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Dawson, David A., Hunt, Alistair, Shaw, Jon et al. (1 more author) (2018) The Economic Value of Climate Information in Adaptation Decisions : Learning in the Sea-level Rise and Coastal Infrastructure Context. Ecological Economics. pp. 1-10. ISSN 0921-8009

https://doi.org/10.1016/j.ecolecon.2018.03.027

Ecological Economics 150 (2018) 1–10

Contents lists available at ScienceDirect

Ecological Economics

journal homepage: www.elsevier.com/locate/ecolecon

The Economic Value of Climate Information in Adaptation Decisions: Learning in the Sea-level Rise and Coastal Infrastructure Context

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ARTICLE INFO

Keywords:
Infrastructure
Investment appraisal
Real options
Climate adaptation
Sea-level rise
Learning
Uncertainty

ABSTRACT

Traditional methods of investment appraisal have been criticized in the context of climate change adaptation. Economic assessment of adaptation options needs to explicitly incorporate the uncertainty of future climate conditions and should recognise that uncertainties may diminish over time as a result of improved understanding and learning. Real options analysis (ROA) is an appraisal tool developed to incorporate concepts of flexibility and learning that relies on probabilistic data to characterise uncertainties. It is also a relatively resource-intensive decision support tool. We test whether, and to what extent, learning can result from the use of successive generations of real life climate scenarios, and how non-probabilistic uncertainties can be handled through adapting the principles of ROA in coastal economic adaptation decisions. Using a relatively simple form of ROA on a vulnerable piece of coastal rail infrastructure in the United Kingdom, and two successive UK climate assessments, we estimate the values associated with utilising up-dated information on sea-level rise. The value of learning can be compared to the capital cost of adaptation investment, and may be used to illustrate the potential scale of the value of learning in coastal protection, and other adaptation contexts.

1. Introduction

Global sea levels have risen ~0.20 m in the last century (Church et al., 2013), and there is widespread agreement that sea levels will continue to rise during the 21st century (Jenkins et al., 2009; IPCC, 2014). Along with this increasing hazard, the growth of coastal populations world-wide (Nicholls, 1995) is leading to increased exposure to coastal flooding, particularly for coastal infrastructure that facilitates economic growth in these regions (Hall et al., 2006; Brown et al., 2011). These pressures are likely to require consideration of substantial future infrastructure investment (European Environment Agency, 2014), though the costs of such investments would involve making trade-offs with competing scarce economic resources (Hunt, 2008; Chambwera et al., 2014). In this context, the economic appraisal of adaptation investments for coastal infrastructure becomes an important part of the decision-making process, though public acceptability and technical feasibility remain binding constraints on such an investment decision. This paper investigates practical aspects of such appraisals, particularly relating to the treatment of uncertainties, the role of learning, and the user-friendliness of the methods used to make such appraisals.

For several decades now, determining the accurate magnitude of future sea-level rise (SLR) has been a priority in global/national climate change assessments (IPCC, 1990, 2001, 2013). The complexity and scale of the physical processes involved in estimating future SLR (i.e. glacial, atmospheric, ocean, land), however, means there remains uncertainty surrounding future magnitudes (Horton et al., 2014). Despite the early acknowledgement of the usefulness of probabilistic or stochastic information, the majority of national sea-level projections remain largely deterministic (e.g. Katsman et al., 2011; Lowe et al., 2009; Howard et al., 2014). More recently, though, efforts have been made towards quantification of uncertainties (e.g. Kopp et al., 2014; Grinsted et al., 2014; Jackson and Jevrejeva, 2016), and it is therefore reasonable to ask what effect improved stochastic estimates of sea-level rise

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Abbreviations: AC, adaptation costs; CBA, cost benefit analysis; C_C, capital costs; C_{CM}, coastal maintenance cost; C_{IM}, inland maintenance costs; DC, damage costs; d, lateness (delay) time; DMC, do minimum costs; EBCR, expected benefit cost ratio; ENPV, expected net present value; I_{pass}, direct economic impact of passenger disruption; IPCC, Intergovernmental Panel on Climate Change; L, lateness time; vt, lateness value; n_{pass}, number of passengers; NPV, net present value; PVB, present value benefits; PVC, present value costs; ROA, Real Options Analysis; SES, socio-economic scenario; SLR, sea-level rise; UKCP, United Kingdom Climate Programme; UKCIP, United Kingdom Climate Impact Programme; VTT, value of travel time

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https://doi.org/10.1016/j.ecolecon.2018.03.027
Received 11 August 2017; Received in revised form 2 February 2018; Accepted 27 March 2018

might have on investment decisions related to vulnerable coastal infrastructures.

Traditional economic appraisal techniques such as Cost Benefit Analysis (CBA) are somewhat limited in their effectiveness in handling the type of non-probabilistic uncertainties associated with projections of future climate change (Turner et al., 2007; Watkiss et al., 2015). Furthermore, adaptation decisions such as those associated with infrastructure may not always need to be "all-or-nothing" investments, and as long as some flexibility in construction design exists they can be characterised as choices along defined continua of costs, risks and benefits that change over time. Thus, decision analysis is likely to be improved if it can explicitly incorporate the uncertainty of future conditions in estimating the economic value of adaptation investments. It is also important to recognise that these uncertainties may diminish over time as a result of improvements in forecasting techniques and availability of observational data. In this case, a more dynamic form of decision-making may be beneficial (Mun, 2002).

A variety of methods to better handle uncertainties in adaptation responses to climate change risks has been proposed, including, for example, Real Options Analysis (ROA), Portfolio Analysis (PA) and Robust Decision Making (RDM) (Watkiss et al., 2015; Dittrich et al., 2016). Indeed, there is a recognition in a number of user communities that these methods may have some merit; an often-cited example is the UK guidance on economic appraisal of adaptation published in order to stimulate uptake of such methods (HM Treasury, 2009). Of the potential alternatives to traditional appraisal methods such as CBA, ROA is promoted on the basis that it incorporates the concept of flexibility in responding to changing patterns of uncertainty and learning over time (Dittrich et al., 2016). ROA gives two types of results (or value) that set it apart from conventional economic analysis (Watkiss et al., 2015). Firstly, through the identification of deferred benefits of waiting for new information, rather than investing immediately, it can promote the delaying of adaptation responses. This is possible if the benefits of the new information outweigh the costs of waiting. Alternatively, in projects which fail conventional CBA it can promote initial action or the potential for future investment by providing an economic tool to incorporate the value of flexibility, e.g. to expand, contract or stop adaptation measures.

Evolving from financial options valuation (e.g. Black and Scholes, 1973; Merton, 1973), ROA allows investment decisions to account for future uncertainty by delaying action until more evidence (e.g. data or learning) becomes available, thereby allowing a more informed decision. It allows the decision maker to value the current investment risk with uncertain future outcomes. ROA is therefore likely to be most relevant for long life-time projects where uncertainties may be more significant in the estimation of economic efficiency (Kontogianni et al., 2014; de Neufville et al., 2009). Consequently, it is thought to be particularly useful for infrastructure-based investment decisions that need to account for climate change risks (Glanemann, 2014). Possible improvements in computer processing capabilities, combined with developments in climate science and improved knowledge of the extent and timing of climate change risks as a result of improvements in climate data, are recognised as offering potential means through which learning can occur (Ingham et al., 2007; Hulme and Dessai, 2008; Glanemann, 2014).

Current practice has been slow to adopt these decision methods in adaptation appraisal; anecdotal evidence suggests that their relative complexity and resource-intensiveness may be responsible for the low level of take-up (Herder et al., 2011). Furthermore, the validity of ROA in informing real-world decisions depends in part on the degree to which learning is actually possible. Previous studies (see Woodward et al., 2013; Kontogianni et al., 2014, and; Linquiti and Vonortas, 2012) undertake simulation exercises in the coastal adaptation context that impose hypothetical assumptions regarding rates of learning and decision time-frames in order to demonstrate the principles of ROA. Consequently, it is relatively straightforward to show that the inclusion of a time-dynamic dimension in the economic analysis is likely to be beneficial. In this paper, we test the validity of these assumptions by using national climate data in the context of the analysis of a section of iconic coastal rail infrastructure that is potentially vulnerable to sea-level rise in South-West England (Dawson et al., 2016). Specifically, we utilise two sequential sets of climate projections, endorsed and published by the UK Climate Impacts Programme (UKCIP), that were produced eight years apart from each other but that represent the most recent sets of information to guide adaptation decisions. Thus, our ex post analysis investigates the value of new data sets used in adaptation planning and allows us to identify the option value that can result from learning between successive generations of climate scenario projections that were created precisely for informing real-life decisions. It should be noted, however, that even when new information becomes available and learning is consequently possible, the existence of option value is contingent on there being the opportunity to delay a decision that could be informed by the learning.

The operationalisation of conventional ROA also depends on being able to attach objective probabilities to the alternative scenarios of benefits/costs. As highlighted by Lowe et al. (2009), however, alternative climate scenarios are not currently characterised in terms of their objective probability of occurrence, due to a limited number of historical analogues on which to base such projections. Honest economic analysis is then forced to embrace alternative analytical methods. We therefore explore and demonstrate the extent to which the ROA method can maintain tractability by allowing the application of alternative decision rules – including maximin, maximax and the Laplace criterion (Pearce and Nash, 1981) – to be simulated by the use of subjective, analyst-determined, probabilities. We show that these can be imposed in such a way as to facilitate measures of economic efficiency under alternative assumptions regarding risk attitude preferences, where objective probabilities do not exist (see Section 2).

Finally, we respond to the perception in the potential user community that ROA is too complex to adopt in decision analysis, by identifying the simplest form with which the method can derive results that robustly inform an investment decision. In this way, we look to highlight the extent to which the method can be made accessible and so encourage its take-up in real-world decisions. In the following Section (2), we outline the method of the study, including a description of data used. We then present the results of our ex post analysis in Section 3 and follow with a discussion of their implications for the research area and some concluding remarks in Section 4.

2. Methods and Materials

We apply a modified ROA approach to the ex post economic assessment of the management of a notorious section of coastal transport infrastructure in the UK, part of the London-Penzance railway line in Devon that connects South Devon and Cornwall to the rest of the country. The coastal section of this line between Dawlish and Teignmouth stretches 4.2 miles and is currently protected by extensive coastal defences (Dawson et al., 2016). The defences and track are heavily impacted (i.e. overtopped and damaged) by storms and high waves during winter months and require periodic maintenance and improvement. The largest impact event in living memory saw the line closed for two months in 2014 (Network Rail, 2014), when a stretch of track was destroyed. This event should be seen in the context of recent (e.g. 20th and 21st century) sea-level rise that has resulted in increased overtopping events (see Dawson et al., 2016), as the distance between mean sea level and the crest of the defences is gradually reduced. Furthermore, based on observations and analysis, current projections of future sea-level rise will result in further increases in the frequency of these events (Dixon and Tawn, 1995; Haigh et al., 2011). This will result in higher associated repair costs to the network operator, as well as the disruption to passenger travel, and the prospect of the southwest region of England being left periodically without a main railway line for extended periods.

This study utilises estimates of the impacts of future SLR that incorporates impact/cost data of track incidents derived from an empirical-based trend that is extrapolated forward based on projections of future SLR (Lowe et al., 2009; Dawson et al., 2016). This approach quantifies the costs of increased disruption based on estimated damages to the defences (using historic records) and monetary costs of increased passenger disruption using the value of travel time (VTT) as demonstrated in other studies and guidance (Metroeconomica, 2004; Dawson et al., 2016; Penning-Rowsell et al., 2016). We demonstrate how assessment of alternative adaptation responses to these projected climate risks can be affected by updates in estimation of sea-level parameters over time that potentially resolve some of the uncertainties reflected in these risk estimates. Although other studies provide national and regional level examples that are useful in illustrating the method, (e.g. Kontogianni et al., 2014; Linquiti and Vonortas, 2012; Woodward et al., 2013), the local focus of this paper offers insight to the future application of new climate knowledge and the ROA method at a scale appropriate to many real-world infrastructure decisions. The "real option" tested in this study is the option to delay adaptation investment relating to the London-Penzance railway line until improved knowledge results in the partial resolution of uncertainties in sea-level projections. The benefits of waiting for this information will be calculated through an updated climate impact assessment (eight years later), which can then be compared to the costs of waiting for that information (e.g. damages & repairs from overtopping events).

2.1. *Data Requirements & Treatment*

Our option analysis relates to three adaptation choices recently outlined for the Dawlish-Teignmouth stretch of the rail line by the rail operator (Network Rail, 2014) (see Table 1). These are: a "do minimum" option that maintains the current defences (Baseline); an improvement and up-grading of the current defences (Adaptation One); and a retreat of the line further inland (Adaptation Two). These options form the basis of our ROA study (see Fig. 1a). The sea-level/climate risks with which these options are concerned are derived from the future sea-level projections from both the UKCP02 assessment report (Hulme et al., 2002), and the subsequent, most recent, UKCP09 set of sea-level projections (Lowe et al., 2009). These adaptation options are assumed to have lifetimes of sixty years (as reported by the asset owners). To identify the potential for learning, we consequently utilise projections of SLR for the two sixty year periods (2002–2061; 2010–2069), following the respective publication dates of the two sets of projections.

Fig. 1b outlines the components of the quantitative analysis that comprises the ROA in our study. Of the three key data inputs described further below – SLR projections, models relating SLR to overtopping and impacts on the transport infrastructure, and socio-economic changes on infrastructure use (passenger demand changes) likely to occur during the assessment period – only the SLR projections, based on climate emission scenarios, are attributed probabilities. This allows us to isolate the value of new climate information at the geographical location of interest to us. The projected track damage events based on stochastic SLR projections, and the consequential increase in maintenance and passenger user costs (£), provide baseline (i.e. do minimum) annual costs. Implementation of Adaptations One and Two leads to a decrease in frequency of track damage events and associated impacts, the extent being determined stochastically. The associated economic costs and benefits are estimated to allow option analysis to be undertaken.

2.1.1. *Sea-level Estimates*

We adopt the sea-level estimates from the consecutively published UK Climate assessment reports, UKCIP02 and UKCP09, between which, a number of emission and model uncertainties were addressed (see

Table 1
Summary of "real options" for the London-Penzance railway line used in this study: Baseline conditions taken from (Dawson et al., 2016). Adaptations One and Two costs' constructed from recent resilience report (Network Rail, 2014) with additional information from O'Breasail et al. (2007). See Section 2 for further details.

Adaptation	Description	Length of vulnerable route remaining (km)	Capital cost (£m)	Estimated maintenance costs incl. SLR (£m/year)	Resilience level	Assumptions
Base case: do minimum	Continue to hold the line – repair & reopen	4.6	Nil	1.8 + low/high scenario impacts	Low	Continuation of historical overtopping trend and no complete breach in the next 60 years.
One: Further re-strengthening of existing	Build new defences over a 20-year period. Existing railway used by all trains	4.6	528	1.8 + gradual defence costs	Medium	The line will be built to a new 1 in 100 year design standard (20 year construction phase), from which the historical trend will continue. No complete breach during the remainder of the assessment period.
Two: New inland route	All trains use the new route. Old line abandoned.	Nil	2182	2.7	High	Coastal line abandoned, defences ownership transferred to relevant authority to maintain protection for coastal populations (e.g. Dawlish, Starcross, Teignmouth)

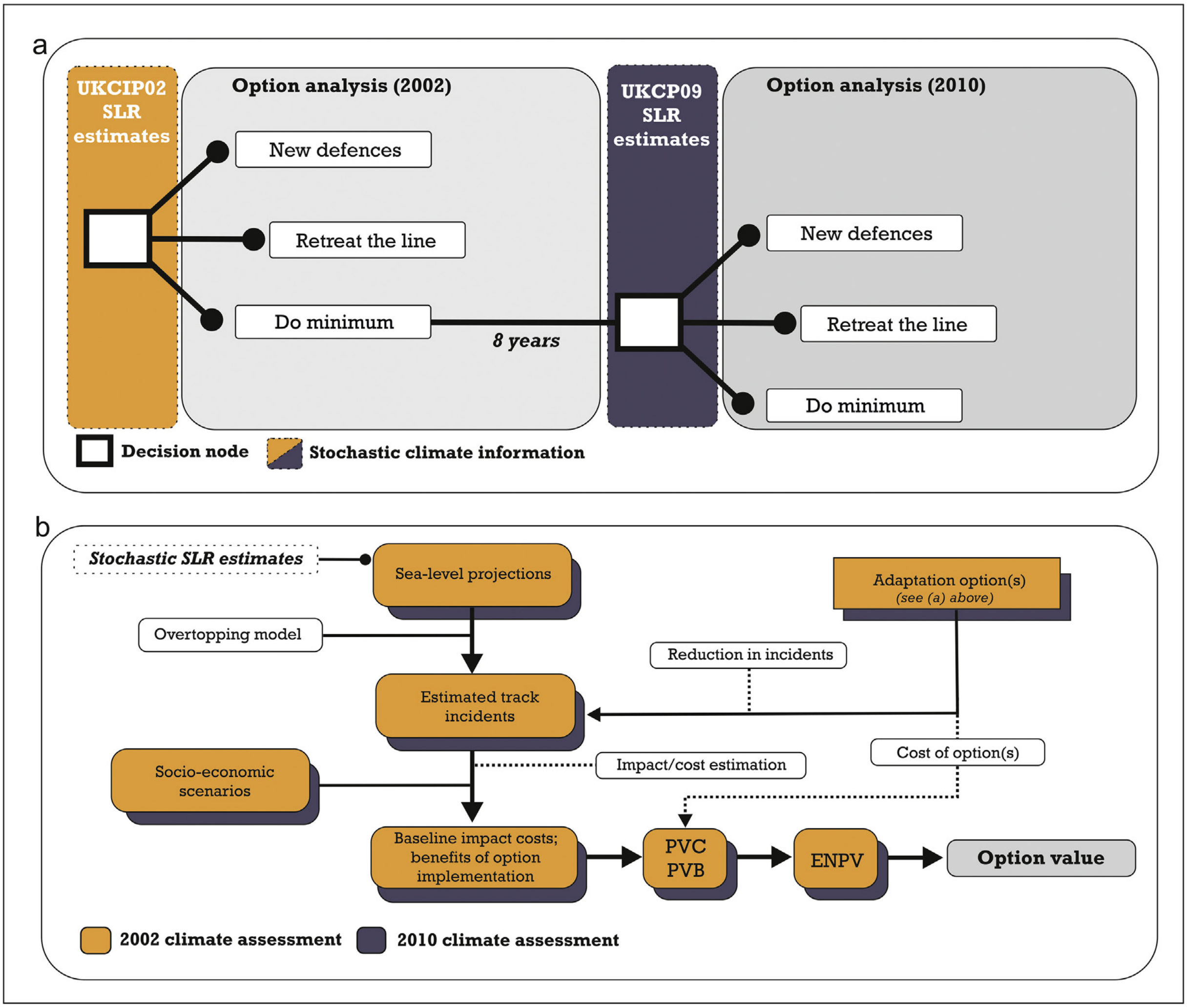

Fig. 1. (a) Framework for real options analysis of adaptation options on the coastal section of the London-Penzance train line; (b) Schematic of rail infrastructure impact assessment.

Table 2

Estimated percentile-based sea-level projections for 2050 low and high emission scenarios using local and global estimates (increase relative to 1961–1990 baseline in centimetres).

	UKCP02	UKCP09
P	Global	Local
Low emissions		
0.05	7.0	10.9
0.50	14.0	19.5
0.95	30.0	28.1
High emissions		
0.05	9.0	12.6
0.50	18.0	27.0
0.95	36.0	41.3

Sources: Hulme et al. (2002); Lowe et al. (2009).

Jenkins et al. (2009) for a detailed review). The two reports were used to establish a chronology of sea-level projections that could be applied to the assessment of the railway. For our first period impact assessment (2002–2061) it was not possible to obtain detailed time series from the regional projections presented; as such the global projections are used. The UKCP09 climate assessment report provides detailed local sea-level projections (25 km grid square) for our second period impact assessment (2010–2069) (Lowe et al., 2009). ROA relies on probabilistic estimates of project benefits and costs being available, but comprehensive probabilistic sea-level projections at a local spatial resolution do not exist. Whilst probability distributions of SLR have been estimated in UKCP09 within individual climate scenarios, using upper and lower estimates as 5th and 95th percentiles, cross-scenario probabilities are not allocated (Hulme et al., 2002; Lowe et al., 2009). Columns 2 and 3 in Table 2 present the SLR estimates associated with the 5th, 50th and 95th percentiles of the distributions for the low and high scenarios for a sample year, 2050, generated from the two assessment reports.

The estimates of relative increases in SLR in three future time periods compared to a baseline period, and estimated cumulative density functions for 2050, are illustrated in Fig. 2a and b. The most significant change between the two assessment reports is the improvement in spatial resolution which was reduced from 50 km to 25 km. In turn, this has allowed important regional factors such as vertical land movement to be modelled and to be included in the projections (e.g. Bradley et al., 2011). The UKCP09 projections were also validated using geological evidence from the region (Gehrels et al., 2011). Broadly, the updated and location specific UKCP09 data present an increase in estimated SLR ($<$ 3.9 cm by 2050), although the range within individual SLR projections (i.e. 5th to 95th estimates) has subsequently narrowed. For example, in 2050 the UKCP09 low emissions estimate range is 5.8 cm smaller than UKCIP02, whilst the high emission ranges narrow by 1.7 cm.

As stated earlier the current projections of SLR do not contain

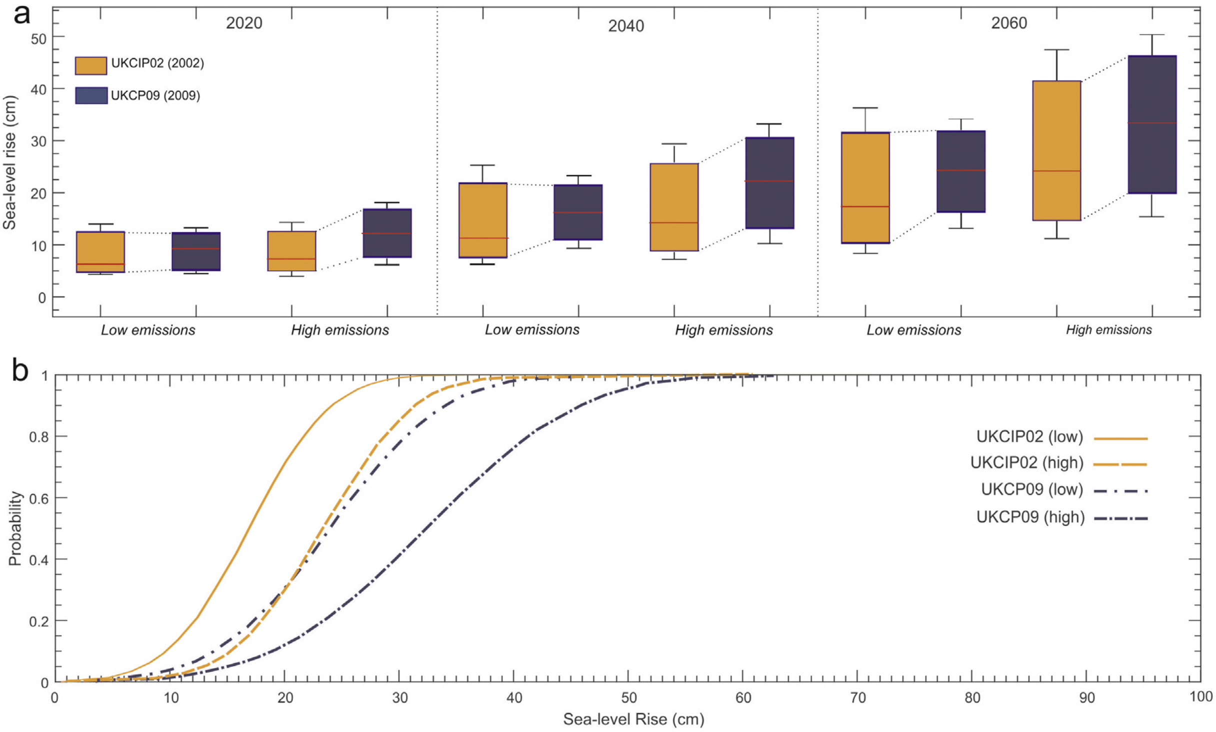

Fig. 2. (a and b). Relative sea-level projections used in study. (a): comparison of relative sea-level estimates for global estimates (UKCIP02) and for local estimates at Dawlish, Devon (UKCP09) obtained for this study. (b): Estimated probabilistic projections for 2060 (assuming normal distribution) for the two UK climate assessment reports. All sea-level estimates are relative to 1990 baseline.
Sources: Hulme et al. (2002); Lowe et al. (2009).

probabilistic values although emerging research is developing in this direction (e.g. Jackson and Jevrejeva, 2016). We therefore construct subjective probabilistic values as a means of simulating attitudes to non-probabilistic risks, i.e. uncertainty. To do so we utilise the various rules that have been developed to characterise alternative attitudes to uncertainty, for example, the Maximax and the Maximin Minimax criterion that reflect the most extreme attitudes/preferences to risk. Section 2.3 provides further details of the approach and values used in the study.

2.1.2. *Infrastructure Impact Estimates*

An empirical-based overtopping model was used to establish the impacts of SLR on coastal infrastructure (Dawson et al., 2016), where a historical relationship between changes in mean sea level and recorded overtopping events on the railway over the period 1916–2009 was established and extrapolated with future projections of mean sea level. This method produced baseline estimates of future overtopping events for the 'do minimum' option under low and high emission sea-level scenarios for both study periods (see Fig. 1 for illustration). The main category of economic impact resulting from overtopping events is that of increase in travel time suffered by rail users (Lakshmanan, 2011; Dawson et al., 2016). Adopting the approach outlined by Metroeconomica (2004) and Penning-Rowsell et al. (2016) we calculate these impacts on the basis of the equation:

$$I_{Pass} = vt^{L} \times d \times n_{Pass} \tag{1}$$

where:

I_{pass} = direct economic impact of passenger disruption; vt = unit value (£/minute) of travel time taken from UK appraisal guidance (Department for Transport, 2017a); L = UK lateness multiplier that represents the fact that unplanned-for lateness is perceived to be more costly than regular travel time (Department for Transport, 2017a); d = lateness time (in minutes) associated with events on the line, based on historical data, (Dawson et al., 2016) and operational restrictions on the line – including: temporary speed reductions; one line working; and; complete closure (Network Rail, 2010); n_{pass} = number of passengers affected by the delays. I_{pass} per event is then multiplied by the number of expected events estimated using the empirical-based overtopping model of Dawson et al. (2016). Freight use is not assessed in this study since it is insignificant on this route. Wider economic impacts, including agglomeration and labour effects, have been recognised as being potentially important in infrastructure appraisal, (Department for Transport, 2016), but estimation of these impacts remains contentious and appropriate methods are not well-established. Consequently, these impacts have not been quantified here, either.

2.1.3. *Socio-economic Estimates*

Estimating gross climate impacts and impacts net of adaptation on the basis of SLR projections and associated overtopping trends imposed on current rail use patterns would ignore potentially significant non-climate factors in the impact analysis (Berkhout et al., 2002). In order to represent these dimensions, we utilise socio-economic scenarios (SES) that provide quantitative projections of rail demand under alternative potential futures. Specifically, we adopt two socio-economic scenarios that – based on projected population growth rates – are consistent with the assumptions used to generate the low and high climate emission/SLR scenarios. For the 2002 assessment report analysis, we utilise data from UKCIP (2001), whilst for the 2010 assessment report analysis we use passenger demand forecasts obtained from the network operator (Network Rail, 2010). Consequently, these socio-economic projections are contemporaneous for decision making in these two years.

The "global sustainability" and "world market" scenarios are adopted from UKCIP (2001), and the equivalent scenarios – "global responsibility" and "continued profligacy" – are adopted from Network Rail (2010). These projections, coupled with estimated annual passenger journeys, provide estimates of passengers on the Dawlish-Teignmouth section of rail track (Table 3). The passenger forecast

Table 3
Passenger demand data used in current study. Demand changes are capped at 20 years as recommended by appraisal guidance (Department for Transport, 2014).

Appraisal year	Annual passenger journeys between Dawlish-Teignmouth	Estimated rail demand change in appraisal year + 20 years	
		World Market/ High emissions	Global Sustainability/Low emissions
2002	2,891,464	43%	23%
2010	3,957,168	85%	38%

projections were capped at 20 years as recommended by UK appraisal guidance (Department for Transport, 2014) and we retain these levels for all subsequent years until the end of the assessment period. Nevertheless, the projections can be seen to be much higher – by nearly a factor of two – than current passenger numbers.

2.2. Derivation of Adaptation Costs

Following the most recent storm event on the coastal section of the train line in February 2014, Network Rail (2014) identified three possible adaptations to increase its resilience in the face of sea-level rise (Fig. 1a). These include a) the base case of maintaining the existing railway; b) the strengthening of the existing line, and; c) a set of new inland lines. We estimate measures of economic efficiency for options b) and c), relative to the baseline option, a); they are summarised in Table 1. The costs and benefits of these two options are calculated for a 60-year time-period – the assumed lifetime of the options. These costs and benefits are specified as follows:

2.2.1. Baseline Definition: Maintenance of the Existing Railway (Do Minimum)

In the baseline, the existing railway line is maintained to its current defence height for the appraisal period and is subjected to the full impacts of sea-level rise over the assessment period. The baseline assumes existing coastal defences are maintained through on-going maintenance expenditures. SLR, combined with socio-economic change, (SES), results in a profile of damage costs to train users (Eq. (1)) that increases over time. Given the level of defence specified in this case and the two options the impact to local population is judged to be negligible and so is not considered in subsequent calculations.

Do minimum costs (DMC) are then estimated using the following calculation:

$$\mathrm{DMC} = I_{\mathrm{Pass}} + C_{\mathrm{CM}} \tag{2}$$

where: I_{pass} = economic impacts of passenger delays calculated from Eq. (1) and C_{CM} = maintenance on the coastal section of track.

2.2.2. Defence Strengthening (Adaptation One)

The existing route is maintained and comprehensively reinforced through a series of interventions including rock armour, groynes, and heightening and reinforcement of the most critical structures at a total cost of £528 million (Network Rail, 2014). Adaptation costs (AC_1) for this option are:

$$\mathrm{AC}_1 = (C_C)_t \tag{3}$$

where: C_C = the capital cost of investment, in line with the implementation plan presented in Network Rail (2014), is spread evenly over a 20-year period (t = 0–20). Relative to the baseline case defined above, no additional maintenance costs are associated with these capital costs. Present value costs (PVC_1) of adaptation one are estimated as:

$$\mathrm{PVC}_1 = \sum_{t=0}^{T} \frac{\mathrm{AC}_1}{(1+\delta)^t} \tag{4}$$

where: T = 60 (the defined assessment period) and δ = discount factor set at 3.5% for years 0–30 and 3% for years 31–60 in line with UK guidance (HM Treasury, 2003). Damage costs for adaptation one (DC_1) are calculated as:

$$\mathrm{DC}_1 = i_t(I_{\mathrm{Pass}} + C_{\mathrm{CM}})$$

where: i = the parameter that captures the influence, or effectiveness, of the construction of the new defences through the reduction in maintenace and rail user impacts. Damage costs are assumed to fall by 5% per annum as a result of the new defences during the construction phase (when t = 0–20). Following completion of the adaptation measure a gradual reduction of the defences' protection is assumed as a consequence of rising mean sea level. We estimate this effect using a numerical model simulation of the reduction in defence effectiveness (i.e. return period) taken from O'Breasail et al. (2007), where: i = −0.03 (t = 21–38), and − 0.005 (t = 39–60). The damage costs are then used to estimate the present value benefits of Adaptation One using the following formula:

$$\mathrm{PVB}_1 = \sum_{t=0}^{T} \frac{(I_{\mathrm{Pass}} + C_{\mathrm{CM}}) - i_t(I_{\mathrm{Pass}} + C_{\mathrm{CM}})}{(1+\delta)^t} \tag{5}$$

or simply:

$$\mathrm{PVB}_1 = \sum_{t=0}^{T} \frac{\mathrm{DMC} - \mathrm{DC}_1}{(1+\delta)^t} \tag{6}$$

2.2.3. New inland route (Adaptation Two)

An inland route is identified, derived from Network Rail (2014), that has a capital cost of £2.2 billion (Table 1). Costs of Adaptation Two are then:

$$\mathrm{AC}_2 = (C_C + C_{\mathrm{IM}}) \tag{7}$$

where: C_{IM} = inland route maintenance and operating costs. The calculation of Adaptation Two PVC follows Eq. (4) above, whilst the damage costs (DC_2) for Adaptation Two are:

$$\mathrm{DC}_2 = i_t(I_{\mathrm{Pass}}) \tag{8}$$

where: i = 0 as no interventions to the defences are made thus no adjustment to the damage costs are required. The damage costs in this case are assumed to be zero, as the coastal section of railway line is abandoned (ownership of the defences is transferred to the relevant authority for protecting coastal populations at risk). PVB for this option can be calculated:

$$\mathrm{PVB}_2 = \sum_{t=0}^{T} \frac{\mathrm{DMC} - \mathrm{DC}_2}{(1+\delta)^t} \tag{9}$$

2.3. Real Option Analysis: Derivation of Net Present Values and Option Values

In this assessment we follow the general rule of option pricing that the timing of an adaptation action depends upon a comparison between the net present value of adaptation in one time period (in this case, from 2002), with the present value net benefits/costs in a future time period (in this case, from 2010) (Fankhauser et al., 1999). Formally, in deterministic terms, the net present value if adaptation is made in 2002 is:

$$\mathrm{NPV}_{2002} = \sum\nolimits_{t=0}^{T} \frac{\mathrm{PVB}_t}{(1+\delta)^t} - \sum\nolimits_{t=0}^{T} \frac{\mathrm{PVC}_t}{(1+\delta)^t} = \sum\nolimits_{t=0}^{T} \frac{\mathrm{PVB}_t - \mathrm{PVC}_t}{(1+\delta)^t}$$
$$\mathrm{NPV}_{2002} = \sum_{t=0}^{T} \mathrm{PVB}_{2002} - \mathrm{PVC}_{2002} \tag{10}$$

where:

NPV_{2002} equals the net present value of an adaptation measure implemented in 2002 over time (T) for the 60 -ear period and discounted (δ); see previous section for details. Net Present value with implementation in 2010, NPV_{2010} is:

$$NPV_{2010} = \sum_{t=0}^{T} PVB_{2010} - PVC_{2010} \tag{11}$$

A direct comparison yields:

$$(NPV_{2002} - NPV_{2010}) = \sum_{t=0}^{T} (PVB_{2002} - PVC_{2002}) - (PVB_{2010} - PVC_{2010}) \tag{12}$$

The balance of NPV_{2002} and NPV_{2010} is equivalent to the real option price of the investment that the new climate information allows in the period between 2002 and 2010. This real option price represents the value of delaying the decision to invest in the adaptation measure.

In order to integrate climate change uncertainty into an ROA that generates quantitative estimates of the value of new information, we express this uncertainty in risk-based, probabilistic terms. We therefore look to be comparing expected net present values (ENPV), for which the NPVs derived for each alternative state of nature – here, in the form of scenarios – has a probability (p) attached to it. Thus:

$$ENPV = p(NPV_1) + p(NPV_2) + p(NPV_3), \text{ etc.}$$

Therefore, in order to operationalise the projections of SLR in the ROA we must assign probabilities to the high and low SLR scenarios. As previously identified, though, this conflicts with the state of scientific knowledge that exists because there remains insufficient confidence in the climate-SLR modelling processes for their uncertainties to be characterised probabilistically. Consequently, we interpret probability (p) in a different way. The usual process for including NPV data in decision making under uncertainty is to estimate the ENPV – a risk neutral measure – and then allow the decision maker to impose their attitude to risk in the decision context before making the final decision. Given that we have no reliable knowledge of what p should be for each SLR scenario, however, it is useful instead to consider the values of p to be a means of simulating attitudes to non-probabilistic risks, i.e. unquantified uncertainty. Thus, the values given to each p capture the effect of assuming a particular attitude to uncertainty. In this way, the various rules that have been developed to characterise alternative attitudes to uncertainty – including the Maximax and the Minimax as representing the extremes of this characterisation – can be incorporated into the NPV economic efficiency decision rule. The resulting ENPV measures are then interpreted as an indication of economic efficiency, given a specific attitude to uncertainty.

In order to operationalise this approach we specify values for p at six points across the distribution of SLR defined by the low-high scenario range for each future year. Specifically, we select three points – defined by the 5th, 50th and 95th percentiles – in each of the two scenarios, consistent with the approach adopted in presentation of the UKCP09 projections. We identify ENPVs for three archetype attitudes to uncertainty:

- The Optimist – characterised in the Maximax decision rule, which implicitly allocates more weight to the outcome that gives the best pay-off across the scenarios. In our decision context this is equivalent to assuming relatively low levels of SLR;
- The Pessimist – characterised in the Maximin decision rule, which implicitly allocates more weight to the outcome that gives the least worst pay-off across the scenarios. In our decision context this is equivalent to assuming relatively high levels of SLR;
- The Neutralist – characterised in the Laplace decision rule, and also known as the principle of insufficient reason, since it assumes – in the absence of any evidence to the contrary – that all outcomes are equally probable. Thus, in our decision context, we assume that each of the six SLR scenario points is given the same weight.

Table 4
Probability values for future sea-level projections used to calculate ENPV, and associated 'attitude' towards uncertainty.

Scenario/percentile	Optimist	Pessimist	Neutralist
Low – 5th	0.90	0.02	0.16
Low – 50th	0.02	0.02	0.16
Low – 95th	0.02	0.02	0.16
High – 5th	0.02	0.02	0.16
High – 50th	0.02	0.02	0.16
High – 95th	0.02	0.90	0.16

The values of p that we adopt in our analyses are presented in Table 4. Clearly, these values are relatively arbitrary and chosen to reflect the corresponding risk attitude in indicative terms; they can straightforwardly be adjusted in sensitivity analysis.

3. Results

Following implementation of the ROA approach outlined in Fig. 1b, the quantitative outputs were estimated and are presented in Table 5. The fourth column of Table 5 presents estimates of the expected net present values (ENPVs) for the two adaptation measures considered, derived from the two sequential sets of climate projections and using the recommended discount rate and travel time values recommended in UK public project and policy appraisal guidance (e.g. HM Treasury, 2003; Department for Transport, 2014). The resulting option values, as well as the expected benefit-cost ratios associated with the ENPVs, are presented in the fifth and sixth columns, respectively. Whilst it is the case, in this example, that the new information has no impact on the conclusion and none of the adaptation measures appear to pass the economic efficiency criterion the investment decision is straightforward. In many cases the conclusion will depend on the attitude to uncertainty assumed. In this case, the decision-maker will be expected to adopt a specific attitude and choose to invest or not, informed by the results of the analysis. These results are disaggregated according to our three-category classification of attitudes to uncertainty. The bottom set of rows presents results with no socio-economic change and assume a neutralist attitude.

Whilst the negative ENPVs indicate the economic inefficiency of both adaptation measures, the more notable finding is the substantial

Table 5
Economic assessment of adaptation options of the Dawlish-Teignmouth section of the London-Penzance railway (£2015). EBCR = expected benefit cost ratio, ENPV = expected net present value.

Attitude	Adaptation	Assessment report	ENPV	Option value	EBCR
Optimist	(1) Defence strengthening	UKCIP02	−309	65	0.20
		UKCP09	−244		0.37
	(2) New line	UKCIP02	−950	86	0.07
		UKCP09	−864		0.16
Neutralist	(1) Defence strengthening	UKCIP02	−258	98	0.30
		UKCP09	−160		0.55
	(2) New line	UKCIP02	−870	124	0.11
		UKCP09	−746		0.23
Pessimist	(1) Defence strengthening	UKCIP02	−214	152	0.45
		UKCP09	−62		0.84
	(2) New line	UKCIP02	−852	187	0.17
		UKCP09	−665		0.35
No socio-economic change (Neutralist)	(1) Defence strengthening	UKCIP02	−275	65	0.25
		UKCP09	−210		0.42
	(2) New line	UKCIP02	−900	68	0.08
		UKCP09	−833		0.15

option values generated, varying broadly between £65m–£152m and £86m–£187m for Adaptation One (Defence Strengthening) and Adaptation Two (New Line), respectively. On average, these values equate to 20% and 6% of the capital cost of investment for the two adaptation measures. It should be noted in this context that the sign of the option value is irrelevant. For example, if the ENPV values for UKCP02 and UKCP09 for each adaptation measure in Table 5 were reversed, the option values would be negative in absolute terms. The benefit (or value) in delaying adaptation and incorporating new learning would be attributed to the avoidance of over investment based on pessimistic estimates of future SLR. Thus, it is the ENPV's dimensions relative to each other that is the important measure, and option values that result from adopting the Pessimist attitude would therefore remain as the most important in this case.

The characterisation of different uncertainty attitudes has a significant impact on the option values: a pessimistic attitude generates the highest option values, roughly 25% and 55% higher than neutralist and optimist attitudes, respectively. Table 5 also serves to highlight the role of socio-economic data – in our simulation represented by projections of future passenger demand changes. Comparison between the second block of rows (neutralist, with SES), and the fourth block of rows (neutralist, without SES), identifies that option values are 35% and 45% higher for a New Line and Defence strengthening, respectively, if passenger demand projections are incorporated into the Present Value estimations. Although the results in Table 5 reflect the importance of the projected future ranges of both sea-level rise and passenger demand changes, we also need to consider uncertainties in other parameters in the economic analysis. Consequently, our sensitivity analysis examines the roles of the two most important economic parameters – the discount rate and the value of travel time (VTT) – that have been adopted in the estimation process.

For both variables, alternative, defensible, values are specified and the simulations are re-run with these values. Two alternative discount rates are adopted – 6% and 1.4%. The higher rate of 6% is justified by adopted to reflect the rates reported in the UK Climate Change Committee as being typical for private operators engaged in projects designed to meet social objectives (CCC, 2011). The lower rate of 1.4% is justified by the fact that it was the central rate deployed in the economic assessment of climate change reported in the Stern Review (Stern, 2007). Upper and lower values of travel time were defined on the basis of the range suggested in guidance on the economic appraisal of transport projects (Department for Transport, 2017b). This guidance recommended values of ± 25% of the recommended (central) value. The central and sensitivity values for the two variables are summarised in Table 6.

Fig. 3 presents the option values that are generated when these sensitivity values are incorporated into our analysis. Examining the impact on discount rates alone, deviation from our central estimate (red line) across the three uncertainty attitudes ranges from −42% and 69% for Adaptation One and −44% and 77% for Adaptation Two. The lower discount rate corresponds with the high increase in option value, and vice versa. Including sensitivity values associated with the VTT used to calculate PVB, the deviations are more sizeable. In this case, option values are reduced from our central analysis by 68% and 80% for Adaptation One and Two, respectively. Increases in average option value across all risk attitude specifications are 179% for Adaption One, and 246% for Adaptation Two.

Table 6
Central and sensitivity values: Discount Rates and Travel Time Values.

	Lower	Central	High
Discount rate (%)	1.4	3.5[a]	6
Value of Travel Time (£/minute)	10.78	13.48	16.85

Note: Sensitivities around VTT are illustrated by commuters' user values.

[a] Value declines > 30 years.

4. Discussion & Conclusions

In this ex post study we have applied a modified ROA approach to the economic appraisal of a stretch of coastal infrastructure. We have used empirical data and models to generate option values for adaptation measures over an eight year time period defined by the publication of two sets of UK climate change projections in 2002 and 2010. Whilst ROA has been championed as an approach to improve economic decision making under uncertainty, allowing flexibility and learning in infrastructure investment, our use of consecutive climate change projections allows us to undertake an ex post investigation of the value of new data sets formally promoted for adaptation planning in the UK. This contrasts with a host of previous studies that restricted themselves to ex ante analysis based on the use of illustrative climate projection data. Where previous approaches have identified additional economic value of adopting an ROA approach that recognises the utility of new climate data, the new data has not been attributed to any specific improvement in modelling capabilities. However, the sets of climate data used in these simulations have been bounded by what are judged by the authors of these studies to be plausible climate change scenarios – see recent studies such as Kontogianni et al. (2014) and van der Pol et al. (2016). Our approach, based on the use of formal, promoted, climate projections responds to Linquiti and Vonortas' (2012) exhortation regarding the need to characterise the economic value of research to improve the quality of such projections. Specifically, by identifying the option price – i.e. the value attributed to delaying the adaptation investment decision – we implicitly recognise the worth of such research into improved climate projections. This worth is likely to increase as further improvements in the quality of climate data – and further climate projection iterations - are made, though the extent to which the flexibility in decision-making can be maintained is dependent on institutional and technical implementation constraints.

A key innovation in our method is the use of subjective, analyst-determined probabilities to simulate alternative attitudes to uncertainty under different future climate scenarios, in the absence of objectively determined probabilities and given the computational mechanics required by ROA. We propose that in the likely continued absence of objectively determined probabilities in adaptation analysis, this innovation should be considered for adoption in ROA applications since it effectively captures the range of attitudes towards uncertainty likely to be expressed by stakeholders. This form of sensitivity, along with the testing of key parameters, serves to make explicit the treatment of uncertainty and so encourages transparency in the discussion by stakeholders of the quantitative analysis.

In addition to our objective of injecting greater realism in the interpretation of climate projection data sets, we also set out to test the extent to which ROA can be simplified and therefore made more appealing to the broader community of climate adaptation analysts, whilst not losing its robustness and associated credibility. The overall structure in which the methodological components sit is outlined in Fig. 1. Whilst this structure is designed to be easily understood, it becomes clear in the subsequent descriptions of the methodological components that the volume and range of data is substantial and requires input from a variety of technical competences. It should also be clear that the ROA does not require any data additional to that needed for undertaking a standard cost-benefit analysis; the only extra effort needed on behalf of the analyst is that used to apply consecutive sets of climate projections and impact data in the economic analysis. Indeed, the exogenous, analyst-specified probability sets used to characterise attitudes to uncertainty are simpler to define than objective probabilities based on historical observation.

Regarding the value of new climate information, the option values derived from this ex post analysis can be attributed directly to the improvement in sea-level estimation between 2002 and 2010. Specifically, an investment decision made in 2002 would have been based on analysis that underestimated the extent of the adaptation

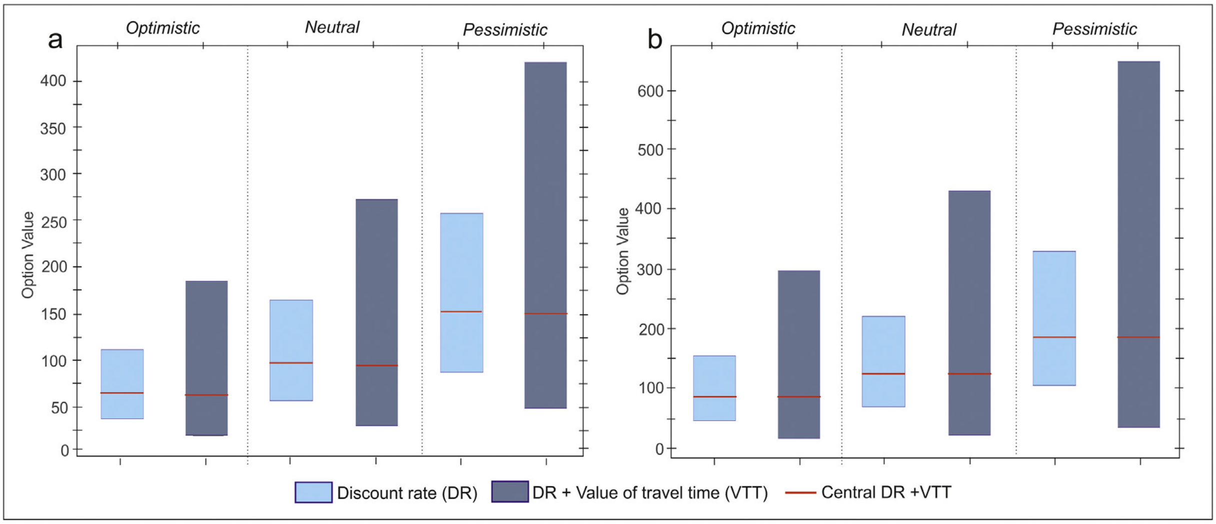

Fig. 3. Sensitivity analysis of option value to discount rates (DR) and value of travel time (VTT) values (see Table 6 for details). (a) Adaptation One option value. (b): Adaptation Two option value. Boxes: data limits, and red line represents central values used in the study (Table 5). All values in £ millions (2015 prices). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

benefits relative to those in 2010, themselves resulting from the higher sea-level estimates presented in the 2010 assessment report. The value gained by delaying the decision, and therefore giving the decision maker the opportunity to re-evaluate the adaptation measures is estimated to be equivalent, using central and neutralist valuation parameters, to approximately 6%–20% of the capital cost of adaptations on the railway line (Adaptations Two and One, respectively). We acknowledge this is a rather specified observation from an individual case study but it is in line with previous estimates of the likely dimensions of option values (Ingham et al., 2006).

The option value identified can also be utilised to decide whether – and to what extent – resources should be invested in scientific research that helps reduce future uncertainties through ‘active learning’ (Kontogianni et al., 2014). In considering results from Adaptation One, we demonstrate that the up-dated sea-level projections resulted in option values for the section coastal railway of £12.2 million per year, equivalent to ~£3 million per km of track per year. Since in the UK there are around 800 km of coastal railway, through a simple multiplication we derive a value of £17 billion (or £2 billion per year) from the improved sea-level projections to UK coastal rail infrastructure. Of course, the validity of such a figure depends on comparable risks, and costs and benefits of adaptation measures, existing over the entire 800 km which is clearly not likely to be the case. But, it does serve to indicate that the benefits of improved climate information may well be considerable in comparison to the cost of generating new scientific information. We also include socio-economic projections in our analysis, and these are shown to significantly affect the dimensions of the benefit estimates, increasing the size of the adaptation benefits by about 40%, and thereby making their role in infrastructure adaptation investment decisions significant. It is noted, however, that the last set of national socio-economic scenarios were developed in 2001 (UKCIP, 2001). In the absence of a new set of these scenarios, the robustness of future climate change impact and adaptation assessments in the UK is likely to be increasingly limited and non-comparable.

Clearly our study is undertaken only at a local level in one location, but it does provide initial empirical evidence that the pursuit of new improved sea-level information, and the understanding of climate science more generally, has a real economic value in adaptation economics and future decision making. The principal caveat is that the validity of our findings is dependent on the assumption that climate and sea-level projections will improve with each generation of such assessments and projections, and be recognised as doing so in the eyes of analysts and stakeholders. As our understanding and ability to model the climate system improves, it is indeed likely that uncertainties will reduce. The pace of climate projections improvements will not be generic, however, and will in part be dependent on the resource available to progress specific parameters of research. Furthermore, we cannot rule out the possibility that the ranges in climate projections may become greater before they become smaller, as modelling incorporates more relevant climatological factors (Jenkins et al., 2009). This presents a further expositional and analytical challenge that the climate research community is yet to grapple with, and exacerbates the potentially disruptive role of analysts' and stakeholders' ambiguity to information relating to climate projections.

Acknowledgements

Funding for the research reported in this paper was supported by the Leverhulme Trust’s Early Career Fellowship Scheme (ECF-2014-177) and the European Commission DG Research ECONADAPT project (603906). Contributing research was also funded by provided by Great Western Research, Network Rail, and Devon and Cornwall Councils.

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