Adaptive flood risk management under climate change uncertainty using real options and optimisation

M Woodward[1], Z Kapelan[2] and B Gouldby[1]

[1] HR Wallingford, Howbery Park, Wallingford, Oxfordshire, OX10 8BA
[2] College of Engineering, Mathematics and Physical Sciences, University of Exeter, Exeter, Devon, UK

Published in the Journal of Risk Analysis, July 2013

Abstract

It is well recognised that adaptive and flexible flood risk strategies are required to account for future uncertainties. Development of such strategies is however, a challenge. Climate change alone is a significant complication but in addition complexities exist trying to identify the most appropriate set of mitigation measures, or interventions. There are a range of economic and environmental performance measures that require consideration and the spatial and temporal aspects of evaluating the performance of these is complex. All of these elements pose severe difficulties to decision makers. This paper describes a decision support methodology that has the capability to assess the most appropriate set of interventions to make in a flood system and the opportune time to make these interventions, given the future uncertainties. The flood risk strategies have been explicitly designed to allow for flexible adaptive measures by capturing the concepts of Real Options to evaluate potential flood risk management opportunities. A state of the art flood risk analysis tool is employed to evaluate the risk associated to each strategy over future points in time and a multi-objective genetic algorithm is utilised to search for the optimal adaptive strategies. The modelling system has been applied to a reach on the Thames Estuary (London, England), and initial results show the inclusion of flexibility is advantageous while the outputs provide decision makers with supplementary knowledge which previously has not been considered.

Keywords

Decision tree analysis, economics, flood risk management, multiobjective optimisation, Real Options

1. Introduction

Making decisions on long term flood risk management intervention strategies is complex. Methods are required that are capable of identifying the better performing intervention measures whilst also taking into account the most effective spatial locations and the most beneficial timing. Given the large portfolio of potential flood risk mitigation measures, identifying the most appropriate long term strategy is challenging. This problem is further compounded due to the evolving nature of flood risk, in particular with regard to climate change. The plausible range of future climate change comprises significant uncertainty, presenting decision makers with considerable challenges with regard to long term planning.

It is widely recognised that the future uncertainties of climate change need to be accounted for within the development of long term strategies to ensure an economical investment and a consistent level of protection (eg. Lempert et al., 1996, Evans et al., 2004, Environment Agency, 2009e, DEFRA, 2010, Merz et al., 2010). Traditional approaches do not lend themselves to adequately account for climate change uncertainty. In the past, strategies were developed, without accounting for future variability (Milly et al., 2008). The requirement to account for climate change uncertainty has therefore been the subject of significant research (Adger et al., 2005, Ingham et al., 2007, Hallegatte, 2009) and methods have been proposed to account for the future uncertainty (Hall and Harvey, 2009, Gersonius et al., 2010, Lempert and Groves, 2010).

Real Options analysis is a recognised approach for encouraging appropriate climate change adaptation and mitigation investment decisions (Dobes, 2008, DEFRA, 2010, Gersonius et al., 2010, Woodward et al., 2011b, Linquiti and Vonortas, 2012). In this paper, the concepts of Real Options and optimisation are applied within the context of flood risk management in coastal areas under climate change uncertainty. This methodology makes use of decision trees and multi-objective optimisation to determine the best adaptable intervention strategies over a long-term planning horizon.

2. Background

2.1. Decision making under climate change uncertainty

The uncertainty in the future climate is significant and its impact on flood risk management decision making is considered to be severe (Ranger et al, 2010). There are a number of methods that can be applied to aid decision making under severe uncertainty. Wald's Maximin (Wald, 1945) or Laplace's Principle of Indifference (Keynes, 1921) are well known traditional examples. These methods implicitly reflect a particular attitude to uncertainty. Implementation of Laplace's principle is much less conservative compared to that of Wald's maximin, for example. More recently there has been an increasing trend to develop methods that seek to identify mitigations measures that are described as robust. The concept of robustness is generally defined as having the ability to perform well over a range of future scenarios. Many of these authors indicate that there is a distinct choice to be made between robustness and optimisation and that robust methods are preferable (Lempert 2006, Adger 2009; Ben-Haim 2012).

It is of note however, that the primary objective of a number of these methods is to maximise robustness, it is thus evident that optimisation approaches can be coupled with the concept of robustness. Research has been undertaken in this regard within the field of robust optimisation. Robust optimisation provides techniques to find the best possible outcome whilst accounting for uncertainties (Ben-Tal and Nemirovski, 1998, Ben-Tal et al., 2006, Beyer and Sendhoff, 2007). With these approaches there is no need to make a choice between an optimisation or a robustness method, the objective function of the optimisation problem is simply cast in terms of robustness criteria. Or, in other words, robustness is maximised. This distinction is discussed further by Sniedovich (2011).

Within the analysis described below the concepts of robustness and optimisation are coupled and hence there are parallels with the philosophy of robust optimisation. Note, however, that in a conventional robust optimisation approach which makes use of some fixed, rigid intervention strategy, robustness is achieved by incorporating flexibility within intervention options (i.e. flexibility and the ability to adapt often provides robustness). In the methodology presented here, the robustness is achieved by continuously monitoring the uncertain variable(s) of interest (e.g. sea level rise) and allowing for optional, adaptive/flexible intervention strategies to be implemented/modified in the future, if and when necessary. All this reduces the need for large redundant capacity to be built into the flood defence system. The concepts of robustness and optimisation are further described below.

2.2. Real Options in flood risk management

In flood risk management, a robust strategy is considered to perform well by reducing flood risk through economically viable and environmentally sensitive mitigation measures. Previous work in this area (eg. Bruijn et al., 2008, Hall and Harvey, 2009) have sought to develop strategies that are robust to climate change uncertainties. The strategies that have been developed, are however, still fixed over the planning horizon and although they account for climate change variability they are based on particular assumptions about future change. The magnitude of future change is however, subject to severe uncertainty (Rayner, 2010). Rates of change may therefore be faster or slower than the rates assumed and therefore the planned time steps when interventions are required will change. Strategies developed using these approaches may therefore typically require large initial costs and can often result in sunk costs if a future state occurs which the infrastructure was not tested against (Gersonius et al., 2010).

The core principle of Real Options analysis is the ability to value flexibility (Dixit and Pindyck 1994). This principle encourages the identification of opportunities for incorporating flexibility into the decision making process. Essentially, Real Options allows a decision maker to make changes to an investment decision when new information arises in the future. Opportunities such as *delaying* the investment, *abandoning*, *switching*, *expanding*, *contracting* or having multiple options interacting together are potential choices for decision makers (Copeland and Antikarov, 2001, Schwartz and Trigeorgis 2004). For example, where it is beyond doubt that a flood defence has come to the end of its useful life and requires major refurbishment there are a range of possible decisions. Assuming a worst case climate change scenario and constructing a flood defence based on this assumption is likely to be sub-optimum as it requires significant up-front expenditure and may well constitute an over-design should the worst case scenario not be realised. Constructing a defence that is inherently flexible and capable of future modification is one approach for implementing flexibility within a flood risk system. A flood defence system that is constructed in an innovative way enabling increases in the level of protection to be readily achievable, should there be a requirement, is an example of embedding a Real Option. The option to raise the level of protection (e.g. raise the crest level) is purchased at the outset. The decision whether to exercise the option is delayed to a future date when more information regarding future climate change impacts, for example, is known (Woodward et al., 2011b).

There may however, be uncertainty regarding the nature of the mitigation measure. A range of options may exist that could include whether to refurbish a defence, set-back a defence or continue with maintenance activities, the cost of which may rise as the structure approaches the end of its design life. Delaying the decision to refurbish and continue with the maintenance is another example of implementing Real Options based concepts. Flexibility is maintained and the decision to refurbish or setback is delayed until more information is known. The cost of the option is the increase in maintenance costs as the structure deteriorates. The value of the option lies in the decision to delay major investments until future uncertainties are reduced.

There are many methods and tools available to value flexibility and undertake Real Options Analysis. Many are based on financial valuation methods including the Black-Scholes formula (Black and Scholes, 1973, Merton, 1973) and the discrete-time option pricing formula (Cox et al., 1979). It is often argued that financial valuation methods such as these are not suitable for valuing Real Options (Copeland and Antikarov, 2001). Wang and de Neufville (2005) explain that Real Options can be broadly classified into two categories, Real

Options ‘in’ systems and Real Options ‘on’ systems. Real Options ‘on’ systems are Real Options that focus on the external factors of a system and would benefit most from financial valuation methods. Real Options ‘in’ systems, on the other hand, incorporate flexibility into the structural design of the system and valuing this flexibility using financial tools is less suitable. Methods for Real Options analysis were identified and include partial differential equations (McDonald and Siegel, 1986), binomial (Copeland and Antikarov, 2001) and trinomial (Zhao and Tseng, 2003) decision trees and stochastic dynamic programming (Wang and de Neufville, 2004).

In the analysis described below, the use of Real Options is aligned with Real Options ‘in’ systems where flexibility is inherently captured within the engineering design of the system. De Neufville et al (2005) provides an approach to value flexibility for a Real Options ‘in’ systems project and the approach adopted in this paper follows a similar procedure evaluating flexibility as the difference between an option with embedded flexibility and an option defined in a more conventional, deterministic way.

In addition to the above, a decision tree approach is also employed enabling Real, and other more conventional intervention, options to be incorporated within an intervention strategy, allowing multiple optional intervention paths into the future dependant on the nature and level of climate change. All this, in turn, enables more effective adaptation of the analysed engineering system to climate change.

2.3. Optimisation methods

Formal optimisation methods have been applied to flood risk management decision making problems for many years (eg. Danzig 1956, Voortman and Vrijling, 2003). More recently evolutionary multiobjective optimisation techniques have been developed that have the capability to consider a wide range of multiple objectives simultaneously whilst searching through a large portfolio of potential decision variables see for example (Savic and Walters, 1997, Kapelan et al., 2003, Behzadian et al., 2009, Dorini et al., 2010, Weickgenannt et al., 2010). However despite the obvious advantages, multiobjective optimisation has rarely been applied to flood risk management problems. Woodward et al (2011a) has recently applied the Non-dominated Sorting Genetic Algorithm II (NSGAII), an evolutionary multiobjective optimisation method (Deb et al., 2000), to optimise for short term flood risk intervention strategies where climate change uncertainty is not a consideration. The analysis described here extends upon the work presented by Woodward et al (2011a) to aid the development of long term flood risk strategies where climate change uncertainty is significant.

3. Methodology

3.1. Problem

The problem of coastal flood risk management is complex and typically involves a range of performance measures. For the purposes of demonstrating the concepts of the methodology it is formulated and solved here as a multi-objective objective optimisation problem. The two objectives are as follows:

$$f_1(x) = \max(Benefit) \quad (1)$$

$$f_2(x) = \min(Cost) \quad (2)$$

where *Benefit* represents the reduced flood risk in the analysed area over a long-term planning horizon (see equation (5) below) due to the implementation of a specific intervention (or mitigation measure), when compared to the “do nothing” scenario. *Cost* represents the total cost incurred over the same time period due to any interventions implemented and the operation and maintenance costs of the flood defence system (see equation (9) below).

In order to facilitate the evaluation of flexibility and adaptability, intervention strategies considered are represented as decision trees with multiple paths into the future (see Figure 1), rather than representing intervention strategies as single paths fixed over the planning horizon. The structure of the adaptable intervention strategy coded as a decision tree consists of specific paths at each time step of the planning horizon, where each path or decision node corresponds to a set of intervention measures. The intervention measures considered at each decision node include raising the crest level of the defence (this is constrained based upon the existing defence footprint specification) and enhancing the defence foundation footprint to enable additional crest level raising. In addition, different maintenance regimes of the defences are also considered.

The intervention measures, coded as decision trees, inherently include flexibility providing opportunities to delay, contract, expand and abandon investment decisions, depending on how the uncertain future actually unfolds (i.e. how the sea level rises in the case study shown here). Thus the value of flexibility is explicitly evaluated within the method, thereby incorporating Real "in" Option analysis. The decision variables within the optimisation process not only include the intervention measures but also the threshold values on uncertain climate change variables. This means information on the optimal timing to make an intervention, given the future climate change realisation, is provided to decision makers.

The decision variables are represented using the following vector:

$$X = (X_s, X_m, T_h) = (x_{s_1}, x_{s_2}, \ldots, x_{s_n}, x_{m_1}, x_{m_2}, \ldots, x_{m_n}, T_{h_1}, \ldots, T_{h_y}) \tag{3}$$

where X_s and X_m, are sub-vectors which represent the specific intervention to apply to each of the defences *d*, in the flood system such that $X_s = (x_{s_1}, x_{s_2}, \ldots, x_{s_n})$ and $X_m = (x_{m_1}, x_{m_2}, \ldots, x_{m_n})$ where *n* equals the total number of defences in the flood system, T_h is the threshold value between decision paths and *y* is the total number of threshold values. Structural interventions, X_s such as raising the height of a defence are defined as discrete variables. The decision variable X_m can take the value of four possible maintenance options including no maintenance, low, medium and high.

3.2. Climate Change Uncertainty Characterisation and Quantification

The decision tree intervention strategies shown in Figure 1 are evaluated over the three UKCP09 high, medium and low emission scenarios (Murphy et al., 2009) focusing specifically on sea level rise. The data provided within the three emission scenarios on sea level rise include yearly predicted increases from 1990 to 2100 for the 5th, 50th and 95th percentiles. For a given emission scenario, the 5th and 95th percentiles are at equidistance from the mean showing evenly distributed data. A normal distribution was therefore used to represent the uncertainty on sea level rise values for a given emission scenario (see Figure 2). It was then possible to sample from that distribution to produce a range of future realisations to evaluate the intervention strategies against. For any specific realisation, the quantile sampled for the first time-step was used for subsequent time-steps to ensure credible realisations were obtained.

Although the three emission scenarios were used, it is important to note that no information on the likelihood of the three scenarios is provided within UKCP09 (see Stainforth et al., 2007 for a further discussion on this topic). The approach applied in the case study example was therefore to sample from the three distributions assuming they are equally likely. The methodology is not however, prescriptive in this regard and consideration of other approaches or weightings is readily achievable.

The uncertainties relating to climate change are accounted for by evaluating each intervention strategy over the full range of future sea level realisations. Given a future realisation, the decision path taken is determined according to a threshold value that has been sampled from the normal distributions of sea level rise. At each time-step, if the sea level rise of a given realisation is greater than the threshold, the higher path is taken, if less the lower path is taken.

3.3. Flood Risk Assessment

Each adaptable intervention strategy (coded as a decision tree) is evaluated over the range of sampled future scenarios using a risk analysis model and an intervention costing module. The risk analysis model used has been applied to support the development of a long term flood risk intervention strategy on the Thames Estuary and the Environment Agency's National Flood Risk Assessment (Gouldby et al., 2008).

The model considers a system of flood protection infrastructure protecting the floodplain (Figure 3). The floodplain is divided into a series of impact zones and further divided into impact cells. The hydraulic loading conditions, (water levels, for example) are represented as continuous random variables acting upon the system of defence sections. The performance of the flood defences is defined by fragility curves (NRC, 1995, Simm et al., 2009, Schultz et al., 2010). Defence system states are sampled using a standard Monte-Carlo procedure for each of the loading levels and a hydraulic flood spreading model is used to represent the propagation of floodwater across the floodplain according to the topography of the land. The economic consequence of flooding is estimated using depth damage curves which analyse the damage to properties according to the spread of floodwater (Penning-Rowsell et al., 2005). The model evaluates the spatial variation in risk which is defined as:

$$R = \int \sum_{i=1}^{2^n} P(d_i|l) f_L(l) g(d_i, l) dL \qquad (4)$$

where R is the risk expressed as Expected Annual Damage (EAD), n is the total number of defence sections, l is the hydraulic load at each defence throughout the system, $f_L(l)$ is the probability density function of hydraulic load, d is a specific defence system state and i is the defence system state index. The function (g) represents the consequences of a single discrete flood event (defined in terms of a specific hydraulic loading level and a defence system state).

The risk analysis model can be used to calculate the present day and future flood risk, accounting for climate change and mitigation measures that are implemented. More specifically, calculation of the flood risk associated with structural and non-structural interventions, X_s, and routine defence maintenance, X_m. can be incorporated in the model by modifying the fragility curves, defence information or depth-damage functions. Climate change scenarios are represented by modifying the extreme value distributions of hydraulic loads while socio-economic development scenarios are represented by modifying the depth-damage functions.

For a given climate change realisation (e.g. sea level realisation), the actual path through the decision tree is determined and the risk analysis model is then used to calculate the associated risk R for that path (see equation (4)). The risk of a given intervention strategy at any point in time is a function of the intervention measures, the extreme flood events, l, and the performance of the defence infrastructure X_p such that $R = g(X_s, X_m, l, X_p)$. The benefits for that path and given realisation can then be obtained as the difference between the ‘do nothing’ option and the path where interventions are applied. The ‘do nothing’ option applies no interventions or defence maintenance over the lifetime of the strategy. The benefits are therefore:

$$Benefit = \sum_{t=1}^{T} \frac{g\left(X_s, X_m, l, X_p\right)_t - g(l, X_p)_t}{(1+r)^t} \qquad (5)$$

Where T is the total number of planning horizon time-steps considered in an intervention strategy, t represents the time-step index and r is the discount rate.

For each intervention strategy there is a requirement to run the risk analysis tool for every sea level rise projection to obtain the benefits over a wide range of samples. Depending on the size of the sample, this can become computationally expensive. For this reason, a relationship between the outputs of the risk analysis tool (EAD) and sea level rise has been established for each intervention strategy analysed, to reduce the number of model simulations required. The EAD obtained for each sea level rise sample was found to follow an exponential relationship:

$$y = Ae^{bx} \qquad (6)$$

where x represents a given sea level rise value, A and b are constants specific to an intervention strategy and y is the EAD for a given intervention strategy at the sea level rise value x. For each intervention strategy, the flood risk analysis model is run for the maximum and minimum sea level rise values to generate the respective maximum and minimum EAD values. A and b can then be determined using simultaneous equations to produce the exponential relationship for that intervention strategy. It is then possible to determine the EAD values for the remaining sea level rise samples for that intervention strategy using the generated relationship (see example relationship curve in Figure 4). The exponential relationship (equation 6) was tested for a range of different sea level realisations and different intervention strategies for the case study area below, each time showing consistent results. With this relationship (i.e. surrogate model), it is possible to significantly reduce the overall computational cost as generating a curve for any intervention strategy evaluated requires only two full runs of the risk analysis model.

3.4. Costs

The approach to costing the intervention options developed here identifies costs for 61 different defence classes used within the risk model which were formulated for the National Flood Risk Assessment of England, (Environment Agency, 2009a). The basis of the cost model established by Woodward et al (2011a) extends the Cost Estimation Model given by Phillips (2008). The costs associated with structural interventions, C_s, take into consideration the mobilisation (M) and operating costs (O_d), the quantity of work required (Q_j) and the costs of materials (W_j):

$$C_s = M + O_D + \sum_{j=1}^{m} Q_j W_j \qquad (7)$$

where m is the number of maintenance and construction items.

Maintenance costs, C_m, for four different levels can be evaluated: do nothing, low, medium and high. The different maintenance levels are reflected within the model by different rates of deterioration, associated with the fragility curves, Gouldby et al (2008). The rates used with in this model are obtained from the Environment Agency of England and Wales (2009d) with the associated costs obtained from (Environment

Agency, 2009c).The total costs, C_t, for a given point in time is simply the maintenance costs plus the structural intervention costs:

$$C_t = C_s + C_m \tag{8}$$

The total cost of an intervention path sums up the costs at each point in time and then discounts these back to the present day such:

$$Cost = \sum_{t=1}^{T} \frac{C_t}{(1+r)^t} \tag{9}$$

Where *r* represents the discount rate, *T* is the number of time periods and C_t is the total cost for time period *t* as defined in equation (5).

The overall methodology described in this paper is illustrated in a flow chart in Figure 5.

4. Case Study

The methodology has been applied on an area of the Thames Estuary (Figure 6). The Thames Estuary in London, England is an area that is susceptible to flooding. A large scale flood event could have a devastating impact as it accommodates over a million residents and workers, 500,000 homes and 40,000 non-residential properties (Environment Agency, 2009a, Dawson et al., 2005, Lavery and Donavan, 2005, Lonsdale et al., 2008). The threat of flooding on the Thames Estuary occurs from a number of different sources, including high sea levels and surges propagating from the North Sea into the Estuary and extreme fluvial flows along the Thames and its tributaries (Environment Agency, 2009b). Protection against flooding is provided by a range of fixed defences and actively operated barriers and flood gates. The majority of the defences were designed to protect against a 1-in-1000 year flood however, at the present day these flood defences are gradually deteriorating. In the longer term, with the potential impacts of climate change, the need to consider a range of intervention measures is evident. It is however recognised in the planning for the future of the Thames Estuary that the decisions made today can impact the ability to adapt in the future. It is important to ensure that the flood management system put in place does not become a burden for future generations but is adaptable to any changes faced (Environment Agency, 2009b). For example, if it is likely that there will be a requirement to raise or adapt flood defences, it is necessary to ensure that space is provided now to allow for these changes in the future. The Thames Estuary is therefore a suitable case study to investigate the use of the Real Options concepts and optimisation methods described in this paper for flood risk management.

For reasons of computational practicality, this study focuses on a specific reach, Thamesmead, within the Estuary, (Figure 6). It is important to note that some data have been somewhat modified and hence the results presented here do not reflect the true risk within Thamesmead. This area contains 79 defences which have been classified into five groups according to defence characteristics (e.g. Defence Type and Condition Grade) and location. The five groups consist of a range of defence types including brick and masonry and sheet pile vertical walls, and rip-rap and rigid embankments.

The case study looks at two different situations (Case 1 and Case 2). Firstly, the optimisation model is applied in a deterministic manner whereby only one future climate change realisation is considered, the 50th quartile of the high UKCP09 emission scenario. For this case where it is assumed that the future is certain, there is no need to build in flexibility and thus use a decision tree structure. The strategy is instead a single fixed path over the planning horizon. The second case assumes the future is uncertain and therefore considers multiple future realisations, adopting the decision tree structure for the intervention options to enable flexibility in long term planning. Two differing future paths are considered in this case study to demonstrate the Real Options decision tree approach. A comparison of the two approaches is also undertaken.

In both cases, the intervention strategies consider a planning horizon of 100 years with intervention measures considered at every 50 year time step. The decision variables which are considered within the intervention strategies include raising the crest level of defences, increasing the capacity of the defences for future expansion and the level of maintenance applied. The NSGA2 parameters used for all optimisation runs are summarised in Table I.

4.1. Results and Discussion

Figure 7 displays the optimal Pareto front obtained in Case 1 evaluated against one future realisation, showing the trade-off between flood risk reduction and costs. A range of intervention strategies on the Pareto front have been highlighted including the strategy with the highest Net Present Value (NPV) (triangle) and the highest Benefit Cost Ratio (BCR) (square) for illustrative purposes. NPV is the present value of the net benefit (difference between benefit and cost).

Using the respective positioning of these strategies on the Pareto front, decision makers can make a well informed decision, comparing the different strategies available to select the most appropriate. A solution cannot be improved with respect to one objective without causing a negative effect on the other objective. For example improving the benefit will result in an increase in the cost. Decisions can also be determined according to specific target levels that must be met for each criterion. For example a specific flood risk reduction level that must be reached or if there is a constraint in the total expenditure allowed.

Table II displays a summary of the 5 optimal strategies from the Pareto front that have been highlighted. Comparing strategies C and D it can be seen that, for a minimal increase in cost, the benefits in terms of flood risk reduction can be significantly improved, favouring strategy C. Similarly, comparing strategy B and C, the increase in benefits for strategy B does not outweigh the considerable increase in costs.

The suggested intervention measures for these five strategies vary (see Table II). Strategy E for example, applies the minimum number of intervention options, only applying a low maintenance regime and achieves the highest BCR. For an increase in cost and a large increase in flood risk reduction, strategy D applies a medium level of maintenance instead of a low level. To achieve a further increase in flood risk reduction, structural interventions are required.

Strategies A, B and C comprise either a low or medium maintenance over the 100 years as well as a height increase to at least one group of defences in at least one of the time steps. In all three solutions, the defences in group 1 are increased by 1.33m. Group 1 defences protect a highly developed area in a vulnerable location to storm surges, and by increasing the height of these defences enables a significant amount of the risk to be reduced.

Figure 8 displays results from Case 2, where the Pareto front of the 200th generation was optimised for flexible long term strategies which inherently capture the Real Options concepts. A total of 1000 sea level rise samples were used to evaluate each intervention strategy on the Pareto front. Four intervention strategies on the Pareto front have been identified, solutions A to D, including the solution with the highest NPV (triangular point) and the highest BCR (square point). Table III displays the benefits, costs, NPV and BCR for these strategies while Figure 9 displays the structure of each of the four solutions and the intervention measures for each path.

Solution B obtains the highest NPV. This solution comprises the incorporation of refined foundations to three groups of defences at the first time step, to enable further elevation increase, as well as raising two of these groups. At the next time step of solution B, the bottom path represents a 'do nothing' option which is the chosen path for sea level realisations with a rise less than 0.37m. In this case, if the sea level rise increase does not go beyond this threshold no additional investment needs to be spent on interventions. For the sea level realisations which have a sea level greater than 0.37m the top intervention path is taken where the defences crest levels will be raised. 61 % of the 1,000 sea level rise samples were directed to the top path while only 29% took the bottom. For solutions C and D, it is also recommended that if the sea level rises above 0.37m it is optimal to take the top path, otherwise take the bottom.

Strategy A on the other hand comprises taking the top path if the sea level rise increase goes beyond 0.52m, otherwise take the bottom path. Solution B achieves a very similar benefit compared to solution A but for a significantly lower cost which improves the overall NPV. The difference in cost can be attributed to the way the flexibility is used. Strategy A here does not purchase the 'insurance policy' for the second time step (i.e. does not extend the defences footprint at the first time step in order to have the opportunity at a later date to increase the height. Instead Strategy A delays any decision to widen or raise the defence). For strategy A, if the sea level rise is beyond the threshold, a greater capacity for crest level raising therefore needs to be introduced. This requires additional costs. Although the option is flexible in that a decision is delayed until more is known about the future impacts of climate change, the costs in the way this flexibility is used is less favourable. Solutions B and C instead purchase this 'insurance policy' to enable flexibility to be inherently built into the defences. B is then able to achieve similar benefits to A but for a reduction in costs of 56% and thus showing B to be more favourable.

In this case study, strategy A applies Real "On" Options, using a delay in the investment. Flexibility is not built into the design of the defences as the defences infrastructure needs to be modified in the second time step if the top path is taken. Strategy C applies Real "In" Options by building flexibility into the design of the system. In the second time step, the defence can be easily adapted to account for an increase in sea level rise.

This inclusion of flexibility, Real "On" Options increases the cost of the investment compared to strategies without flexibility. In this example, even with the increase in cost, the incorporation of flexibility can still improve the overall investment decision, this can be seen through the comparison of the Case 1 and Case 2 results.

In order to compare the adaptable strategies (i.e. strategies obtained assuming an uncertain future) with the deterministic strategies (i.e. strategies obtained assuming a certain future), the Pareto fronts obtained using the two approaches have been re-evaluated with the same set of 1000 future sea level rise samples. This enables the comparison of the performance of the two sets of solutions in a like with like situation. Figure 10 displays the two re-evaluated Pareto fronts. From this figure it can be seen that the inclusion of flexibility within the intervention strategies has increased the overall cost of the solutions when there is an uncertain future. This inclusion of flexibility does however also provide the opportunity to significantly increase the benefits in terms of flood risk reduction resulting in a considerable improvement to the overall investment. For example, the decision tree based optimisation overall has been able to obtain solutions with significantly higher benefits than the deterministic approach. This is partly due to the additional optional paths in the decision tree solutions. Each path can be optimised to a smaller range of climate change samples and therefore provide better flood protection. Additionally, the deterministic solutions were optimised according to one climate change realisation and therefore when analysing the solutions over a range of samples, it is likely that these solutions will not fair so well under different samples and thus bring in less benefits.

For example, strategies A_d and A_{RO} both have similar costs with A_{RO} incurring a 13% higher cost than A_d. But in return A_{RO} receives a 29% higher benefit. This improves the overall NPV by 29%. The intervention options for A_d apply a medium maintenance to group 1 and 3 across both time steps. A_{RO} instead enhances the foundations of G1 and G4 in the first time step and is then able to raise the crest level along the top path if the sea level rise is above 0.30m or spend less money and only apply maintenance to group 1 if the sea level is less than 0.30m. In addition to the above, strategies B_d and B_{RO} have similar costs (differ only by 0.7%) but the flexible strategy B_{RO} returns a larger benefit by 8% and again improves the NPV, this time by 9% (see Table IV). Strategy B_d only raises and widens the defences in group 1 by 1m. B_{RO} is able to widen the base of the defences in Group 1 and 4 in the first time step, then in the second time step decides on the height of the crest level increase according to the climate change realisation. If the sea level increases beyond 0.56m, it is suggested the defences are raised by 1m in group 1 and apply maintenance to group 4 where as if it doesn't go beyond this threshold, a raise of 0.66m to group 1 is suggested. Having the flexibility within the strategy enables a more effective investment to be planned.

From these two examples it can be seen that with similar costs, the adaptable strategies (coded as decision trees) that make use of the Real Options concept will return higher benefits and thus dominate (in the Pareto sense) the deterministic, rigid strategies. This is because the decision tree solutions have been designed to account for the future uncertainties of climate change by developing alternative, customised strategies appropriate for specific realisations of climate change thus covering, in a flexible manner, a large range of possible future realisations. In addition to this, the concept of Real Options, which effectively acts as an insurance policy, is ensuring that the options available to the decision maker are kept open in the future (at a cost), i.e. that certain intervention options can be implemented later on, if, when and in the quantity required. The deterministic solutions on the other hand were developed based on a single forecasted future realisation only and without allowing for any flexibility in the intervention strategy. Therefore in the face of uncertainty where many different scenarios could potentially occur, the deterministic solutions may not be sufficient. These are therefore not as favourable and have been shown to be dominated by solutions which account for the future uncertainties of climate change.

5. Conclusions

This paper describes a new methodology to support decision making in long-term flood risk management. An existing flood risk assessment model has been coupled with a costing model, an NSGA2 multi-objective optimisation algorithm and the concepts of Real Options and adaptive engineering design with intervention strategies represented using decision trees specified over the pre-defined planning horizon. The resulting system trials different flexible intervention measures, using the intelligent option searching characteristics of the NSGAII, it then evaluates the costs associated with the interventions and their benefits, in terms of flood risk reduction taking account of future climate change uncertainty. This process is iterated until a Pareto Front, or "trade off" curve, is formed producing optimal decision tree strategies for flood risk management.

The decision trees display the most appropriate intervention measures at various planning horizon time steps depending on the how the future unfolds. Threshold values are optimised to determine, given a future projection, which intervention route is best to follow. The use of Real Options Analysis enables the flexibility within the decision trees to be valued and thus account for the future uncertainties of climate change.

The use of evolutionary multi-objective optimisation algorithms has the potential to provide a greater range of information to decision makers. The system is capable of outputting a set of trade off solutions which present a range of potential flood risk mitigation intervention strategies. Each strategy is optimal according to given criteria (costs, benefits) and presents information describing the most appropriate intervention measures to implement, when and where. The application of the new methodology an area of the Thames Estuary demonstrates the benefits that Real Options optimisation can bring to flood risk management decision making.

Future work will include applying the methodology developed and presented here to even more complex real-life case studies with wider range of intervention measures considered and more detailed decision tree structures considered. Future work will also consider transferring some of the concepts shown here to other water engineering systems (e.g. urban water infrastructure systems).

6. References

Adger, W. N., Arnell, N. W. & Tompkins, E. L. (2005) Successful adaptation to climate change across scales. Global Environmental Change-Human and Policy Dimensions, 15, 77-86.

Adger, W. N., Dessai, S., Goulden, M., Hulme, M., Lorenzoni, Nelson, D. R., Naess, L. O., Wolf, J. and Wreford, A (2009) Are there social limits to adaptation to climate change? *Climatic Change*, 93, 335-354

Behzadian, K., Kapelan, Z., Savic, D. & Ardeshir, A. (2009) Stochastic Sampling Design using Multiobjective Genetic Algorithm and Adaptive Neural Networks. *Environmental Modelling and Software,* 24**,** 530-541.

Ben-Haim, Y. (2012) Doing our best: Optimization and the management of risk. Risk Analysis, 32, 1326-1332

Ben-Tal, A. and Nemirovski, A (1998) Robust Convex Optimization, *Mathematics of Operations Research*, 23, 769-805

Ben-Tal, A., Boyd, S. and Nemirovski, A (2006) Extending Scope of Robust Optimization: Comprehensive Robust Counterparts of Uncertain Problems. *Mathematical Programming, Series B*, 107, 63-89

Beyer, H. G. & Sendhoff, B. (2007) Robust optimization - A comprehensive survey. *Computer Methods in Applied Mechanics and Engineering,* 196**,** 3190-3218.

Black, F. & Scholes, M. (1973) The pricing of options and corporate liabilities. *Journal of Political Economy,* 81**,** 637 - 654.

Bruijn, K. D., Klijn, F., Mcgahey, C., Mens, M. & Wolfert, H. (2008) Long- term strategies for flood risk management: scenario definition and strategic alternative design. FLOODsite Consortium, T14_08_01.

Copeland, T. & Antikarov, V. (2001) *Real Options A Practitioner's Guide*, Texere LLC, New York.

Cox, J., Ross, S. & Rubenstein, M. (1979) Option pricing: A simplified approach. *Journal of Financial Economics,* 7**,** 229 - 263.

Danzig, D. Van. (1956) Economic decision problems for flood prevention. *Econometrica 24*, 276-287

Dawson, R. J., Hall, J., Bates, P. D. and Nicholls, R. J. (2005) Quantified Analysis of the Probability of Flooding in the Thames Estuary under Imaginable Worst-case Sea Level Rise Scenarios. *Water Resources Development*, 21, 577-591

De Neufville, R., Scholtes, S. & Wang, T. (2005) Real options by spreadsheet: Parking garage case example. *Journal of Infrastructure Systems,* 12.

Deb, K., Agrawal, S., Pratap, A. & Meyarivan, T. (2000) A fast elitist non-dominated sorting genetic algorithm for multi-objective optimisation: NSGA II. *Parallel Problem Solving from Nature PPSN VI. Springer Berlin/Heidelberg*.

Defra (2010) Flood and Coastal Erosion Risk Management appraisal guidance.

Dixit, A. K. & Pindyck, R. S., (1994) Investment under Uncertainty. Princeton University Press, Princeton, New Jersey

Dobes, L. (2008) Getting Real about Adapting to Climate Change: Using 'Real Options' to Address the Uncertainties. *Agenda,* 15**,** 55 - 69.

Dorini, G., Jonkergouw, P., Kapelan, Z. & Savic, D. (2010) SLOTS: Effective Algorithm for Sensor Placement in Water Distibution Systems. *Journal of Water Resources Planning and Management,* 136.

Environment Agency (2009a) Flooding in England: A National Assessment of Flood Risk. Environment Agency, Bristol, UK.

Environment Agency (2009b) Fluvial Design Guide. http://evidence.environment-agency.gov.uk/FCERM/en/FluvialDesignGuide.aspx.

Environment Agency (2009c) Guidance on Capital and Maintenance costs and different asset types for whole life costing. Outcome MSF 9.2 from PAMS (Performance-based Asset Management System). Environment Agency, Bristol.

Environment Agency (2009d) Guidance on Determining Asset Deterioration and the Use of Condition Grade Deterioration Curves SR2.

Environment Agency (2009e) Investing for the future. Flood and coastal risk management in England: a long-term investment strategy. Bristol, UK., Environment Agency.

Evans, E., Ashley, R., Hall, J., Penning-Roswell, E., Saul, A., Sayers, P., Thorne, C. & Watkinson, A. (2004) Foresight. Future flooding. Scientific Summary: Volume I - Future risk and their drivers. Office of Science and Technology, London, UK.

Gersonius, B., Ashley, R., Pathirana, A. & Zevenbergen, C. (2010) Managing the flooding system's resiliency to climate change. *Proceedings of the Institution of Civil Engineers-Engineering Sustainability,* 163**,** 15-22

Gouldby, B., Sayers, P., Mulet-Marti, J., Hassan, M. & Benwell, D. (2008) A methodology for regional-scale flood risk assessment. *Water Management,* 000**,** 1 - 14.

Hall, J. & Harvey, H. (2009) Decision making under severe uncertainties for flood risk management: a case study of info-gap robustness analysis. 7th ISE and 8th HIC. Chile.

Hallegatte, S. (2009) Strategies to adapt to an uncertain climate change. *Global Environmental Change-Human and Policy Dimensions,* 19**,** 240-247.

HM Treasury (2003) The Green Book, Appraisal and Evaluation in Central Government. Treasury Guidance. London:TSO.

Ingham, A., Ma, J. & Ulph, A. (2007) Climate change, mitigation and adaptation with uncertainty and learning. *Energy Policy,* 35**,** 5354-5369.

Kapelan, Z., Savic, D. & Walters, G. (2003) Multiobjective Sampling Design for Water Distribution Model Calibration. *ASCE Journal of Water Resources Planning and Management,* 129**,** 466-479.

Keynes, J. (1921) *A Treatise on Probability,* London: Macmillian.

Lavery, S and Donovan, B (2005) Flood risk management in the Thames Estuary looking ahead 100 years. *Philosophical transactions of the Royal Society A*, 363, 1455-1474

Lempert, R. J., Schlesinger, M. E. and Bankes, S. C. (1996) When we don't know the costs or the benefits: Adaptive strategies for abating climate change. *Climate Change*, 33, 235-274

Lempert, R. J., Groves, D. G., Popper, S. W. and Bankes, S. C (2006) A General, Analytic Method for generating robust strategies and narrative scenarios. *Management Science*, 56, 514-528

Lempert, R. J. & Groves, D. G. (2010) Identifying and evaluating robust adaptive policy responses to climate change for water management agencies in the American west. *Technological Forecasting and Social Change,* 77**,** 960-974.

Linquiti, P. & Vonortas, N. (2012) The value of flexibility in adapting to climate change: A Real Options analysis of investments in coastal defense. *Climate Change Economics*, 3.

Lonsdale, K. G., Downing, T. E., Nicholls R. J., Parker, D., Vafeidis, A. T, Dawson, R. and Hall, J. (2008) Plausible responses to the threat of rapid sea-level rise in the Thames Estuary. *Climatic Change*, 91, 145-169

Mcdonald, R. & Siegel, D. (1986) The value of waiting to invest. *Quarterly Journal of Economics,* 101**,** 707 - 727.

Merton, R. (1973) An Intertemporal Capital Asset Pricing Model. *Econometrica,* 41**,** 867 - 887.

Merz, B., Hall, J., Disse, M. and Schumann, A. (2010) Fluvial flood risk management in a changing world. *Natural Hazards Earth System Science*, 10, 509-527

Milly, P. C. D., Betancourt, J., Falkenmark, M., Hirsch, R. M., Kundzewicz, Z. W., Lettenmaier, D. P. & Stouffer, R. J. (2008) Stationarity Is Dead: Whither Water Management? *Science*, 319, 573-574

Murphy, J. M., Sexton, D. M. H., Jenkins, G. J., Boorman, P. M., Booth, B. B. B., Brown, C. C., Clark, R. T., Collins, M., Harris, G. R., Kendon, E. J., Betts, R. A., Brown, S. J., Howard, T. P., Humphrey, K. A., Mccarthy, M. P., Mcdonald, R. E., Stephens, A., Wallace, C., Warren, R., Wilby, R. & Wood, R. A. (2009) UK Climate Projections Science Report: Climate change projections. Met Office Hadley Centre, Exeter.

NRC (1995) *Flood Risk Management and the American River Basin: An Evaluation*, National Academy Press, Washington, D.C. (USA).

Penning-Rowsell, E., Johnson, C., Tunstall, S., Tapsell, S., Morris, J., Chatterton, J. & Green, C. (2005) *The Benefits of Flood and Coastal Risk Management: A manual of assessment techniques*, Middlesex University Flood Hazard Research Centre.

Phillips, T. (2008) Unpublished note on the Cost estimation model for WP4.4 in FRMRC1: Time dependent defence reliability analysis and option searching. University of Newcastle.

Ranger, N., Millner, A., Dietz, S., Fankhauser, S., Lopez, A. & Rute, G. (2010) Adaptation in the UK: a decision-making process. Policy brief. Grantham Research Institute on Climate Change and the Environment and the Centre for Climate Change Economics and Policy.

Savic, D. & Walters, G. (1997) Genetic Algorithms for least-cost design of water distribution networks. *Journal of Water Resources Planning and Management,* 123**,** 67-77.

Schultz, M., Gouldby, B., Simm, J. & Wibowo, J. (2010) Beyond the Factor of Saftey: Developing Fragility Curves to Characterize System Reliability. Water Resources Infrastructure Program. USACE, Washington, D.C. ERDC SR-10-1.

Schwartz, E. S. & Trigeorgis, L. (2004) Real Options and Investment under Uncertainty, Classical Readings and Recent Contributions. Massachusetts Institute of Technology

Simm, J., Gouldby, B., Sayers, P., Flikweert, J., Wersching, S. & Bramley, M. (2009) Representing fragility of flood and coastal defences: Getting into the detail. IN Samuels, P., Huntington, S., Allsop, W. & Harrop, J. (Eds.) *Flood Risk Management: Research and Practice.* Taylor and Francis Group, London, UK.

Sniedovich, M. (2011) A classical decision theoretic perspective on worst case analysis. Working paper MS-03-09

Stainforth, D. A., Downing, T. E., Washington, R., Lopez, A. & New, M., (2007) Issues in the interpretation of climate model ensembles to inform decisions. Philosophical Transactions of the Royal Society Series A, 365, 2163-2177

Voortman, H. & Vrijling, J. (2003) Time-dependent reliability analysis of coastal flood defence systems. *Proceedings European Safety and Reliability conference (ESREL).*

Wald, A. (1945) Statistical Decision Functions which Minimize the Maximum Risk. *Annals of Mathematics,* 46**,** 265-280.

Wang, T. & De Neufville, R. (2004) Building Real Options into Physical Systems with Stochastic Mixed-Integer Programming. *8th Real Options Annual International Conference.* Montreal, Canada.

Wang, T. & De Neufville, R. (2005) Real Options "in" Projects. *9th Real Options Annual Conference.* Paris, France.

Weickgenannt, M., Kapelan, Z., Blokker, M. & Savic, D. (2010) Risk-Based Sensor Placement for Contaminant Detection in Water Distibution Systems. *Journal of Water Resources Planning and Management,* 136.

Woodward, M., Gouldby, B., Kapelan, Z. & Hames, D. (2011a) Multiobjective Optimisation for Improved Management of Flood Risk. *ASCE Journal of Water Resources Planning and Management,* (In Review).

Woodward, M., Gouldby, B., Kapelan, Z., Khu, S. T. & Townend, I. (2011b) Real Options in Flood Risk Management Decision Making. *Journal of Flood Risk Management,* 4**,** 339-349.

Zhao, T. & Tseng, C. (2003) Valuing Flexibility in Infrastructure Expansion. *Journal of Infrastructure Systems,* 9**,** 89 - 97.

7. Figures

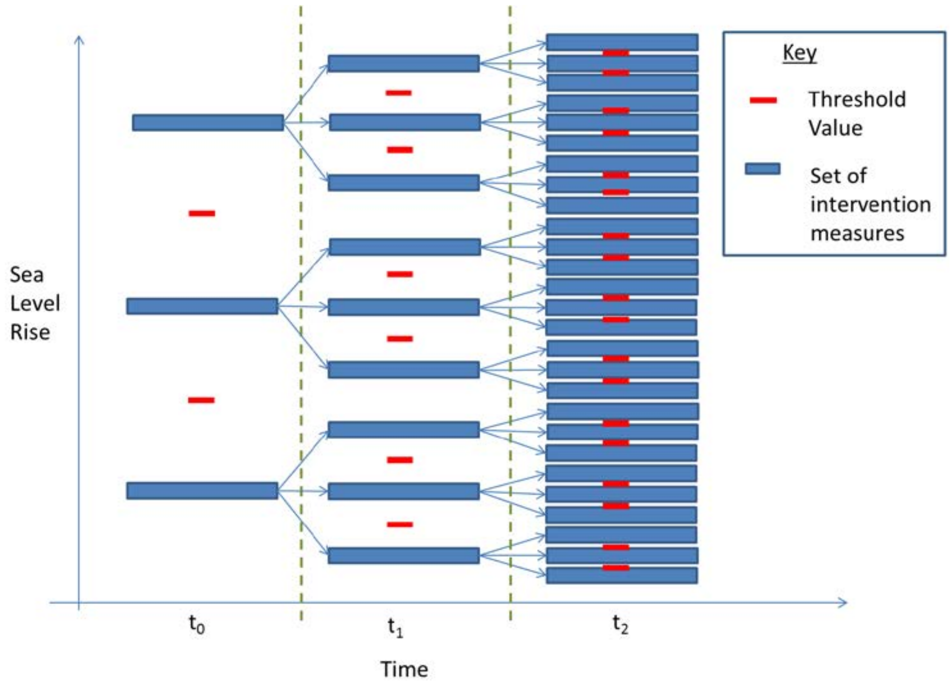

Figure 1: Intervention strategy represented as decision tree

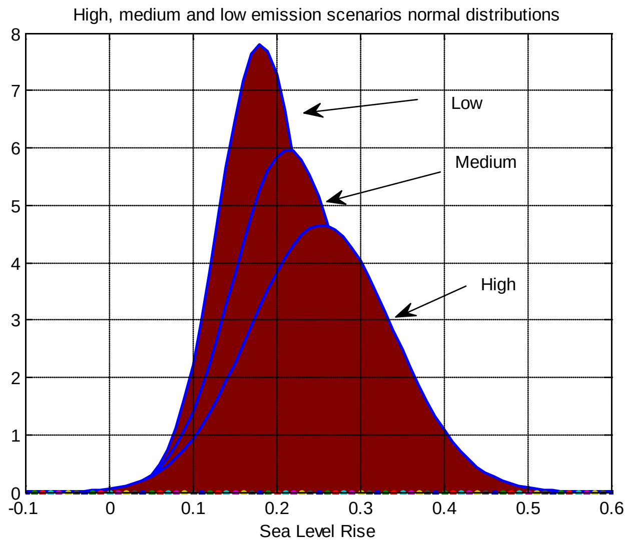

Figure 2: Normal distributions of sea level rise for each high, medium and low emission scenario for the year 2030

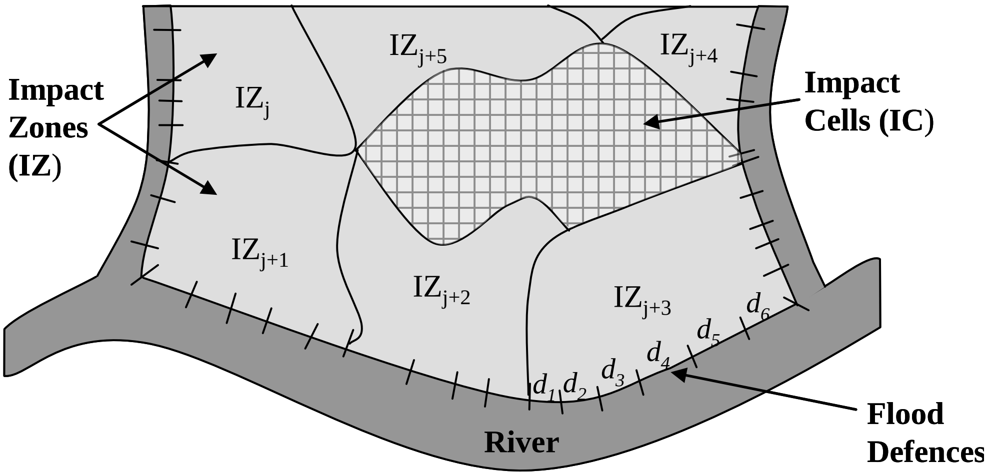

Figure 3: Conceptual illustration of the modelled system (Gouldby et al., 2008)

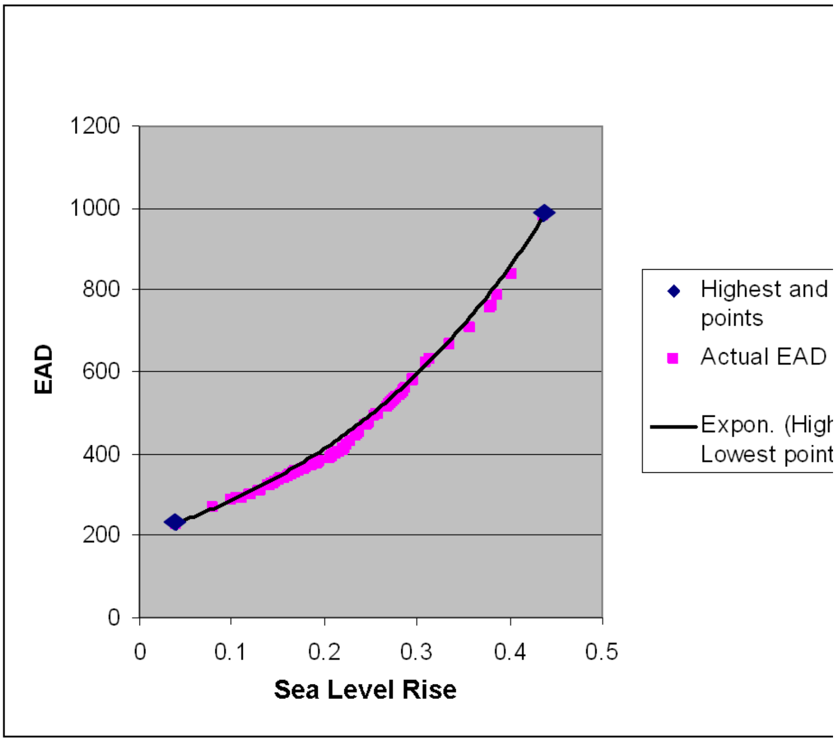

Figure 4: Exponential relationship between EAD and sea level rise

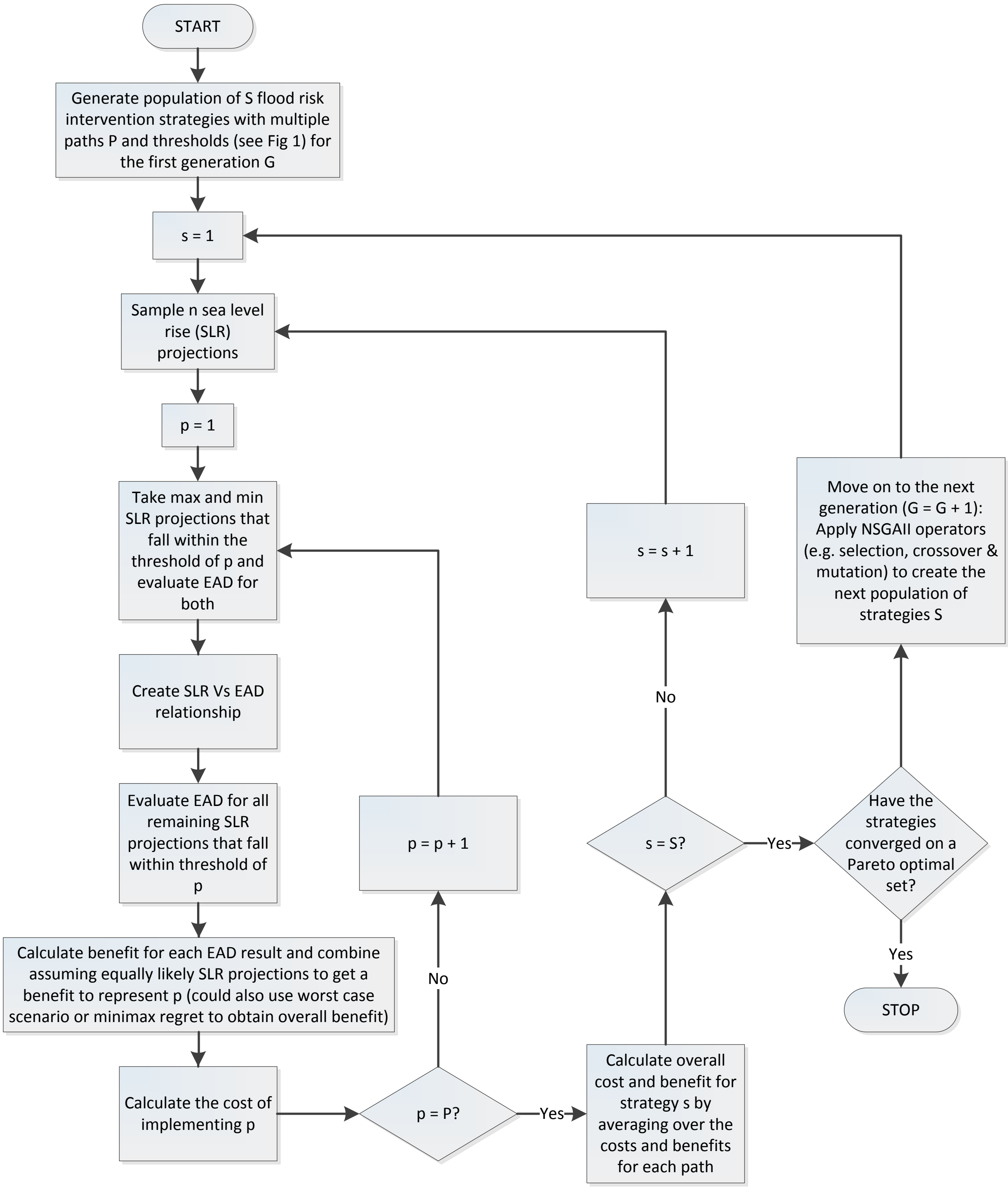

Figure 5: Flow chart of the methodology

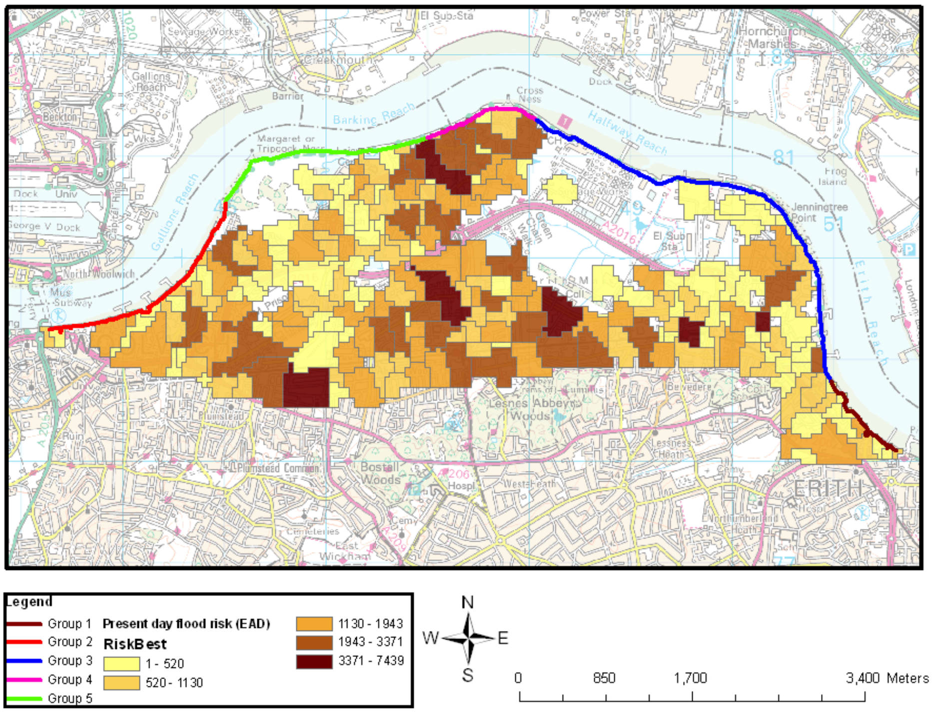

Figure 6: The present day flood risk to the flood area of interest on the Thames Estuary with the 5 groups of defences protecting the floodplain

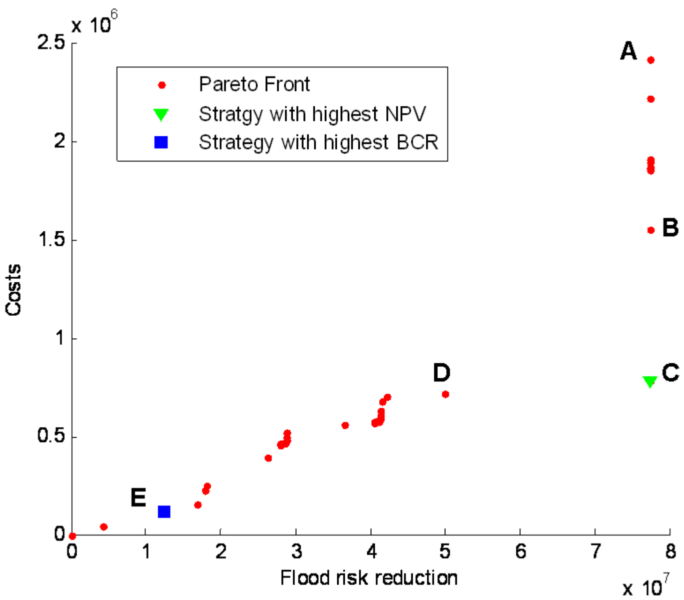

Figure 7: Pareto front obtained using deterministic optimisation approach

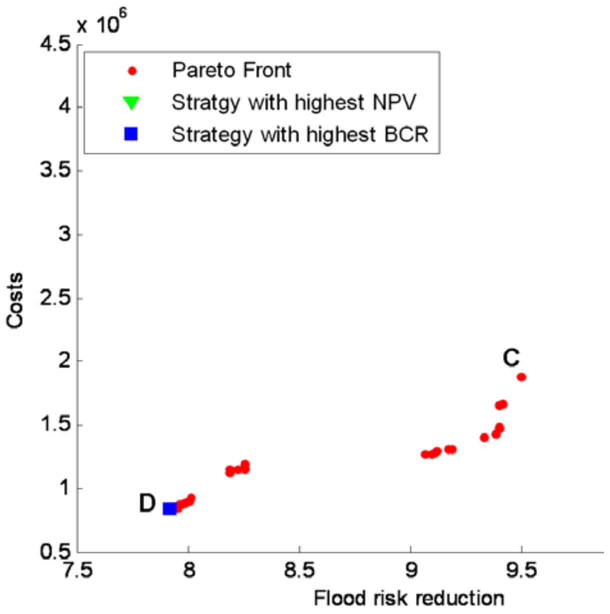

Figure 8: Pareto Front obtained using Real Options-based optimisation

Strategy A

G1	G2	G3	G4	G5
1.33	0.00	0.00	1.33	0.33
0.5	1.0	0.5	3.0	0.5
0	L	0	L	L

G1	G2	G3	G4	G5
1.33	0.00	0.33	0.46	0.36
0.5	2.5	0.5	2.5	3.0
M	0	0	0	M

Threshold Value:
0.52m

G1	G2	G3	G4	G5
1.00	0.36	0.00	0.00	0.30
0.0	0.0	0.0	0.0	0.0
0	L	0	0	L

2010 T_1 2060 T_2 2100

Strategy B

G1	G2	G3	G4	G5
1.33	0.00	0.00	0.00	0.33
1.5	0.0	0.0	3.0	0.5
0	0	0	0	0

G1	G2	G3	G4	G5
1.33	0.00	0.00	0.00	0.46
0.5	0.0	0.0	0.0	0.0
M	0	0	0	0

Threshold Value:
0.37m

G1	G2	G3	G4	G5
0.00	0.00	0.00	0.00	0.00
0.0	0.0	0.0	0.0	0.0
0	0	0	0	0

2010 T_1 2060 T_2 2100

Strategy C

G1	G2	G3	G4	G5
0.00	0.00	0.00	0.33	0.00
1.0	0.5	0.0	3.0	0.5
0	0	L	0	0

G1	G2	G3	G4	G5
1.33	0.00	0.00	0.00	0.46
0.0	0.0	0.0	0.0	0.0
M	0	0	0	0

Threshold Value:
0.37m

G1	G2	G3	G4	G5
0.46	0.00	0.00	0.00	0.00
0.0	0.0	0.0	0.0	0.0
0	0	0	0	0

2010 T_1 2060 T_2 2100

Strategy D

G1	G2	G3	G4	G5
0.00	0.00	0.00	0.00	0.00
0.0	0.0	0.0	3.0	0.5
0	0	0	0	0

G1	G2	G3	G4	G5
1.33	0.00	0.00	0.00	0.46
0.5	0.0	0.0	0.0	0.0
L	0	0	0	0

Threshold Value:
0.37m

G1	G2	G3	G4	G5
0.30	0.00	0.00	0.00	0.00
0.0	0.0	0.0	0.0	0.0
0	0	0	0	0

Figure 9: Summary of the intervention strategies identified in Figure 6. Each strategy is a decision tree with two optional paths at the second time step (T2) with the percentage of samples evaluated at each path undertaken. The first row of each block represents the group (G) where the interventions are being implemented, the second row represents height increases in metres, the third row represents width increases in metres and the final row represents the defence maintenance (0 = no maintenance, L = low, M = medium, H = high)

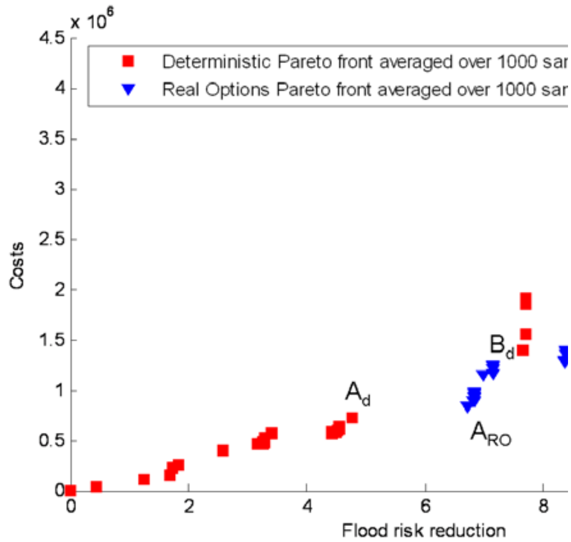

Figure 10: The Pareto Front of the Real Options optimisation and deterministic optimisation.

8. Tables

Table 1: Summary of the NSGA parameters used

Parameter Description	Value
Generations	200
Population Size	500
Crossover Type	Bit tournament crossover
Crossover Rate	0.7
Mutation Rate	0.03
Discount Rate	Based on the Green Book declining discount rate (HM Treasury, 2009)

Table 2: Summary of the benefits, costs, NPV, BCR and intervention measures of select strategies from the Pareto front highlighted in Figure 5.

Strategy	Benefit (£M)	Cost (£M)	NPV (£M)	BCR	Intervention Measures
A	77.31	2.41	74.89	32.08	Time Step 1 Raise G1 by 1.33m, G2 by 1.00m and G4 by 0.33m Time Step 2 Raise G3 by 0.66m Medium Maintenance to G3 and G4
B	77.29	1.55	75.74	49.86	Time Step 1 Raise G1 by 1.33m, apply medium maintenance to G3 Time Step 2 Apply medium maintenance to G3
C	77.28	0.79	76.49	97.82	Time Step 1 Low maintenance to G1,G3 and G4 Time Step 2 Raise G1 by 1.33m Low maintenance to G3
D	49.87	0.72	49.15	69.26	Time Step 1 Medium maintenance to G1, G3 and G4 Time Step 2 Medium Maintenance to G3
E	12.53	0.11	12.42	113.91	Time step 1 Low maintenance to G1, G3 and G4

Table 3: The benefits, costs, NPV and BCR of the solutions highlighted in Figure 6

Strategy	Benefit £M	Cost £M	NPV £M	BCR
A	104.45	4.31	100.14	24.23
B	104.22	1.88	102.34	55.44
C	94.97	1.87	93.10	50.79
D	79.23	0.84	78.39	94.32

Table 4: A comparison of two solutions from the Real Options Pareto front and Deterministic Pareto front when evaluated over the same 1000 climate change scenarios as highlighted in Figure 8

Strategy	Benefit £M	Cost £M	NPV £M	BCR
Ad	47.76	0.72	47.04	66.33
ARO	67.20	0.83	66.37	80.96
% difference	28.93	13.25	29.12	18.07
Bd	76.58	1.38	75.20	55.49
BRO	83.81	1.40	82.41	59.86
% difference	8.63	1.43	8.75	7.97