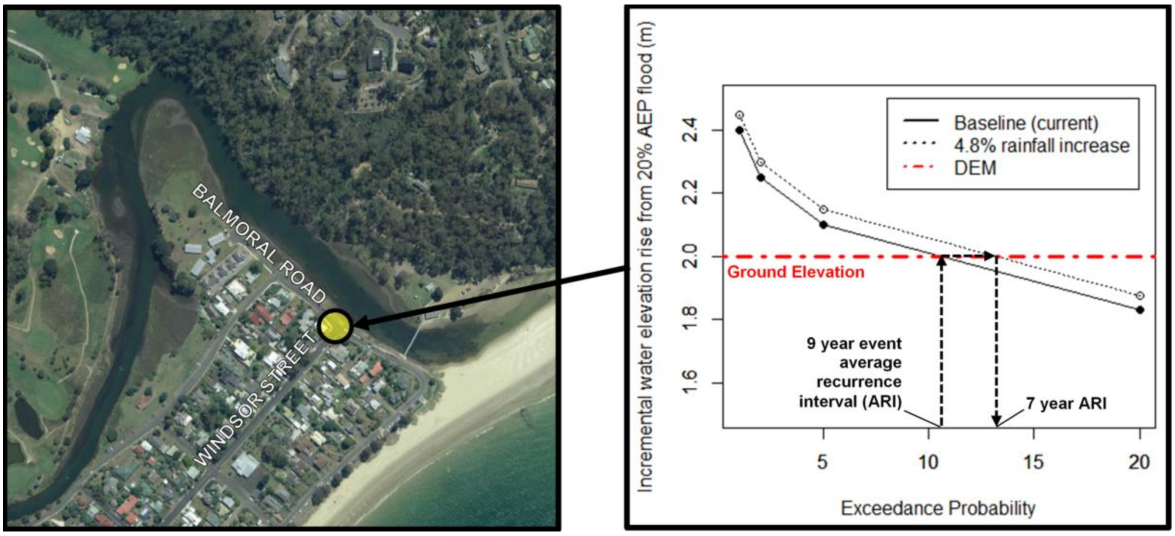

Fig. 7 Selected location at the intersection of Windsor Street and Balmoral Road (circled – left panel) that could be used to observe changing coastal flood risk. The average change to peak flood water elevations (above AHD) for a 20% AEP flood event with increased rainfall intensity of 4.8% is shown in the right panel.

The case study presented here made an important assumption that measurable adaptation objectives and tolerable impacts could be defined and agreed upon in the community. The study was also limited to a small subset of the possible values that may exist in the community. In practice, public collective decision-making processes are likely to face contested adaptation goals and conflicting knowledge among stakeholders (Bosomworth et al. 2017), whilst social power inequalities and varying short-term interests can hamper long-term planning efforts (Few et al. 2007). Although there are increasing calls for social impacts to be better accounted for in climate change impact assessments and to evaluate adaptation responses (Adger et al. 2009; Downing 2012), such considerations are not straightforward due to complex and subjective interactions among values, ethics, priorities, culture, knowledge, and power structures, all of which change with time (Adger et al. 2009). Engagement with community stakeholders may be a useful starting point to identify contested values in the scoping phase of adaptation planning and to define key issues (e.g. Barnett et al. 2014). This can then form a basis for identifying the adaptation objectives, metrics and tolerable impacts upon which subsequent analysis is based. The use of decision relevant information produced by activities such as scenario discovery can better inform participants at various stages of the planning process and can also strengthen the credibility of the resultant strategy. Although deliberation with analysis is increasingly being recognised in complex environmental policy problems (National Research Council 2009), further research is needed to explore how this can be most effectively utilised in a combined RDM and DAPP approach.

4.3 The prospects and limitations: Towards better informed planning

The case study highlights that there is a need to improve the accuracy of simulation modelling, in particular the generation of rules of thumb and proxy floodwater rasters. Simplifications in the model meant parameters such as flood duration, contamination, debris, rate of rise, and flood velocity were omitted, which can cause overall damage estimates to be underestimated (Merz et al. 2010; Middelmann-Fernandes 2010). Similarly, the use of the Bruun rule is likely to be overly simplistic given (among other things) it does not consider coastal storms that can exacerbate beach erosion nor other coastal processes that may affect the shoreline response. Notwithstanding these limitations, changing beach widths can be easily monitored by coastal authorities, community groups, or residents to confirm trends in the face of uncertainty (e.g. ACECRC n.d.; UNESCO 2005), and the beach management authority could develop contingency plans to address unexpected near-term beach loss.

The timing at which adaptation tipping points were projected in this study was relatively simple by focussing on a small set of projected changes to key variables. The use of transient scenarios to identify a range of use-by years (e.g. Haasnoot et al., 2015) is a potential improvement to the methodology presented in Section 3.6, as it would allow different rates of change (positive and negative) for the key conditions describing adaptation tipping points to be combined across many cases. This could better inform the timing of adaptation tipping points to support the development of long-term master plans and future resource requirements.

Implementation of the presented methodology requires data availability, technical capability, and financial resources to perform the analysis, collect data, and monitor change over time. Given that technical knowledge and financial constraints are likely to remain a barrier for local government in the near-term, such resources could be centralised in a nationally coordinated authority. This authority could work with local government to apply a nationally consistent approach to describe conditions leading to adaptation tipping points and develop adaptation pathways. The presented method could also be applied at a municipal, state or national scale to identify coastal settlements that are most vulnerable to changing coastal flood hazards, using the timing at which their adaptation tipping points would be exceeded as an indicator. For resource-constrained authorities, the ability to prioritise adaptation investment towards those communities that yield the greatest risk mitigation benefits would improve the allocation of scarce financial resources.

It is too early to fully understand the effectiveness of the illustrated methodology in this study given that it reflects *ex ante* planning, yet such conditions are faced in all risk identification activities. What the methodology offers is a new way of integrating two state-of-the-art decision support tools so that decision-makers can explore and identify future vulnerabilities to coastal inundation and design adaptation pathways.

5 Conclusions

This research has examined whether RDM can be embedded within a DAPP framework to improve planning for changing coastal flooding risks. Our method was underpinned by GIS software, open source data, and programming languages, making it pragmatic and possible to replicate in other coastal communities.

The use of RDM to uncover sensitivities in the existing system to changing coastal flood patterns focuses the attention of decision-makers towards those uncertainties that are most relevant for achieving their adaptation objectives. This is useful not only for understanding *what* change leads to intolerable risk and *when* such change might occur, but considers more broadly how societal development, land use, and existing building regulations might exacerbate impacts from changing coastal flood patterns.

A better understanding of the key conditions that lead to adaptation tipping points in flood risk management can support targeted data collection, monitoring activities, and adaptation responses. It can also help identify signposts in the adaptation pathway. However, detecting changes in multiple factors can be difficult given natural variability, and challenges are enhanced by sparse long-term data records and little financial resources allocated to coastal monitoring activities. Furthermore, reaching agreement on the adaptation objectives, a clear definition of what the community deems as tolerable impacts and exploring how deliberation with analysis is most effectively used in a combined RDM and DAPP approach remains a question for further research.

The use of scenario discovery to describe conditions leading to adaptation tipping points offers an alternative conceptualisation of the DAPP approach, which uses transient scenarios to focus on the timeframe at which an adaptation tipping point is reached. In a combined RDM and DAPP approach, transient scenarios could be used after scenario discovery to project the timing of adaptation tipping points based upon changes to a reduced set of key factors. This sequence of steps would improve the description of adaptation tipping points and the basis for projecting the use-by year of existing and future adaptation policies.

Our study illustrates that RDM can be a powerful method to uncover a small set of conditions that together can characterise adaptation tipping points in the face of uncertain environmental change and the simulation results are well suited for use within a DAPP framework. Notwithstanding the challenges that remain around simulation modelling and detection of environmental change, the ability to make sense of complex environmental dynamics for use in vulnerability assessments and adaptation planning can provide much needed support to coastal authorities who are facing increasing pressure to minimise costly impacts and ensure the sustainability of their communities.

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References

ABS (2010) Household and Family Projections, Australia, 2006 to 2013. Cat no 3236.0, ABS. http://www.abs.gov.au/ausstats/abs@.nsf/0/8CD306B3C1B2C30CCA25773B0017D008?opendocument. Accessed 22 June 2017.

ABS (2013) 2011 Census QuickStats. ABS. http://www.censusdata.abs.gov.au/census_services/getproduct/census/2011/quickstat/SSC60179?opendocument&navpos=220. Accessed 30 May 2017.

ABS (2017) Average weekly earnings, Australia, Nov 2016. Cat no 6302.0, ABS. http://www.abs.gov.au/AUSSTATS/abs@.nsf/Lookup/6302.0Main+Features1Nov%202016?OpenDocument. Accessed 23 June 2017.

ACECRC (n.d.) The Tasmanian Shoreline Monitoring and Archiving Project (TASMARC). ACECRC. http://www.tasmarc.info/. Accessed 30 May 2017.

Adger, W.N., Dessai, S., Goulden, M., Hulme, M., Lorenzoni, I., Nelson, D.R., Naess, L.O., Wolf, J., & Wreford A. (2009) Are there social limits to adaptation to climate change? Clim Chang, 93, 335-354. http://dx.doi.org/10.1007/s10584-008-9520-z

Bankes, S.C. (1993). Exploratory modeling for policy analysis. Oper Res, 41, 435-449. https://doi.org/10.1287/opre.41.3.435

Bates, B., McLuckie, D., Westra, S., Johnson, F., Green, J., Mummery, J., & Abbs, D. (2016) Climate change considerations. Book 1 in Australian Rainfall and Runoff – A guide to flood estimation. Commonwealth of Australia. http://book.arr.org.au.s3-website-ap-southeast-2.amazonaws.com/#b1_ch6_f_yzgm5. Accessed 23 June 2017.

Barnett, J., Graham, S., Mortreux, C., Fincher, R., Waters, E., & Hurlimann, A. (2014) A local coastal adaptation pathway. Nat Clim Chang, 4, 1103-1108. http://dx.doi.org/10.1038/nclimate2383

Bhave, A.G., Conway, D., Dessai, S., & Stainforth, D.A. (2016) Barriers and opportunities for robust decision making approaches to support climate change adaptation in the developing world. Clim Risk Manag, 14, 1-10. http://dx.doi.org/10.1016/j.crm.2016.09.004

Bonzanigo, L., & Kalra, N. (2014) Making informed investment decisions in an uncertain world. A short demonstration. Policy Research Working Paper 6765. http://www-wds.worldbank.org/external/default/WDSContentServer/IW3P/IB/2014/02/03/000158349_20140203130155/Rendered/PDF/WPS6765.pdf. Accessed 30 December 2015.

Bosomworth, K., Leit, P., Harwood, A., & Wallis, P.J. (2017). What's the problem in adaptation pathways planning? The potential of a diagnostic problem-structuring approach. Environ Sci Policy, 76, 23-28. http://dx.doi.org/10.1016/j.envsci.2017.06.007

Breiman, L., Friedman, J.H., Olshen, R.A., Stone, C.J. (1993) Classification and Regression Trees, Chapman & Hall/CRC, USA.

Bruun, P. (1962) Sea-level rise as a cause of shore erosion. J Waterw Harb Div-ASCE, 889, 117-132.

Bryant, B.P. (2016). Sdtoolkit: Scenario discovery tools to support robust decision making (v2.33-1).

Bryant, B.P., & Lempert, R.J. (2010) Thinking inside the box: A participatory, computer-assisted approach to scenario discovery. Technol Forecast Soc Chang, 77, 34-49. http://dx.doi.org/10.1016/j.techfore.2009.08.002

Carnell, R. (2016). Lhs: Latin hypercube samples (v0.14).

Carley, J., Blacka, M., Cox, R., Attwater, C., & Watson, P. (2008) Modelling coastal processes and hazards to assess sea level rise impacts for integration into a planning scheme. IPWEA National Conference Climate Change Response, Coffs Harbour, 1-11.

CoastAdapt (2016) CoastAdapt Shoreline Explorer: Derwent – D'Entrecasteaux, NCCARF, https://coastadapt.com.au/sites/default/files/docs/sediment_compartments/TAS01.04.05.pdf. Accessed 20 March 2017.

Cooper, J.A.G., & Pilkey, O.H. (2004) Sea-level rise and shoreline retreat: time to abandon the Bruun Rule. Glob Planet Chang, 43, 157-171. http://dx.doi.org/10.1016/j.gloplacha.2004.07.001

Commonwealth of Australia (2011) Climate Change Risks to Coastal Buildings and Infrastructure – A supplement to the first pass national assessment. Commonwealth of Australia, http://www.environment.gov.au/system/files/resources/0f56e5e6-e25e-4183-bbef-ca61e56777ef/files/risks-coastal-buildings.pdf. Accessed 15 July 2015.

CSRIO & Bureau of Meteorology (2015) Climate Change in Australia. Commonwealth of Australia. https://www.climatechangeinaustralia.gov.au/en/. Accessed 23 June 2017.

Daron, J. (2015) Challenges in using a Robust Decision Making approach to guide climate change adaptation in South Africa. Clim Chang, 132, 459-473. http://dx.doi.org/10.1007/s10584-014-1242-9

de Moel, H., Jongman, B., Kreibich, H., Merz, B., Penning-Rowsell, E., & Ward, P.J. (2015) Flood risk assessments at different spatial scales. Mitig Adapt Strat Glob Chang, 20, 865-890. http://dx.doi.org/10.1007/s11027-015-9654-z

Deloitte Access Economics (2013) Building our nation's resilience to natural disasters. Deloitte, http://australianbusinessroundtable.com.au/assets/documents/White%20Paper%20Sections/DAE%20Roundtable%20Paper%20June%202013.pdf. Accessed 26 May 2017.

Department of Environment and Climate Change (2007) Residential flood damages. NSW Government. http://www.environment.nsw.gov.au/resources/floodplains/guideline-residential-flood-damages.pdf. Accessed 23 June 2017.

Dewulf, A., Craps, M., Bouwen, R., Taillieu, T., & Pahl-Wostl, C. (2005) Integrated management of natural resources: dealing with ambiguous issues, multiple actors and diverging frames. Water Sci Tech, 52, 115-124.

Dittrich, R., Wreford, A., Moran, D. (2016) A survey of decision-making approaches for climate change adaptation: Are robust methods the way forward? Ecol Econ, 122, 79-89. http://dx.doi.org/10.1016/j.ecolecon.2015.12.006

Downing, T.E. (2012) Views of the frontiers in climate change adaptation economics. WIREs Clim Chang, 3, 161-170. http://dx.doi.org/10.1002/wcc.157

DPIPWE (2015) Open data. Department of Primary Industries, Parks, Water and Environment, Tasmania. http://listdata.thelist.tas.gov.au/opendata/. Accessed 21 March 2017.

Dunford, M.A., Power, L., & Cook, B. (2014) National Exposure Information System (NEXIS) Building Exposure – Statistical Area Level 1 (SA1). Geosciences Australia. http://www.ga.gov.au/metadata-gateway/metadata/record/gcat_82220. Accessed 07 April 2017.

Egorova, R., van Noortwijk, J.M., & Holterman, S.R. (2008) Uncertainty in flood damage estimation. Int J River Basin Manag, 6, 139-148. http://dx.doi.org/10.1080/15715124.2008.9635343

Few, R., Brown, K., & Tompkins, E.L. (2007) Public participation and climate change adaptation: avoiding the illusion of inclusion. Clim Policy, 7, 46-59. http://dx.doi.org/10.1080/14693062.2007.9685637

Friedman, J.H., & Fisher, N.I. (1999) Bump hunting in high-dimensional data. Stat Comput, 9, 123-143. http://dx.doi.org/10.1023/A:1008894516817

Geosciences Australia (2012) Flood vulnerability functions for Australian Buildings. Summary of the Current Geosciences Australia Model Suite. Commonwealth of Australia, Canberra.

Haasnoot, M., Middelkoop, H., Offermans, A., Beek, E., & van Deursen, W.P.A. (2012) Exploring pathways for sustainable water management in river deltas in a changing environment. Clim Chang, 115, 795-819. http://dx.doi.org/10.1007/s10584-012-0444-2

Haasnoot, M., Kwakkel, J.H., Walker, W.E., ter Maat, J. (2013) Dynamic adaptive policy pathways: A method for crafting robust decisions for a deeply uncertain world. Glob Environ Chang, 23, 485-498. http://dx.doi.org/10.1016/j.gloenvcha.2012.12.006

Haasnoot, M, Schellekens, J, Beersma, J.J., Middelkoop, H, & Kwadijk, J.C.J. (2015). Transient scenarios for robust climate change adaptation illustrated for water management in The Netherlands. Environmental Research Letters, 10, 105008. http://dx.doi.org/10.1088/1748-9326/10/10/105008

Hallegatte, S. (2009) Strategies to adapt to an uncertain climate change. Glob Environ Chang, 19, 240-247. http://dx.doi.org/10.1016/j.gloenvcha.2008.12.003

Hermans, L.M., Haasnoot, M., ter Maat, J., & Kwakkel, J.H. (2017). Designing monitoring arrangements for collaborative learning about adaptation pathways. Environ Sci Policy, 69, 29-38. http://dx.doi.org/10.1016/j.envsci.2016.12.005

Hunter, J. (2010) Estimating sea-level extremes under conditions of uncertain sea-level rise. Clim Chang, 99, 331-350. http://dx.doi.org/10.1007/s10584-009-9671-6

IPCC (2012) Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report to Working Groups I and II of the Intergovernmental Panel on Climate Change, Field, C. B. *et al* (eds), IPCC, Cambridge University Press, Cambridge and New York.

Jones, R.N., Patwardhan, A., Cohen, S.J., Dessai, S., Lammel, A., Lempert, R.J., Mirza, M.M.Q., & von Storch, H. (2014) Foundations for decision making. In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Field, C. B. *et al (eds),* Cambridge University Press, Cambridge and New York, 195-228.

Kalra, N., Groves, D.G., Bonzanigo, L., Perez, E.M., Ramos, C., Brandon, C., & Cabanillas, I.R. (2015) Robust Decision-Making in the Water Sector. A Strategy for Implementing Lima's Long-Term Water Resources Master Plan. Policy Research Working

Paper 7439. World Bank Group. http://www-wds.worldbank.org/external/default/WDSContentServer/WDSP/IB/2015/10/15/090224b08314a2b3/3_0/Rendered/PDF/Robust0decisio0esources0master0plan.pdf. Accessed 21 July 2016.

Kingborough Council (2017) Kingston Beach Flood Study. Kingborough Council, Tasmania. http://www.kingborough.tas.gov.au/webdata/resources/files/Kingston%20Beach%20Flood%20Study%202016%20(reduced).pdf. Accessed 20 February 2017.

Klijn, F., Kreibich, H., de Moel, H., & Penning-Rowsell, E. (2015) Adaptive flood risk management planning based on a comprehensive flood risk conceptualisation. Mitig Adapt Strat Glob Chang, 20, 845-864. http://dx.doi.org/10.1007/s11027-015-9638-z

Kwadijk, J., Haasnoot, M., Mulder, J., Hoogvliet, M., Jeuken, A., van der Krogt, R., van Oostrom, N., Schelfhout, H., van Velzen, E., van Waveren, H., & de Wit, M. (2010) Using adaptation tipping points to prepare for climate change and sea level rise: a case study in the Netherlands. WIREs Clim Chang, 1, 729-740. http://dx.doi.org/10.1002/wcc.64

Kwakkel, J.H., Walker, W.E., & Haasnoot, M. (2016a) Coping with the Wickedness of Public Policy Problems: Approaches for Decision Making under Deep Uncertainty. J Water Resour Pl.-ASCE, 01816001. http://dx.doi.org/10.1061/(ASCE)WR.1943-5452.0000626

Kwakkel, J.H., Haasnoot, M., & Walker, W.E. (2016b) Comparing Robust Decision-Making and Dynamic Adaptive Policy Pathways for model-based decision support under deep uncertainty. Environ Model Softw, 86, 168-183. http://dx.doi.org/10.1016/j.envsoft.2016.09.017

Kwakkel, J.H., & Jaxa-Rozen, M. (2016). Improving scenario discovery for handling heterogeneous uncertainties and multinomial classified outcomes. Environ Model Softw, 79, 311-321. http://dx.doi.org/10.1016/j.envsoft.2015.11.020

Kwakkel, J.H., (2017). The Exploratory Modeling Workbench: An open source toolkit for exploratory modeling, scenario discovery, and (multi-objective) robust decision making. Environ Model Softw, 96, 239-250. http://dx.doi.org/10.1016/j.envsoft.2017.06.054

Lawrence, J., & Haasnoot, M. (2017) What it took to catalyse uptake of dynamic adaptive pathways planning to address climate change uncertainty. Environ Sci Policy, 68, 47-57. http://dx.doi.org/10.1016/j.envsci.2016.12.003

Lempert, R. (2013) Scenarios that illuminate vulnerabilities and robust responses. Clim Chang, 117, 627-646. http://dx.doi.org/10.1007/s10584-012-0574-6

Lempert, R.J., Bryant, B.P., & Bankes, S.C. (2008) Comparing algorithms for scenario discovery. RAND Corporation, https://www.rand.org/content/dam/rand/pubs/working_papers/2008/RAND_WR557.pdf. Accessed 28 March 2017.

Lempert, R., Kalra, N., Peyraud, S., Mao, Z., Bach Tan, S., Cira, D., & Lotsch, A. (2013) Ensuring Robust Flood Risk Management in Ho Chi Minh City. Policy Research Working Paper 6465. The World Bank, Washington, D.C.

Lempert, R.J., Popper, S.W., & Bankes, S.C. (2003) Shaping the Next One Hundred Years: New Methods for Quantitative, Long-Term Policy Analysis. RAND Corporation, Santa Monica, CA.

Mantegna, G., White, C.J., Remenyi, T.A., Corney, S.P., & Fox-Hughes, P. (2017). Simulating sub-daily Intensity-Frequency-Duration curves in Australia using a dynamical high-resolution regional climate model. J Hydrol, 554, 277-291. https://doi.org/10.1016/j.jhydrol.2017.09.025

Mariani, A., Shand, T.D., Carley, J.T., Goodwin, I.D., Splinter, K., Davey, E.K., Flocard, F., & Turner, I.L. (2012) Generic Design Coastal Erosion Volumes and Setbacks for Australia. Antarctic Climate and Ecosystems Cooperative Research Centre. http://acecrc.org.au/wp-content/uploads/2015/03/TR-Generic-design-coastal-erosion-volumes-and-setbacks-for-Australia.pdf. Accessed 30 May 2017.

McInnes, K.L., Chruch, J., Monselesan, D., Hunter, J.R., O'Grady, J.G., Haigh, I.D., & Zhang, X. (2015) Information for Australian impact and adaptation planning in response to sea-level rise. Aust Meteorol Oceanogr J, 65, 127-149.

McInnes, K.L., Monselesan, D., O ’Grady, J., Church, J., & Zhang, X. (2016) Sea-Level Rise and Allowances for Tasmania based on the IPCC AR5. Report for the Tasmanian Department of Premier and Cabinet. CSIRO, Australia.

Merz, B., Kreibich, H., Schwarze, R., Thieken, A. (2010). Review article "Assessment of economic flood damage". Nat Hazards Earth Syst Sci, 10, 1697-1724. http://dx.doi.org/10.5194/nhess-10-1697-2010

Middelmann-Fernandes, M.H. (2010) Flood damage estimation beyond stage-damage functions: an Australian example. J Flood Risk Manag, 3, 88-96. http://dx.doi.org/10.1111/j.1753-318X.2009.01058.x

Milly, P.C.D., Betancourt, J., Falkenmark, M., Hirsch, R.M., Kundzewicz, Z.W., Lettenmaier, D.P., & Stouffer, R.J. (2008). Stationarity Is Dead: Whither Water Management? Sci, 319, 573-574. http://dx.doi.org/10.1126/science.1151915

Nalau, J., Preston, B.L., & Maloney, M.C. (2015). Is adaptation a local responsibility? Environ Sci Policy, 48, 89-98. http://dx.doi.org/10.1016/j.envsci.2014.12.011

National Emergency Management Committee (2010). National Emergency Risk Assessment Guidelines, Hobart, Tasmania.

National Research Council (2009). Informing decisions in a changing climate. Panel on strategies and methods for climate-related decision support. The National Academies Press, Washington D.C.

Nicholls, R.J., & Cazenave, A. (2010). Sea-Level Rise and Its Impact on Coastal Zones. Sci, 328, 1517-1520. http://dx.doi.org/10.1126/science.1185782

Pianosi, F., Beven, K., Freer, J., Hall, J.W., Rougier, J., Stephenson, D.B., & Wagener, T. (2016) Sensitivity analysis of environmental models: A systematic review with practical workflow. Environ Model Softw, 79, 214-232. http://dx.doi.org/10.1016/j.envsoft.2016.02.008

Ramm, T.D., White, C.J., & Franks, S.W. (2015) Accounting for uncertainty in cost benefit analysis: a generalised framework for natural hazard adaptation in the coastal zone. 36th Hydrology and Water Resources Symposium. Hobart, Tasmania, 510-517.

Ramm, T.D., White, C.J., Chan, A., & Watson, C.S. (2017a) A review of decision analysis methods used in long-term coastal adaptation studies in Australia. Clim Risk Manag. 17C, 35-51. https://dx.doi.org/10.1016/j.crm.2017.06.005

Ramm, T.D., Graham, S., White, C.J., & Watson, C.S. (2017b) Advancing values-based approaches to climate change adaptation: a case study from Australia. Environ Sci Policy, 76, 113-123. https://doi.org/10.1016/j.envsci.2017.06.014

Rawlinsons (2017) Australian Construction Handbook, Rawlinsons Publishing, Perth, Western Australia.

Reeder, T., & Ranger, N. (2011) How do you adapt in an uncertain world? Lessons from the Thames Estuary 2100 project, Washington, DC. https://www.wri.org/sites/default/files/uploads/wrr_reeder_and_ranger_uncertainty.pdf. Accessed 11 December 2017.

Sharples, C. (2016) Information Priorities for Resolving Priority Coastal Hazard Adaptation Responses in Kingborough Local Government Area, southern Tasmania. Report to Kingborough Council. University of Tasmania. http://www.kingborough.tas.gov.au/webdata/resources/files/Kingborough%20CoastalHazardPriorities%20(Sharples%202016).pdf. Accessed 21 March 2017.

Teng, J., Jakeman, A.J., Vaze, J., Croke, B.F.W., Dutta, D., & Kim, S. (2017). Flood inundation modelling: A review of methods, recent advances and uncertainty analysis. Environ Model Softw, 90, 201-216. http://dx.doi.org/10.1016/j.envsoft.2017.01.006

UNESCO (2005) Introduction to Sandwatch: An educational tool for sustainable development. Coastal region and small island papers 19, UNESCO, Paris.

Walker, W.E., Haasnoot, M., & Kwakkel, J.H. (2013) Adapt or perish: A review of planning approaches for adaptation under deep uncertainty. Sustain, 5, 955-979. http://dx.doi.org/10.3390/su5030955

Ward, T., Butler, E., & Hill, B. (1998) Environmental indicators for national state of the environment reporting – Estuaries and the Sea, Australia: State of the Environment (Environmental Indicator Reports). Department of the Environment, https://www.environment.gov.au/system/files/pages/f59cdc73-e8ca-4bd9-8592-586357a70082/files/estuaries.pdf. Accessed 30 March 2017.

Watkiss, P., & Hunt, A. (2013) Method overview: Decision support methods for adaptation, Briefing Note 1. Summary of methods and case study examples from the MEDIATION project. Funded by the EC's 7FWP.

Werners, S.E., Pfenninger, S., van Slobbe, E., Haasnoot, M., Kwakkel, J.H., & Swart, R.J. (2013). Thresholds, tipping and turning points for sustainability under climate change. Curr Opin Environ Sustain, 5, 334-340. https://doi.org/10.1016/j.cosust.2013.06.005

White, C.J., Grose, M.R., Corney, S.P., Bennett, J.C., Holz, G.K., Sanabria, L.A., McInness, K.L., Cechet, R.P., Gaynor, S.M., & Bindoff, N.L. (2010) Climate futures for Tasmania: extreme events technical report. Antarctic Climate and Ecosystems Cooperative Research Centre, Hobart, Tasmania.

White, C.J., McInnes, K.L., Cechet, R.P., Corney, S.P., Grose, M.R., Holz, G.K., Katzfey, J.J., & Bindoff, N.L. (2013) On regional dynamical downscaling for the assessment and projection of temperature and precipitation extremes across Tasmania, Australia. Clim Dyn, 41, 3145-3165. https://doi.org/10.1007/s00382-013-1718-8

Woodroffe, C.D. (2003) Coasts: form, process, and evolution. Cambridge University Press, Cambridge.