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27 Abstract

28 Assessing changing coastal flood risk becomes increasingly uncertain across multi-29 decadal timeframes. This uncertainty is a fundamental complexity faced in vulnerability assessments and adaptation planning. Robust decision making (RDM) and dynamic 30 31 adaptive policy pathways (DAPP) are two state-of-the-art decision support methods that 32 are useful in such situations. In this study we use RDM to identify a small set of conditions 33 that cause unacceptable impacts from coastal flooding, signifying that an adaptation 34 tipping point is reached. Flexible adaptation pathways can then be designed using the 35 DAPP framework. The methodology is illustrated using a case study in Australia and 36 underpinned by a geographic information system model. The results suggest that 37 conditions identified in scenario discovery direct the attention of decision-makers towards 38 a small number of uncertainties most influential on the vulnerability of a community to 39 changing flood patterns. This can facilitate targeted data collection and coastal monitoring 40 activities when resources are scarce. Importantly, it can also be employed to illustrate 41 more broadly how uncontrolled societal development, land use and historic building 42 regulations might exacerbate flood impacts in low-lying urban areas. Notwithstanding the 43 challenges that remain around simulation modelling and detection of environmental 44 change, the results from our study suggest that RDM can be embedded within a DAPP 45 framework to better plan for changing coastal flood risks.

46 Keywords

- 47 Adaptation, climate change, inundation, tipping point, uncertainty, vulnerability
- 48
- 49
- 50
- 51

52 Highlights

| 53 | • | GIS software, open source data and programming languages can support coastal |
|----|---|--|
| 54 | | flood risk management activities |
| 55 | • | Scenario discovery helps simplify complex environmental changes for use in |
| 56 | | vulnerability assessment and adaptation planning |
| 57 | - | Scenario discovery can be used to describe conditions leading to adaptation |
| 58 | | tipping points |
| 59 | - | The timing of adaptation responses can be better informed by knowledge of key |
| 60 | | sensitivities in existing management controls |
| 61 | - | Insights from scenario discovery can facilitate targeted data collection and coastal |
| 62 | | monitoring activities |
| 63 | | |
| | | |

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74 **1** Introduction

75 Increasing rates of sea-level rise have the potential to alter coastal flooding regimes 76 around the world (Hunter 2010; McInnes et al. 2015; Nicholls and Cazenave 2010), 77 placing increasing pressure on decision-makers to minimise physical, environmental and 78 social impacts. However, understanding what changes could lead to unacceptable 79 impacts within the community and when such changes might occur is challenged by 80 ambiguity (Dewulf et al. 2005), different risk perceptions (Jones et al. 2014), multi-decadal 81 climate variability (Hallegatte 2009) and long-term uncertainty associated with varying 82 regional responses to climate change.

83 Various decision support tools have been proposed to guide decision-makers through 84 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 85 86 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 87 88 decision support tools (Kwakkel et al. 2016a). Deep uncertainty describes dynamic 89 conditions where there is limited knowledge and agreement on the use of models, 90 description of parameters in those models and what impacts are considered (Lempert et 91 al. 2003; Kwakkel et al. 2016a). Decision-makers are likely to encounter deep uncertainty 92 when assessing the vulnerability of a community to changing coastal inundation patterns 93 that may be experienced decades from now, or through coastal development and land 94 use planning whereby near-term investments will influence urbanisation patterns over the 95 coming decades.

96 RDM is a decision support method that evaluates the robustness of *new* policy options 97 such as a flood alleviation scheme. DAPP is an adaptive management framework that 98 begins by considering what future scenarios will cause *existing* management controls to 99 fail, before evaluating the suitability and timing of new policy options. Both methods use 100 hundreds to thousands of non-probabilistic 'what-if' scenarios to explore the impact of the

101 uncertain future on the performance of new (or existing) adaptation policies, allowing key 102 sensitivities of the policy to be identified. When external changes cause the existing 103 system or future adaptation plans to no longer meet decision-maker objectives, an 104 adaptation tipping point is reached and new actions should be implemented (Kwadijk et al. 105 2010). Adaptation tipping points provide a practical way to communicate risks to the 106 community associated with a changing built and natural environment (Werners et al. 107 2013). This focuses coastal flood risk management towards understanding the sensitivity 108 of an urban area to change and assessing when management responses might be 109 needed to keep impacts at a tolerable level (Kwadijk et al. 2010).

110 RDM and DAPP aim to design robust policies, and they achieve this in different ways. 111 RDM identifies adaptation policies that perform satisfactorily under many different future 112 scenarios, whilst DAPP provides an adaptive management framework within which 113 flexibility is created, allowing progressive review and update of policy options as more 114 information becomes available (see Appendix A in the Online Resource for a comparison 115 of RDM and DAPP). Importantly both approaches have the potential to provide 116 complementary information to decision-makers under conditions of deep uncertainty 117 (Kwakkel et al. 2016b).

118 There are few examples from local government that use RDM or DAPP to assess the 119 vulnerability of low-lying areas to coastal inundation and design adaptation pathways. This 120 could be due to many factors including unclear adaptation responsibilities in government 121 (Nalau et al. 2015), limited awareness of new decision support tools (Lawrence and 122 Haasnoot 2017), limited availability of relevant data to undertake such an analysis (Bhave 123 et al. 2016) and technological or financial constraints. Simplified applications of RDM (e.g. 124 Daron 2015) and adaptation pathways (e.g. Barnett et al. 2014) have been demonstrated 125 for resource-constrained decision-makers. However, the growing global repository of 126 spatial data and open source programming code (e.g. the exploratory modelling 127 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).

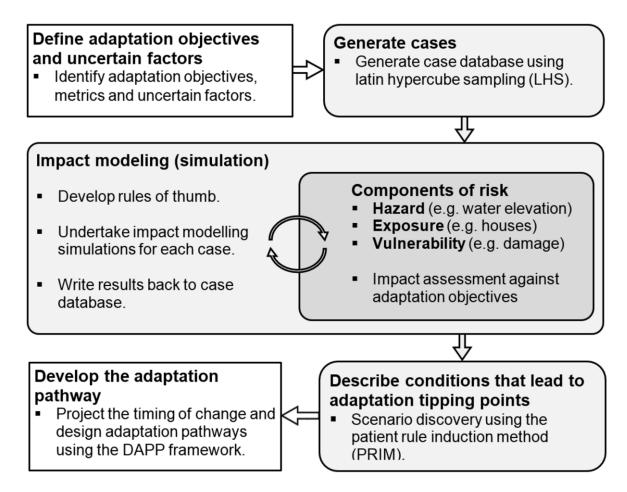
Many of the adaptation pathway examples to date in coastal flood risk management describe conditions that lead to an adaptation tipping point with a single parameter like sea-level rise (Reeder and Ranger 2011) or storm surge height (Kwadijk et al. 2010). This conceptualisation of risk suggests that 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.

137 We contribute to adaptation pathways planning research by exploring whether RDM and 138 DAPP methods can be integrated to support coastal adaptation planning under conditions 139 of uncertainty. We propose that RDM is well suited to describe a set of conditions where 140 existing or future plans would no longer satisfy adaptation objectives in low-lying urban 141 areas, signifying that an adaptation tipping point is reached. Knowledge of conditions that 142 lead to adaptation tipping points can be used to further develop adaptation pathways 143 using the DAPP framework, whereby each pathway represents a different set of 144 adaptation options sequenced over time. A more comprehensive understanding of an 145 area's sensitivity to coastal inundation allows questions such as 'what change in the built 146 and natural environmental is important?' and 'when might such change occur?' to be 147 explored. A similar philosophy was used by Kalra et al. (2015) to manage water resources 148 in Lima. However, we are not aware of any literature that proposes the integration of RDM 149 and DAPP for use in coastal flood risk management and adaptation planning. The 150 methodology presented herein uses open source spatial datasets and programming 151 languages for the benefit of resource constrained decision-makers. However, it relies on 152 commonly used commercial software (ArcGIS) and flood modelling capability. We 153 illustrate the potential for the approach on a case study site in Kingston Beach, Australia, 154 to identify what future change might lead to unacceptable coastal flood impacts to people, property and lifestyle objectives. 155

156 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 157 158 is important to avoid an increasing burden on the nation's resources. A greater upfront 159 investment in risk identification and adaptation planning using state-of-the-art decision 160 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 161 162 approach is demonstrated with a case study in Section 3. The implications and prospects 163 of the method are discussed in Section 4, with conclusions drawn in Section 5.

164 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.



172

- 173 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
- 175 Sections 2.1 to 2.7.

176

177 2.1 Define adaptation objectives

178 Adaptation objectives describe what coastal decision-makers are trying to achieve by

179 managing coastal inundation impacts. The objectives can be guided by organisational

180 requirements or through stakeholder engagement. An example of an adaptation objective

- 181 that accounts for physical impacts might be *minimising the length of critical access roads*
- 182 *inundated during a flood*, whilst an environmental adaptation objective might be
- 183 minimising the loss of beach and dune area (e.g. Ward et al. 1998). Both of these
- 184 objectives could also relate to intangible social values held by local residents, such as
- 185 ensuring recreational opportunities, aesthetic value and an ongoing feeling of safety.

186 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.

194 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' package¹), which then become inputs to the computational experiments.

202 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.

208 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

212 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.

220 **2.6 Describe conditions that lead to adaptation tipping points**

221 Scenario discovery searches through results in the case database and aims to identify a 222 small number of 'candidate scenarios' (Fig. 2) that best identify 'cases of interest' 223 (Lempert 2013). Cases of interest are those cases that result in acceptable impacts to 224 adaptation objectives. A candidate scenario describes a cluster of cases and resembles a 225 subspace of the uncertainty space that is explored in the computational experiments. It is 226 defined by a small set of factors and intervals (i.e. conditions) that capture a high 227 concentration of cases of interest. Should the small set of identified conditions occur 228 simultaneously in the future, an adaptation tipping point is likely to be reached and an 229 adaptation response would be needed to maintain impacts to the adaptation objectives at 230 or below the desired tolerance. Identifying a small number of candidate scenarios through 231 scenario discovery helps to keep the result interpretable for decision-makers.

The 'sdtoolkit' R package² 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

237 2016).

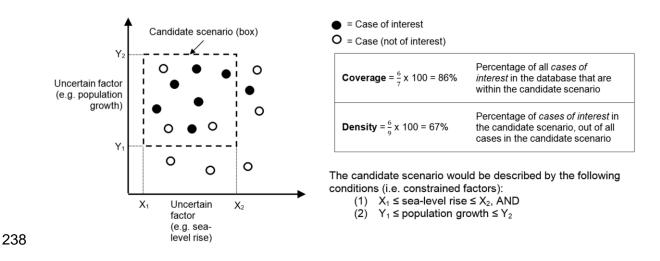


Fig. 2 Key concepts used in scenario discovery. Filled circles represent cases of interest.
The candidate scenario is defined as a box (dashed line) that constrains key input factors.
Coverage and density describe the quality of the candidate scenario.

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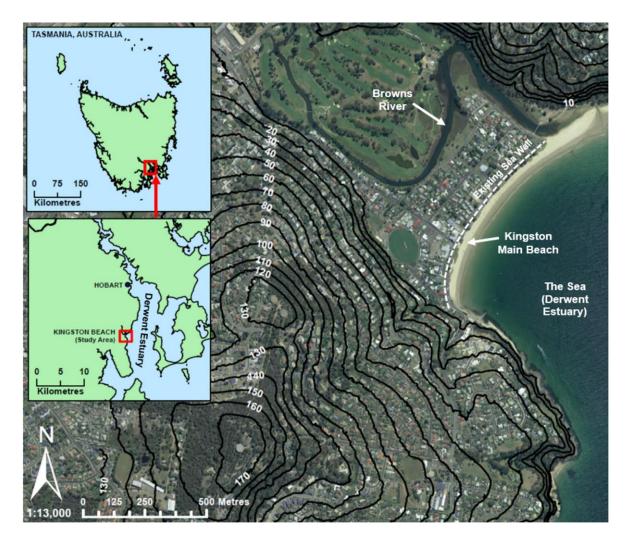
243 The quality of the candidate scenario is measured by its 'coverage' and 'density' (Fig. 2). 244 Coverage describes the cases of interest captured by the candidate scenario as a 245 proportion of all cases of interest in the entire results database. Density describes the 246 percentage of the cases of interest captured by the candidate scenario out of all cases 247 captured by the candidate scenario (Bryant and Lempert 2010; Lempert et al. 2013). 248 Other diagnostic measures, such as the guasi p-value and reproducibility statistics, are 249 useful for understanding the significance of the constrained factors in the candidate 250 scenarios (for more details see Bryant and Lempert 2010).

251 2.7 Develop the adaptation pathway

252 Once conditions under which adaptation objectives are no longer achieved have been 253 identified through scenario discovery, scientific trends and projections can be considered 254 to understand 1) the potential for such conditions to occur in the future based upon 255 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).

258 3 Case study: Kingston Beach, Tasmania

The method presented in Section 2 is illustrated for the case of the coastal suburb of 259 260 Kingston Beach, Tasmania (Australia). The study area is located approximately 13 km 261 south of the capital city of Hobart (Fig. 3). A unique aspect of the study area is that 262 approximately 86% of the housing stock located in low-lying areas were built before 1980 263 (Dunford et al. 2014). Thus, they were built prior to the introduction of higher building 264 standards. The suburb is predominantly residential, with approximately 20-40 small 265 businesses in low-lying areas and many natural landscapes including beaches, grassland, 266 saltmarshes and forests. Whilst new dwellings will be subject to more stringent building 267 regulations and land use planning controls, the characteristics (e.g. floor level, building 268 materials) of many existing houses in the study area could remain unchanged for decades. 269 Therefore these houses may have increasing exposure and vulnerability to changing flood 270 hazards in the future. Extreme sea-levels from storm tides are considered to be a lower 271 threat to people and property in the study area compared to the inundation threat of 272 riverine flooding from Browns River. However, sea-level rise will threaten low-lying coastal 273 landscapes of significant social and cultural value, such as the Kingston Main Beach 274 (Ramm et al. 2017b).



275

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.

280

281 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.

291

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 |

- Datum (Kingborough Council 2017, p.47) and reflects the average of spring tide high water observations over a 19 year period (Woodroffe 2003).
- 301

298

302 3.2 Define uncertain factors

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

| | Uncertain factor | Adaptation objective | | | | Range ^{a.} | | |
|-------------------|--|----------------------|--------------|-----------------------|--------------------------|--|---------------------------|--|
| Risk dimension | | (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.} | \checkmark | \checkmark | | -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.} | | \checkmark | | \$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) |

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

308 ^{a.} The range is not limited to scientific consensus (e.g. IPCC) and can be inclusive of resident perceptions.

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

The raster cell size is 4 m² 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).

314 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).

317 **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.

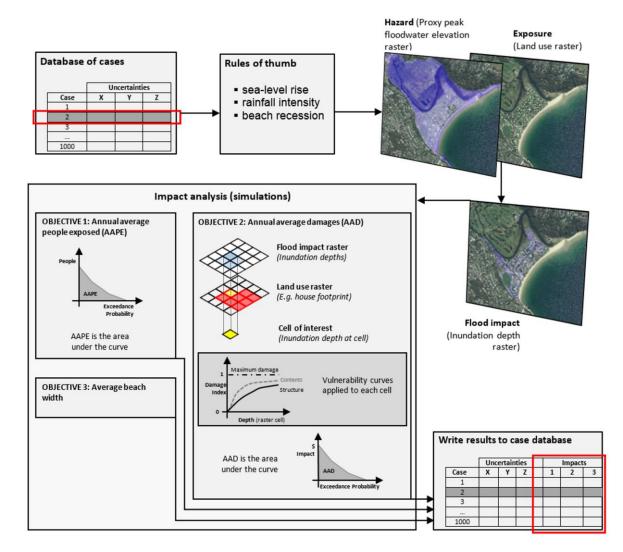
323 Peak floodwater elevation maps were developed by Kingborough Council using SWMM 324 2D hydrodynamic modelling software for 11 different scenarios (see Appendix B in the 325 Online Resource for details). This allowed the current-day baseline risk to people and 326 property in Table 1 to be established. The 11 scenarios also allowed the relationship 327 between sea-level rise and peak floodwater elevation to be investigated, revealing that a 1 328 m rise in sea-level only increases the peak floodwater elevation by 1 cm. The relationship 329 between rainfall intensity and floodwater elevation was based upon prior flood study work 330 by Kingborough Council, which suggested that the peak floodwater elevation of Browns 331 River changed by about 0.1 m per 10% increase in the 9-hour rainfall intensity 332 (Kingborough Council 2017, p.40). The baseline scenarios from the hydrodynamic 333 modelling were converted into peak floodwater elevation raster grids. These grids could 334 then be adjusted using the rule of thumb relationships in the simulation model, depending 335 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.

349 **3.5 Impact modelling (simulation)**

350 A schematic diagram of the model used to simulate impacts against the three adaptation 351 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 352 353 shapefiles using georectified aerial imagery, and a 2 m x 2 m raster grid was specified for 354 all geoprocessing analysis. This provided adequate model resolution whilst improving the 355 processing speed, which was important when raster grids were converted into NumPy 356 arrays to evaluate coastal flood impacts. Looping through each row in the case database 357 and applying the rules of thumb allowed different proxy flood depth rasters to be 358 generated (peak floodwater levels). These rasters could then be overlayed above the land 359 use raster to identify exposed dwellings and to determine the vulnerability of those 360 dwelling in terms of damage costs (see Appendix C in the Online Resource for details on 361 the data and geoprocessing tools used in the simulation model).



362

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).

368

369 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).

375 3.5.2 Calculating AAD

376 Calculation of the AAD to dwellings was based upon established practice used to assess 377 monetary flood impacts (de Moel et al. 2015; Egorova et al. 2008). The proxy peak 378 floodwater surface was used to determine an inundation depth at each 2 m x 2 m raster 379 cell, from which vulnerability curves were applied to exposed dwellings to determine a 380 damage index. The damage index reflects the percentage of damage relative to the full 381 replacement cost. A separate vulnerability curve was used to assess damages to the 382 house structure (i.e. fixed elements) and contents (i.e. movable assets), and vulnerability 383 curves were guided by empirical data from Geosciences Australia (2012) (see Appendix D 384 in the Online Resource for details). The monetary impact to all dwellings in each case was 385 calculated by summing the damage across all raster cells for the 1%, 2%, 5% and 20% 386 AEP events, allowing the AAD to be determined using the trapezoidal rule (Ramm et al. 387 2015).

388 **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.

396 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

402 and Q4 in Fig. 5b). Scatter plots were used as an initial diagnostic tool to visualise the
403 sensitivity of the individual input factors on the adaptation objectives (Pianosi et al. 2016).

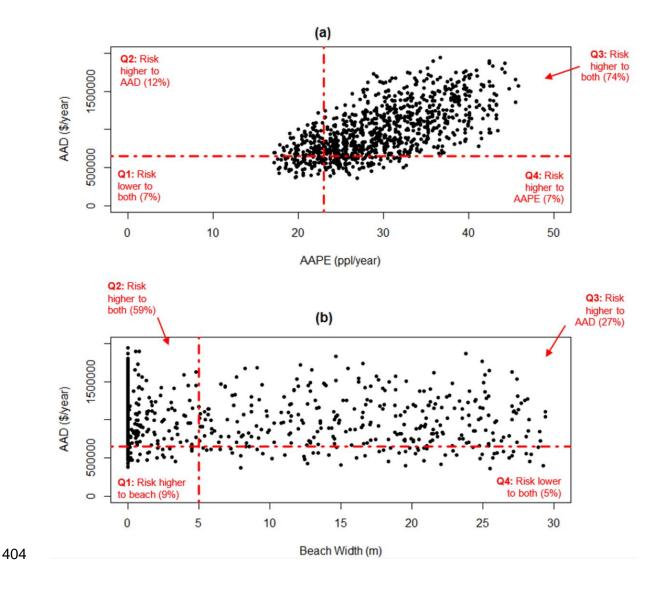


Fig. 5 Plot of impacts to (a) AAPE and AAD objectives and (b) average beach width and
AAD objectives, for the 1,000 cases. The upper bound of tolerable impacts to the
objectives (see Table 1) are defined by red dashed lines. The percentage of cases in each
quadrant of the plot is also shown (denoted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

412 **3.6 Describe conditions that lead to adaptation tipping points**

Scenario discovery validated observations made from the scatter plots that rainfall 413 414 intensity and maximum structural damage costs were the most important uncertainties in 415 defining the candidate scenario for the AAD adaptation objective. The significance of 416 these variables was confirmed by the reproducibility statistics and p-values at the 0.05 417 level. Coverage and density trade-offs were further investigated for a range of candidate 418 scenarios (see Appendix E in the Online Resource for further details). The strongest 419 candidate scenarios for the three adaptation objectives are summarised in Table 3. These 420 candidate scenarios describe the conditions beyond which coastal inundation impacts 421 related to the adaptation objectives are unacceptable (i.e. signify adaptation tipping points 422 are reached).

423

Table 3: Scenario discovery results showing candidate scenarios beyond which impactsrelated 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%, <i>AND</i> Average people per house < 2.4 | 194 / 1000 | 73% / 88% | | | | | |
| 2: AAD | 9-hour rainfall intensity < 6.3% <i>AND</i> Maximum structural damage < \$1,536/m² | 167 / 1000 | 75% / 76% | | | | | |
| 3: Beach width | Sea-level rise < 0.3m <i>AND</i> Bruun factor < 83 | 320 / 1000 | 70% / 97% | | | | | |

426

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).

431 For the environmental factors, projections for lower (RCP4.5) and higher (RCP8.5) 432 emissions scenarios are useful to understand timeframes for a range of potential changes 433 (Bates et al. 2016). Time-series were available for projected mean sea-level rise in coastal 434 council areas (McInnes et al. 2016), providing an indication of when the conditions 435 associated with this uncertain factor might be exceeded. Additionally, guidance was 436 sought from the Australian Rainfall and Runoff guide for projecting changes to rainfall 437 intensity. This relates future rainfall intensity changes to temperature change using a 438 scaling estimate of 5 % per °C of warming, based on the Clausius-Clapeyron vapour 439 pressure relationship (Bates et al. 2016). However, uncertainty remains with this approach, 440 with research suggesting that extreme rainfall intensities could increase by more than 15 % 441 per °C in Tasmania by the end of the century (Mantegna et al. 2017). Projected 442 temperature change was obtained from the Climate Change in Australia web portal 443 (CSIRO and Bureau of Meteorology 2015), which guided the indicative timeframes for 444 changes to rainfall intensity based on the relationship used by Bates et al. (2016). 445 The projections suggest that changing rainfall intensity is likely to cause unacceptable 446 impacts to AAPE between the years 2040-2060, if the average people per house exceeds 447 2.4. The impacts to AAD are projected to remain acceptable for a longer timeframe, until

448 years 2050-2070, if the maximum replacement cost of dwellings exceeds \$1,536/m² in

449 real dollars. The impacts to average beach width may become unacceptable between the

450 years 2060-2070, which is conditional on the Bruun factor exceeding 83 (a conservative

451 value for the study area). Ongoing monitoring of each key factor at local, regional and

452 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.

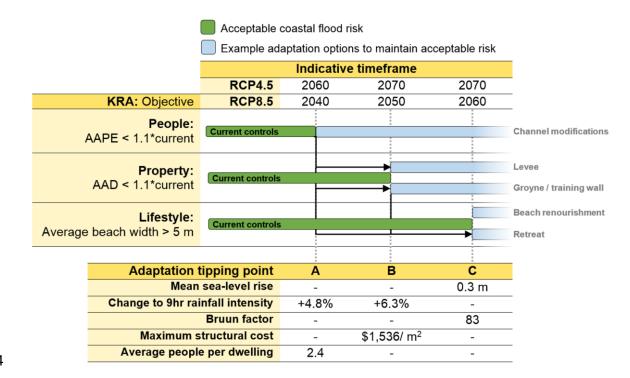
Table 4. Projected timeframe for changing factors. The selected factors are those identified in the candidate scenarios.

| | 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) – 207 | 2060 (RCP4.5) – 2070 (RCP8.5) | RCP8.5) McInnes et al. (2016) | | | \checkmark | | |
| | Changing 9-hour rainfall intensity (<i>relative to present</i>) | 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.} | | | \checkmark | | |
| | Max. structural damage per m ² (<i>real dollars in 2016</i>) | \$1,536/m ² | - | Dunford et al. (2014) ^{b.} | | √ | | | |
| | Average people per house | 2.4 | Minimal change ^{c.} | ABS (2010) | \checkmark | | | | |
| 455 456 457 458 459 460 | ^{a.} No data is available on the Bruun factor for Kingston Beach. Estimates from nearby areas are lower than the value show No projections available. Periodic updates to the structural value are necessary (e.g. NEXIS building exposure database 2014), which are then adjusted from <i>nominal</i> to <i>real</i> dollars using the 'average weekly earnings' figures (Department of E 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). | | | | | | Dunford et al. | | |

462 **3.7 Develop the adaptation pathway**

The key conditions that lead to adaptation tipping points and time projections identified in 463 Section 3.6 can be brought together within a DAPP framework to begin developing an 464 465 adaptation pathway. The steps in the DAPP framework require identifying possible 466 adaptation responses, evaluating the responses, assembling the pathways, identifying 467 preferred pathways, contingency planning, and creating a dynamic adaptive plan 468 (Haasnoot et al. 2013). The key factors identified through scenario discovery can also 469 support the definition of technical signposts in the DAPP process. The first part of the 470 adaptation pathways mapping process for the study area is shown in Fig. 6, which 471 indicates when an adaptation response would be needed to manage the different 472 adaptation objectives in the case where no adaptation measures are taken. Planning and 473 implementation timeframes for each adaptation response needs to consider the lead time 474 as the option progresses through project/policy governance systems. Each subsequent 475 adaptation option identified in the pathway can be assessed for robustness by repeating 476 the steps in Section 2.2 through to Section 2.6, or evaluated using other decision support 477 tools (e.g. Dittrich et al. 2016). Furthermore, some options may impact on multiple 478 adaptation objectives (e.g. a levee could provide benefits to both the AAD and AAPE 479 objectives). Therefore the evaluation of the costs and benefits of each adaptation option 480 would need to consider the implications to multiple objectives.

481



484

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.

491

492 4 Discussion

493 **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 500 government and other coastal authorities to replicate the illustrated method whilst 501 customising it for their local needs.

502 The use of scenario discovery to identify conditions whereby existing plans no longer 503 meet the adaptation objectives can simplify complex changes to the built and natural 504 environment in a meaningful format for stakeholders to understand. As demonstrated in 505 the case study, RDM offers the potential to explore the interaction between a broad set of 506 uncertain hazard, exposure, and vulnerability factors and how they influence coastal 507 inundation impacts. This recognises that societal development, building codes, and other 508 land use policies can exacerbate flood impacts in low-lying communities, especially when 509 coupled with changing flood patterns. This approach is an improvement on seminal 510 adaptation pathway methods that focus on changes to a single hazard parameter (Kwadijk 511 et al. 2010; Reeder and Ranger 2011). However, using multiple uncertain factors to 512 describe conditions leading to adaptation tipping points adds further complexity to the risk 513 monitoring process. Each variable may change in different directions and with varying 514 rates. Therefore a vulnerability assessment to coastal inundation, including periodic 515 monitoring, needs to be done routinely as part of the managing authorities' iterative risk 516 management process.

517 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 518 519 factors to be further explored to better understand leading indicators that signify changing 520 risk (Bonzanigo and Kalra 2014). For example, population growth and housing density is 521 driven by land use and development decisions, which influences the average number of 522 people per dwelling exposed and therefore achievement of the AAPE objective. 523 Techniques like root cause analysis, systems thinking, or hazard chains (Downing 2012) 524 can be undertaken at this stage of the assessment to identify (and treat) causal risk 525 factors that are interconnected but less apparent. These insights can build a case for 526 targeted data collection and monitoring activities in urbanised coastal areas, which is 527 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).

530 The methodology illustrated in the case study takes a different approach to traditional risk 531 management methods, such as the ISO31000 process that is recognised worldwide. Our 532 methodology requires tolerable risks to be defined at the outset and baseline impacts to 533 be assessed, before the sensitivities of the site to coastal inundation are uncovered. 534 Conversely, the ISO31000 process begins with a risk assessment, then prioritises risks 535 based on likelihood and consequence matrices before evaluating whether risks are 536 acceptable, tolerable, or intolerable. Identification of a baseline risk acknowledges that 537 there is already a certain coastal inundation threat that the community has accepted, 538 knowingly or not. This allows analysts to focus their efforts on searching for what changes 539 to the current built and natural environment will cause unacceptable inundation impacts. 540 This makes the process of communicating risks more straightforward and salient to 541 concerned parties, since they can consider how environmental change might affect them 542 relative to what they are experiencing today. An important strength of the ISO31000 543 process over our method is that it considers a much broader set of impacts. For example 544 the National Emergency Risk Assessment Guidelines used in Australian emergency 545 management considers consequences to people, environment, economy, public 546 administration, social setting and infrastructure (National Emergency Management 547 Committee 2010). Our approach was limited to a quantitative assessment of impacts to 548 people, property, and lifestyle objectives. Therefore there is scope for the presented 549 method to increase the number of adaptation objectives and include a qualitative 550 assessment of intangible consequences.

551 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.

558 Translating changes to key variables into observable impacts can provide an evidence-559 based approach to substantiate claims within the community that they may be 560 approaching a threshold or adaptation tipping point. For example, a 4.8% increase in 561 rainfall intensity in the study area suggests that inundation of the Windsor Street / 562 Balmoral Road intersection may occur once every 7 years, instead of 9 years (Fig. 7). 563 Consequently, flooding of this intersection twice in a 7-year timeframe could signal that 564 the rainfall intensity is approaching its adaptation tipping point limit. Although this does not account for changing catchment characteristics (e.g. upstream development) and 565 566 changing extreme rainfall frequencies that can affect the recurrence interval of peak 567 floodwaters, it does serve to convert an otherwise meaningless number into demonstrable 568 evidence that change may be occurring.

569 A similar philosophy was used by Barnett et al. (2014) in their case study at Lakes 570 Entrance, whereby an adaptation response was planned in the event that the esplanade 571 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 572 573 variability. In this regard, local agencies require input from national agencies (e.g. CSIRO, 574 Bureau of Meteorology and Geosciences Australia) who are concerned with the scientific assessment of changes across various spatial and temporal scales. This ensures decision 575 576 are based on robust scientific understanding of changes that are occurring, reducing the 577 chance of reactive decisions being made by coastal authorities in the face of chance 578 events or natural variability.

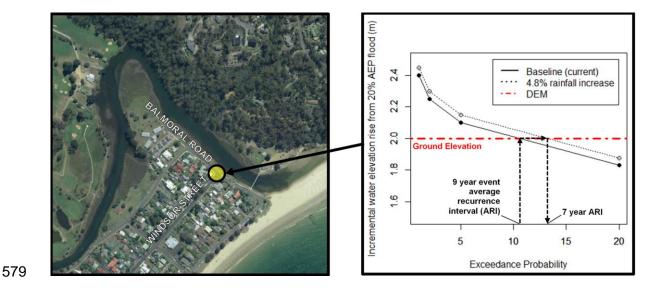


Fig. 7 Selected location at the intersection of Windsor Street and Balmoral Road (circled –
left panel) that could be used to observe changing coastal flood risk. The average change
to peak flood water elevations (above AHD) for a 20% AEP flood event with increased
rainfall intensity of 4.8% is shown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

584

585 The case study presented here made an important assumption that measurable 586 adaptation objectives and tolerable impacts could be defined and agreed upon in the 587 community. The study was also limited to a small subset of the possible values that may 588 exist in the community. In practice, public collective decision-making processes are likely to face contested adaptation goals and conflicting knowledge among stakeholders 589 590 (Bosomworth et al. 2017), whilst social power inequalities and varying short-term interests 591 can hamper long-term planning efforts (Few et al. 2007). Although there are increasing 592 calls for social impacts to be better accounted for in climate change impact assessments 593 and to evaluate adaptation responses (Adger et al. 2009; Downing 2012), such 594 considerations are not straightforward due to complex and subjective interactions among 595 values, ethics, priorities, culture, knowledge, and power structures, all of which change 596 with time (Adger et al. 2009). Engagement with community stakeholders may be a useful 597 starting point to identify contested values in the scoping phase of adaptation planning and 598 to define key issues (e.g. Barnett et al. 2014). This can then form a basis for identifying 599 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 607 608 modelling, in particular the generation of rules of thumb and proxy floodwater rasters. 609 Simplifications in the model meant parameters such as flood duration, contamination, 610 debris, rate of rise, and flood velocity were omitted, which can cause overall damage 611 estimates to be underestimated (Merz et al. 2010; Middelmann-Fernandes 2010). 612 Similarly, the use of the Bruun rule is likely to be overly simplistic given (among other 613 things) it does not consider coastal storms that can exacerbate beach erosion nor other 614 coastal processes that may affect the shoreline response. Notwithstanding these 615 limitations, changing beach widths can be easily monitored by coastal authorities, 616 community groups, or residents to confirm trends in the face of uncertainty (e.g. ACECRC 617 n.d.; UNESCO 2005), and the beach management authority could develop contingency 618 plans to address unexpected near-term beach loss.

619 The timing at which adaptation tipping points were projected in this study was relatively 620 simple by focussing on a small set of projected changes to key variables. The use of 621 transient scenarios to identify a range of use-by years (e.g. Haasnoot et al., 2015) is a 622 potential improvement to the methodology presented in Section 3.6, as it would allow 623 different rates of change (positive and negative) for the key conditions describing 624 adaptation tipping points to be combined across many cases. This could better inform the 625 timing of adaptation tipping points to support the development of long-term master plans 626 and future resource requirements.

627 Implementation of the presented methodology requires data availability, technical 628 capability, and financial resources to perform the analysis, collect data, and monitor 629 change over time. Given that technical knowledge and financial constraints are likely to 630 remain a barrier for local government in the near-term, such resources could be 631 centralised in a nationally coordinated authority. This authority could work with local 632 government to apply a nationally consistent approach to describe conditions leading to 633 adaptation tipping points and develop adaptation pathways. The presented method could 634 also be applied at a municipal, state or national scale to identify coastal settlements that 635 are most vulnerable to changing coastal flood hazards, using the timing at which their 636 adaptation tipping points would be exceeded as an indicator. For resource-constrained 637 authorities, the ability to prioritise adaptation investment towards those communities that 638 yield the greatest risk mitigation benefits would improve the allocation of scarce financial 639 resources.

640 It is too early to fully understand the effectiveness of the illustrated methodology in this 641 study given that it reflects *ex ante* planning, yet such conditions are faced in all risk 642 identification activities. What the methodology offers is a new way of integrating two state-643 of-the-art decision support tools so that decision-makers can explore and identify future 644 vulnerabilities to coastal inundation and design adaptation pathways.

645 **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.

650 The use of RDM to uncover sensitivities in the existing system to changing coastal flood 651 patterns focuses the attention of decision-makers towards those uncertainties that are 652 most relevant for achieving their adaptation objectives. This is useful not only for 653 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.

656 A better understanding of the key conditions that lead to adaptation tipping points in flood 657 risk management can support targeted data collection, monitoring activities, and 658 adaptation responses. It can also help identify signposts in the adaptation pathway. 659 However, detecting changes in multiple factors can be difficult given natural variability, 660 and challenges are enhanced by sparse long-term data records and little financial 661 resources allocated to coastal monitoring activities. Furthermore, reaching agreement on 662 the adaptation objectives, a clear definition of what the community deems as tolerable 663 impacts and exploring how deliberation with analysis is most effectively used in a 664 combined RDM and DAPP approach remains a question for further research.

665 The use of scenario discovery to describe conditions leading to adaptation tipping points 666 offers an alternative conceptualisation of the DAPP approach, which uses transient 667 scenarios to focus on the timeframe at which an adaptation tipping point is reached. In a 668 combined RDM and DAPP approach, transient scenarios could be used after scenario 669 discovery to project the timing of adaptation tipping points based upon changes to a 670 reduced set of key factors. This sequence of steps would improve the description of 671 adaptation tipping points and the basis for projecting the use-by year of existing and future 672 adaptation policies.

673 Our study illustrates that RDM can be a powerful method to uncover a small set of 674 conditions that together can characterise adaptation tipping points in the face of uncertain 675 environmental change and the simulation results are well suited for use within a DAPP 676 framework. Notwithstanding the challenges that remain around simulation modelling and detection of environmental change, the ability to make sense of complex environmental 677 678 dynamics for use in vulnerability assessments and adaptation planning can provide much 679 needed support to coastal authorities who are facing increasing pressure to minimise 680 costly impacts and ensure the sustainability of their communities.

682 **References**

ABS (2010) Household and Family Projections, Australia, 2006 to 2013. Cat no 3236.0,

684 ABS.

- 685 http://www.abs.gov.au/ausstats/abs@.nsf/0/8CD306B3C1B2C30CCA25773B0017D008?
- 686 <u>opendocument.</u> Accessed 22 June 2017.
- 687 ABS (2013) 2011 Census QuickStats. ABS.
- 688 http://www.censusdata.abs.gov.au/census_services/getproduct/census/2011/quickstat/SS
- 689 <u>C60179?opendocument&navpos=220.</u> Accessed 30 May 2017.
- ABS (2017) Average weekly earnings, Australia, Nov 2016. Cat no 6302.0, ABS.
- 691 http://www.abs.gov.au/AUSSTATS/abs@.nsf/Lookup/6302.0Main+Features1Nov%20201
- 692 <u>6?OpenDocument.</u> Accessed 23 June 2017.
- 693 ACECRC (n.d.) The Tasmanian Shoreline Monitoring and Archiving Project (TASMARC).
- 694 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.,
- 696 Wolf, J., & Wreford A. (2009) Are there social limits to adaptation to climate change? Clim
- 697 Chang, 93, 335-354. <u>http://dx.doi.org/10.1007/s10584-008-9520-z</u>
- Bankes, S.C. (1993). Exploratory modeling for policy analysis. Oper Res, 41, 435-449.
- 699 https://doi.org/10.1287/opre.41.3.435
- 700 Bates, B., McLuckie, D., Westra, S., Johnson, F., Green, J., Mummery, J., & Abbs, D.
- 701 (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-
- 703 <u>southeast-2.amazonaws.com/#b1_ch6_f_yzgm5.</u> 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.
- 706 <u>http://dx.doi.org/10.1038/nclimate2383</u>

- 707 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
- 709 developing world. Clim Risk Manag, 14, 1-10. <u>http://dx.doi.org/10.1016/j.crm.2016.09.004</u>
- 710 Bonzanigo, L., & Kalra, N. (2014) Making informed investment decisions in an uncertain
- 711 world. A short demonstration. Policy Research Working Paper 6765. <u>http://www-</u>
- 712 wds.worldbank.org/external/default/WDSContentServer/IW3P/IB/2014/02/03/000158349_
- 713 <u>20140203130155/Rendered/PDF/WPS6765.pdf.</u> 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.
- 716 Environ Sci Policy, 76, 23-28. <u>http://dx.doi.org/10.1016/j.envsci.2017.06.007</u>
- 717 Breiman, L., Friedman, J.H., Olshen, R.A., Stone, C.J. (1993) Classification and
- 718 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.
- 721 Bryant, B.P. (2016). Sdtoolkit: Scenario discovery tools to support robust decision making722 (v2.33-1).
- 723 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.
- 725 <u>http://dx.doi.org/10.1016/j.techfore.2009.08.002</u>
- 726 Carnell, R. (2016). Lhs: Latin hypercube samples (v0.14).
- 727 Carley, J., Blacka, M., Cox, R., Attwater, C., & Watson, P. (2008) Modelling coastal
- 728 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.
- 730 CoastAdapt (2016) CoastAdapt Shoreline Explorer: Derwent D'Entrecasteaux, NCCARF,
- 731 <u>https://coastadapt.com.au/sites/default/files/docs/sediment_compartments/TAS01.04.05.p</u>
- 732 df. Accessed 20 March 2017.

- 733 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.
- 735 <u>http://dx.doi.org/10.1016/j.gloplacha.2004.07.001</u>
- 736 Commonwealth of Australia (2011) Climate Change Risks to Coastal Buildings and
- 737 Infrastructure A supplement to the first pass national assessment. Commonwealth of
- 738 Australia, http://www.environment.gov.au/system/files/resources/0f56e5e6-e25e-4183-
- 739 <u>bbef-ca61e56777ef/files/risks-coastal-buildings.pdf.</u> Accessed 15 July 2015.
- 740 CSRIO & Bureau of Meteorology (2015) Climate Change in Australia. Commonwealth of
- Australia. <u>https://www.climatechangeinaustralia.gov.au/en/.</u> Accessed 23 June 2017.
- 742 Daron, J. (2015) Challenges in using a Robust Decision Making approach to guide climate
- change adaptation in South Africa. Clim Chang, 132, 459-473.
- 744 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-
- 747 890. http://dx.doi.org/10.1007/s11027-015-9654-z
- 748 Deloitte Access Economics (2013) Building our nation's resilience to natural disasters.
- 749 Deloitte,
- 750 http://australianbusinessroundtable.com.au/assets/documents/White%20Paper%20Sectio
- 751 ns/DAE%20Roundtable%20Paper%20June%202013.pdf. Accessed 26 May 2017.
- 752 Department of Environment and Climate Change (2007) Residential flood damages. NSW
- 753 Government. http://www.environment.nsw.gov.au/resources/floodplains/guideline-
- 754 <u>residential-flood-damages.pdf.</u> Accessed 23 June 2017.
- 755 Dewulf, A., Craps, M., Bouwen, R., Taillieu, T., & Pahl-Wostl, C. (2005) Integrated
- 756 management of natural resources: dealing with ambiguous issues, multiple actors and
- 757 diverging frames. Water Sci Tech, 52, 115-124.

- 758 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.
- 760 http://dx.doi.org/10.1016/j.ecolecon.2015.12.006
- 761 Downing, T.E. (2012) Views of the frontiers in climate change adaptation economics.
- 762 WIREs Clim Chang, 3, 161-170. <u>http://dx.doi.org/10.1002/wcc.157</u>
- 763 DPIPWE (2015) Open data. Department of Primary Industries, Parks, Water and
- 764 Environment, Tasmania. <u>http://listdata.thelist.tas.gov.au/opendata/.</u> Accessed 21 March
 765 2017.
- 766 Dunford, M.A., Power, L., & Cook, B. (2014) National Exposure Information System
- 767 (NEXIS) Building Exposure Statistical Area Level 1 (SA1). Geosciences Australia.
- 768 <u>http://www.ga.gov.au/metadata-gateway/metadata/record/gcat_82220.</u> Accessed 07 April
- 769 2017.
- Egorova, R., van Noortwijk, J.M., & Holterman, S.R. (2008) Uncertainty in flood damage
- estimation. Int J River Basin Manag, 6, 139-148.
- 772 <u>http://dx.doi.org/10.1080/15715124.2008.9635343</u>
- Few, R., Brown, K., & Tompkins, E.L. (2007) Public participation and climate change
- adaptation: avoiding the illusion of inclusion. Clim Policy, 7, 46-59.
- 775 <u>http://dx.doi.org/10.1080/14693062.2007.9685637</u>
- Friedman, J.H., & Fisher, N.I. (1999) Bump hunting in high-dimensional data. Stat Comput,
- 777 9, 123-143. <u>http://dx.doi.org/10.1023/A:1008894516817</u>
- 778 Geosciences Australia (2012) Flood vulnerability functions for Australian Buildings.
- 779 Summary of the Current Geosciences Australia Model Suite. Commonwealth of Australia,
- 780 Canberra.
- Haasnoot, M., Middelkoop, H., Offermans, A., Beek, E., & van Deursen, W.P.A. (2012)
- 782 Exploring pathways for sustainable water management in river deltas in a changing
- 783 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
- 785 pathways: A method for crafting robust decisions for a deeply uncertain world. Glob
- 786 Environ Chang, 23, 485-498. <u>http://dx.doi.org/10.1016/j.gloenvcha.2012.12.006</u>
- Haasnoot, M, Schellekens, J, Beersma, J.J., Middelkoop, H, & Kwadijk, J.C.J. (2015).
- 788 Transient scenarios for robust climate change adaptation illustrated for water
- management in The Netherlands. Environmental Research Letters, 10, 105008.
- 790 http://dx.doi.org/10.1088/1748-9326/10/10/105008
- Hallegatte, S. (2009) Strategies to adapt to an uncertain climate change. Glob Environ
- 792 Chang, 19, 240-247. <u>http://dx.doi.org/10.1016/j.gloenvcha.2008.12.003</u>
- 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,
- 795 29-38. <u>http://dx.doi.org/10.1016/j.envsci.2016.12.005</u>
- Hunter, J. (2010) Estimating sea-level extremes under conditions of uncertain sea-level
- rise. Clim Chang, 99, 331-350. <u>http://dx.doi.org/10.1007/s10584-009-9671-6</u>
- 798 IPCC (2012) Managing the Risks of Extreme Events and Disasters to Advance Climate
- 799 Change Adaptation. A Special Report to Working Groups I and II of the Intergovernmental
- 800 Panel on Climate Change, Field, C. B. et al (eds), IPCC, Cambridge University Press,
- 801 Cambridge and New York.
- Jones, R.N., Patwardhan, A., Cohen, S.J., Dessai, S., Lammel, A., Lempert, R.J., Mirza,
- 803 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.
- 805 Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental
- 806 Panel on Climate Change. Field, C. B. et al (eds), Cambridge University Press,
- 807 Cambridge and New York, 195-228.
- 808 Kalra, N., Groves, D.G., Bonzanigo, L., Perez, E.M., Ramos, C., Brandon, C., &
- 809 Cabanillas, I.R. (2015) Robust Decision-Making in the Water Sector. A Strategy for
- 810 Implementing Lima's Long-Term Water Resources Master Plan. Policy Research Working

- 811 Paper 7439. World Bank Group. http://www-
- 812 wds.worldbank.org/external/default/WDSContentServer/WDSP/IB/2015/10/15/090224b08
- 813 <u>314a2b3/3_0/Rendered/PDF/Robust0decisio0esources0master0plan.pdf</u>. Accessed 21
- 814 July 2016.
- 815 Kingborough Council (2017) Kingston Beach Flood Study. Kingborough Council,
- 816 Tasmania.
- 817 http://www.kingborough.tas.gov.au/webdata/resources/files/Kingston%20Beach%20Flood
- 818 <u>%20Study%202016%20(reduced).pdf.</u> Accessed 20 February 2017.
- 819 Klijn, F., Kreibich, H., de Moel, H., & Penning-Rowsell, E. (2015) Adaptive flood risk
- 820 management planning based on a comprehensive flood risk conceptualisation. Mitig
- 821 Adapt Strat Glob Chang, 20, 845-864. <u>http://dx.doi.org/10.1007/s11027-015-9638-z</u>
- 822 Kwadijk, J., Haasnoot, M., Mulder, J., Hoogvliet, M., Jeuken, A., van der Krogt, R., van
- 823 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
- 826 Kwakkel, J.H., Walker, W.E., & Haasnoot, M. (2016a) Coping with the Wickedness of
- 827 Public Policy Problems: Approaches for Decision Making under Deep Uncertainty. J
- 828 Water Resour PI.-ASCE, 01816001. <u>http://dx.doi.org/10.1061/(ASCE)WR.1943-</u>
- 829 <u>5452.0000626</u>
- 830 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.
- 833 <u>http://dx.doi.org/10.1016/j.envsoft.2016.09.017</u>
- Kwakkel, J.H., & Jaxa-Rozen, M. (2016). Improving scenario discovery for handling
- heterogeneous uncertainties and multinomial classified outcomes. Environ Model Softw,
- 836 79, 311-321. <u>http://dx.doi.org/10.1016/j.envsoft.2015.11.020</u>

- 837 Kwakkel, J.H., (2017). The Exploratory Modeling Workbench: An open source toolkit for
- 838 exploratory modeling, scenario discovery, and (multi-objective) robust decision making.
- 839 Environ Model Softw, 96, 239-250. <u>http://dx.doi.org/10.1016/j.envsoft.2017.06.054</u>
- 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.
- 842 <u>http://dx.doi.org/10.1016/j.envsci.2016.12.003</u>
- 843 Lempert, R. (2013) Scenarios that illuminate vulnerabilities and robust responses. Clim
- 844 Chang, 117, 627-646. <u>http://dx.doi.org/10.1007/s10584-012-0574-6</u>
- Lempert, R.J., Bryant, B.P., & Bankes, S.C. (2008) Comparing algorithms for scenario
- 846 discovery. RAND Corporation,
- 847 <u>https://www.rand.org/content/dam/rand/pubs/working_papers/2008/RAND_WR557.pdf.</u>
 848 <u>Accessed 28 March 2017</u>.
- Lempert, R., Kalra, N., Peyraud, S., Mao, Z., Bach Tan, S., Cira, D., & Lotsch, A. (2013)
- 850 Ensuring Robust Flood Risk Management in Ho Chi Minh City. Policy Research Working
- 851 Paper 6465. The World Bank, Washington, D.C.
- Lempert, R.J., Popper, S.W., & Bankes, S.C. (2003) Shaping the Next One Hundred
- 853 Years: New Methods for Quantitative, Long-Term Policy Analysis. RAND Corporation,
- 854 Santa Monica, CA.
- Mantegna, G., White, C.J., Remenyi, T.A., Corney, S.P., & Fox-Hughes, P. (2017).
- 856 Simulating sub-daily Intensity-Frequency-Duration curves in Australia using a dynamical
- high-resolution regional climate model. J Hydrol, 554, 277-291.
- 858 <u>https://doi.org/10.1016/j.jhydrol.2017.09.025</u>
- Mariani, A., Shand, T.D., Carley, J.T., Goodwin, I.D., Splinter, K., Davey, E.K., Flocard, F.,
- 860 & Turner, I.L. (2012) Generic Design Coastal Erosion Volumes and Setbacks for Australia.
- 861 Antarctic Climate and Ecosystems Cooperative Research Centre. <u>http://acecrc.org.au/wp-</u>
- 862 content/uploads/2015/03/TR-Generic-design-coastal-erosion-volumes-and-setbacks-for-
- 863 <u>Australia.pdf.</u> Accessed 30 May 2017.

- McInnes, K.L., Chruch, J., Monselesan, D., Hunter, J.R., O'Grady, J.G., Haigh, I.D., &
- 865 Zhang, X. (2015) Information for Australian impact and adaptation planning in response to
- sea-level rise. Aust Meteorol Oceanogr J, 65, 127-149.
- 867 McInnes, K.L., Monselesan, D., O'Grady, J., Church, J., & Zhang, X. (2016) Sea-Level
- 868 Rise and Allowances for Tasmania based on the IPCC AR5. Report for the Tasmanian
- 869 Department of Premier and Cabinet. CSIRO, Australia.
- 870 Merz, B., Kreibich, H., Schwarze, R., Thieken, A. (2010). Review article "Assessment of
- economic flood damage". Nat Hazards Earth Syst Sci, 10, 1697-1724.
- 872 <u>http://dx.doi.org/10.5194/nhess-10-1697-2010</u>
- 873 Middelmann-Fernandes, M.H. (2010) Flood damage estimation beyond stage-damage
- functions: an Australian example. J Flood Risk Manag, 3, 88-96.
- 875 <u>http://dx.doi.org/10.1111/j.1753-318X.2009.01058.x</u>
- 876 Milly, P.C.D., Betancourt, J., Falkenmark, M., Hirsch, R.M., Kundzewicz, Z.W.,
- 877 Lettenmaier, D.P., & Stouffer, R.J. (2008). Stationarity Is Dead: Whither Water
- 878 Management? Sci, 319, 573-574. <u>http://dx.doi.org/10.1126/science.1151915</u>
- 879 Nalau, J., Preston, B.L., & Maloney, M.C. (2015). Is adaptation a local responsibility?
- 880 Environ Sci Policy, 48, 89-98. <u>http://dx.doi.org/10.1016/j.envsci.2014.12.011</u>
- 881 National Emergency Management Committee (2010). National Emergency Risk
- 882 Assessment Guidelines, Hobart, Tasmania.
- 883 National Research Council (2009). Informing decisions in a changing climate. Panel on
- 884 strategies and methods for climate-related decision support. The National Academies
- 885 Press, Washington D.C.
- Nicholls, R.J., & Cazenave, A. (2010). Sea-Level Rise and Its Impact on Coastal Zones.
- 887 Sci, 328, 1517-1520. <u>http://dx.doi.org/10.1126/science.1185782</u>
- Pianosi, F., Beven, K., Freer, J., Hall, J.W., Rougier, J., Stephenson, D.B., & Wagener, T.
- 889 (2016) Sensitivity analysis of environmental models: A systematic review with practical

- 890 workflow. Environ Model Softw, 79, 214-232.
- 891 <u>http://dx.doi.org/10.1016/j.envsoft.2016.02.008</u>
- 892 Ramm, T.D., White, C.J., & Franks, S.W. (2015) Accounting for uncertainty in cost benefit
- 893 analysis: a generalised framework for natural hazard adaptation in the coastal zone. 36th
- Hydrology and Water Resources Symposium. Hobart, Tasmania, 510-517.
- 895 Ramm, T.D., White, C.J., Chan, A., & Watson, C.S. (2017a) A review of decision analysis
- 896 methods used in long-term coastal adaptation studies in Australia. Clim Risk Manag. 17C,
- 897 35-51. <u>https://dx.doi.org/10.1016/j.crm.2017.06.005</u>
- 898 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,
- 900 76, 113-123. <u>https://doi.org/10.1016/j.envsci.2017.06.014</u>
- 901 Rawlinsons (2017) Australian Construction Handbook, Rawlinsons Publishing, Perth,
- 902 Western Australia.
- 903 Reeder, T., & Ranger, N. (2011) How do you adapt in an uncertain world? Lessons from
- 904 the Thames Estuary 2100 project, Washington, DC.
- 905 <u>https://www.wri.org/sites/default/files/uploads/wrr_reeder_and_ranger_uncertainty.pdf</u>.
- 906 Accessed 11 December 2017.
- 907 Sharples, C. (2016) Information Priorities for Resolving Priority Coastal Hazard Adaptation
- 908 Responses in Kingborough Local Government Area, southern Tasmania. Report to
- 909 Kingborough Council. University of Tasmania.
- 910 http://www.kingborough.tas.gov.au/webdata/resources/files/Kingborough%20CoastalHaza
- 911 rdPriorities%20(Sharples%202016).pdf. Accessed 21 March 2017.
- 912 Teng, J., Jakeman, A.J., Vaze, J., Croke, B.F.W., Dutta, D., & Kim, S. (2017). Flood
- 913 inundation modelling: A review of methods, recent advances and uncertainty analysis.
- 914 Environ Model Softw, 90, 201-216. <u>http://dx.doi.org/10.1016/j.envsoft.2017.01.006</u>

- 915 UNESCO (2005) Introduction to Sandwatch: An educational tool for sustainable
- 916 development. Coastal region and small island papers 19, UNESCO, Paris.
- 917 Walker, W.E., Haasnoot, M., & Kwakkel, J.H. (2013) Adapt or perish: A review of planning
- 918 approaches for adaptation under deep uncertainty. Sustain, 5, 955-979.
- 919 <u>http://dx.doi.org/10.3390/su5030955</u>
- 920 Ward, T., Butler, E., & Hill, B. (1998) Environmental indicators for national state of the
- 921 environment reporting Estuaries and the Sea, Australia: State of the Environment
- 922 (Environmental Indicator Reports). Department of the Environment,
- 923 https://www.environment.gov.au/system/files/pages/f59cdc73-e8ca-4bd9-8592-
- 924 <u>586357a70082/files/estuaries.pdf.</u> Accessed 30 March 2017.
- 925 Watkiss, P., & Hunt, A. (2013) Method overview: Decision support methods for adaptation,
- 926 Briefing Note 1. Summary of methods and case study examples from the MEDIATION
- 927 project. Funded by the EC's 7FWP.
- 928 Werners, S.E., Pfenninger, S., van Slobbe, E., Haasnoot, M., Kwakkel, J.H., & Swart, R.J.
- 929 (2013). Thresholds, tipping and turning points for sustainability under climate change. Curr
- 930 Opin Environ Sustain, 5, 334-340. <u>https://doi.org/10.1016/j.cosust.2013.06.005</u>
- 931 White, C.J., Grose, M.R., Corney, S.P., Bennett, J.C., Holz, G.K., Sanabria, L.A.,
- 932 McInness, K.L., Cechet, R.P., Gaynor, S.M., & Bindoff, N.L. (2010) Climate futures for
- 933 Tasmania: extreme events technical report. Antarctic Climate and Ecosystems
- 934 Cooperative Research Centre, Hobart, Tasmania.
- 935 White, C.J., McInnes, K.L., Cechet, R.P., Corney, S.P., Grose, M.R., Holz, G.K., Katzfey,
- 936 J.J., & Bindoff, N.L. (2013) On regional dynamical downscaling for the assessment and
- 937 projection of temperature and precipitation extremes across Tasmania, Australia. Clim
- 938 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.