1.0 Introduction

The impacts of marine flooding in densely populated and infrastructure-rich coastal cities have received a lot of attention in the climate change impact literature (Bosello and De Cian, 2014). Hurricane Katrina killed more than 900 people from flooding alone on the US Gulf coast in 2005. In Europe, Storm Xynthia killed more than 50 people in 2010 through flooding on the French Atlantic coast. Most recently the super typhoon Haiyan in the Philippines generated storm surges up to 7 m in height and causing widespread damage and considerable fatalities (Lapidez et al., 2015). Coastal areas are characterized by high concentrations of human settlements: population density is on average three times the global mean (McGranahan et al., 2007; Small and Nicholls, 2003) and large numbers of people and assets are already exposed to coastal flooding (Bosello and De Cian, 2014). Exposure to flooding is expected to increase with growing coastal populations and the economic relevance of coastal cities (Nicholls, 2004; Nicholls and de la Vega-Leinert, 2008). Accordingly, the impact of climate change, particularly sea-level rise (SLR) in coastal areas and cities is a major concern (Handmer et al., 2012; Stevens et al., 2015).

Due to its prevalent location in coastal areas, climate change, sea-level rise and extreme events represent significant challenges to the global energy infrastructure and supply (Reichl et al., 2013). The UK Energy Networks Association (ENA) identifies the biggest pressure to be from coastal flooding - if an electrical substation is flooded costs in clean up and repair can be high and ongoing costs from disruption and loss of supply have the potential to add to this significantly (Energy Network Association, 2009). Research has found that electricity generation infrastructure is vulnerable to severe weather and water shortages (Bartos and Chester, 2015; van Vliet et al., 2012); and transmission and distribution infrastructure is likely to be stressed by rising demand and increasing temperatures (Bartos and Chester, 2015; Government Accountability Office, 2014; van Vliet et al., 2012). In addition it is also likely that the impacts may be amplified due to energy system interdependencies, and the compounding effect of multiple climate impacts (Government Accountability Office, 2014).

Increased temperatures contribute to future risk to infrastructure resilience by derating power lines and transformers while also increasing vegetation interference on power lines. An increased likelihood of droughts and heatwaves mean soils are more likely to dry out, creating earthing problems with associated potential ground movement. However, it is currently accepted that the relative impact of these risks will be minor (Figure 1) (Cradden and Harrison, 2013; Energy Network Association, 2009, 2007).

A temperate, maritime nation, the UK is susceptible to coastal flooding (Prime et al., 2015). The storm surges in the winter of 2013/2014 caused a large amount of damage in the UK, particularly to infrastructure located on or near the coast. The events of 2013/2014 were clustered together (Wadey et al., 2014) resulting in the stormiest period in 143 years (Matthews et al., 2014). Being resilient to extreme events like storm surges means that there would be little or no damage to repair which could be considerable after a cluster of extreme events impacting on the coast. Under rising mean sea levels that are expected up to and beyond 2100, the damage from coastal flooding is expected to increase so adaptation must be made to combat rising damage cost. The UK has three times as many coastal facilities than any other European country (Brown et al., 2013). The infrastructure or assets that supply electricity to consumers can be split up into three different types of asset:

- Generation assets
- Transmission assets
- Distribution assets

Generation consists of assets that generate electricity, such as coal, oil and gas power stations, but also include nuclear and renewable sources such as wind and solar. Transmission takes the high voltage electricity generated by power stations and transmits it nationally and internationally to regions for distribution to consumers. Distribution is where the high voltage electricity is stepped down to more useable voltage for local consumption - this is also where renewable electricity supplies tend to feed in. This study focuses on the larger distribution infrastructure at risk, the primary and grid substations. Secondary substations are not considered in this study as they are located in the area that they supply and if they are flooded then the area that they supply is usually also flooded, so the resilience of the local area is more important than the impact of the substation being flooded. Other assets in the electricity networks such as pylons, towers, cables etc. are not believed to be typically impacted by or vulnerable to coastal flooding, unless such flooding is long-term and access for maintenance/repair purposes is prevented. Investment in maintaining and improving the resilience to coastal flooding is therefore important, particularly when the potential impacts of climate change and sea-level rise are considered.

Combating the impacts of a changing climate will require a multidisciplinary approach, consisting of combining a global assessment of climate change expressed as regional projections of relative sea-level rise in conjunction with a flood inundation model assessing the flood risk at the regional scale, with a financial methodology assessing the relative costs of strategic intervention and flooding damage, clean-up and repair. This approach also provides detail on optimal times for investing in building resilience to the impact of climate change.

1.1 Energy Infrastructure, Risks and Investment

All markets require strategic investments in an environment of uncertainty. Typically, the response to this uncertainty is by making corrections on project implementation, investing in stages, and/or deferring projects (Pringles et al., 2015). These decisions to invest or disinvest depend on the development of events and traditional modeling procedures such as cost-benefit analysis (CBA). The UK ENA produced matrix (Figure 1) highlights the different risks that are projected to impact on energy infrastructure by 2100 rated by relative impact and relative likelihood. The greatest impacting and highest likelihood risk to resilience is coastal flooding (R12).

One of the main causes of coastal flooding is from storm surges, which occur when high winds and low atmospheric pressure during a storm raise the level of the tide at the coast. If this occurs in conjunction with a high tide, particularly a spring tide then water levels above the predicted tide can occur resulting in an extreme water level (EWL). This can lead to flooding, resulting in infrastructure damage and failure. It is important that this infrastructure is able to withstand and be resilient to extreme events that could occur now and also in the future. As the infrastructures resilience will decrease due to increasing mean sea-levels (Haigh et al., 2010; Menéndez and Woodworth, 2010; Wahl et al., 2011). If future SLR can be known with any degree of certainty, then cost-effective investments in defenses to maintain and improve the resilience to coastal flooding could be made. Future SLR has a large degree of uncertainty, which increases the longer the time horizon is for the projection of SLR being made (Jevrejeva et al., 2014). This uncertainty makes the decision to invest in flood defenses difficult as building defenses based on the most likely estimate of SLR could result in defenses that are not adequate for the extreme flood events that are realised in the future; equally building defenses to cope with the highest level of SLR projected is highly likely to waste resources due to the low probability of this SLR being attained.

When traditional investment frameworks are applied to infrastructure investments, they readily lead to suboptimal irreversible decisions being made. Under- or over-estimation of the future SLR could lead to investments not being made in substation sites that would benefit from flood defenses and investments being undertaken at sites that are unnecessary. The most widely used traditional investment procedure is known as Discounted Cash Flow (DCF) where the future cash flows of a project are compared with the benefits of the project. This technique allows the summation of the economic performance of the project into a single metric known as Net Present Value (NPV). DCF has limitations in its methodology where any flexibility in investment decisions is not accounted for (Majd and Pindyck, 1987; Phung, 1980).

In investment environments where there is uncertainty, such as the future climate, management flexibility can provide economic value and methods that recognize and value this flexibility has been developed in the past. Real option analysis has proved to be a powerful approach for addressing this valuation flexibility. It has been adapted from financial option analysis, which values stocks and shares to value physical assets. This analysis assesses the implied value of flexibility that is embedded in many investment projects. In contrast to DCF valuation that considers management as a passive player, real options assume that management is an active player able to take advantage of new information. This flexibility results from the acknowledgement that investment plans are modified or deferred in response to the arrival of new information such as updated SLR projections. While the new information can never fully complete the picture, it can help to reduce the uncertainty in investment. Real option analysis has been applied to energy generation projects that consider different types of options and uncertainties - these include, flexible investment in nuclear power plants in Japan, hydroelectric plants in Brazil and renewable energy projects in the UK (Abadie and Chamorro, 2014; Caminha-Noronha et al., 2006; Kiriyama and Suzuki, 2004). Using real option analysis for other areas of the energy industry such as transmission and distribution networks is much more limited, particularly for investments in increasing the resilience of infrastructure.

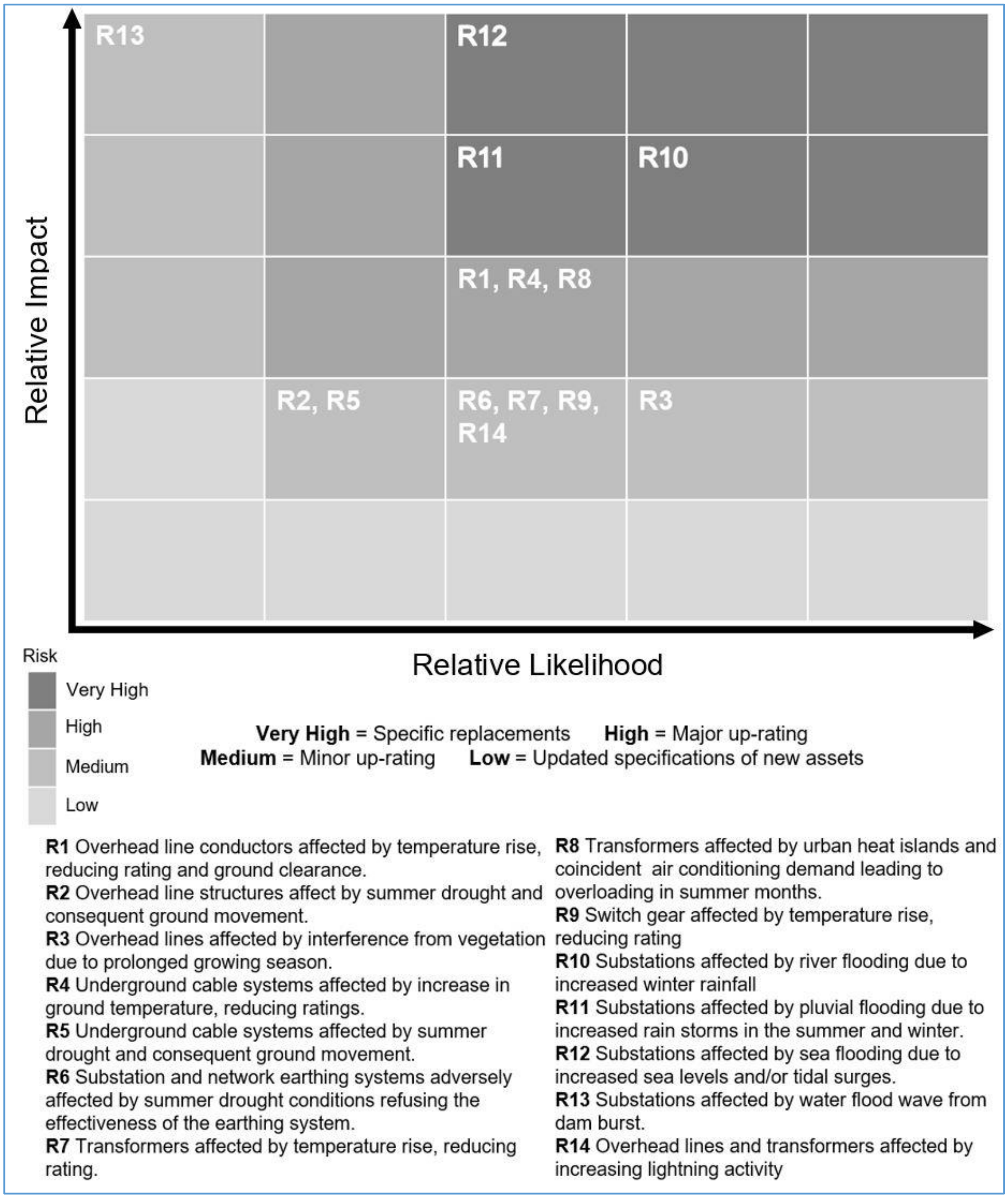

Figure 1: Risk matrix showing biggest projected risks to energy infrastructure up to 2100. This assumes that no adaptation measures are taken and that the high emissions scenario of United Kingdom Climate Projections 2009 (UKCP09) at the 90% probability level is the climate scenario that is realised (Energy Network Association, 2009).

1.2 Study Site

The site selected for this study is part of the northwest UK coastline running from Southport in the south to Morecambe in the north, incorporating Blackpool and Fleetwood. This case study provides an example of the regional flood hazard to infrastructure to demonstrate how the methodology could be applied to other regions. Its location is shown within the wider context of the UK (Figure 2A) and as a close up of the whole area (Figure 2B). The Environment Agency's (EA) flood risk map presented in Figure 2C, indicates large parts of this region are in an area of medium to high flood risk.

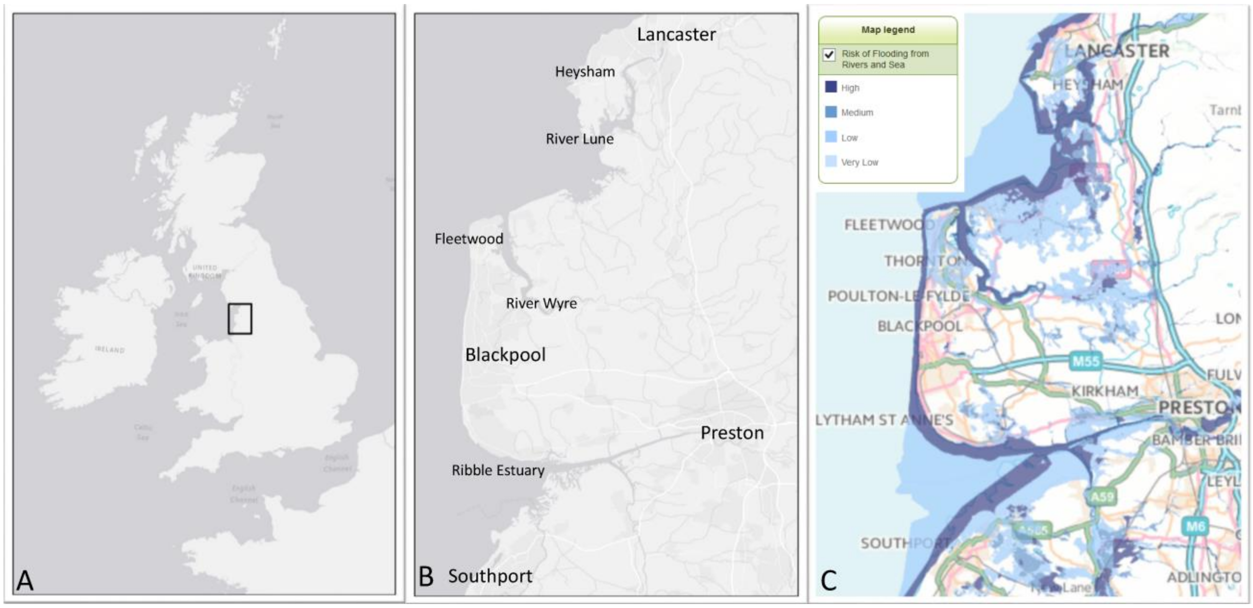

Figure 2A: Map showing location of study area within the United Kingdom. Figure 2B: Map showing close up of study area with place names and finally Figure 2C: showing the extent of the Environment Agency Flood Risk for the study area (Environment Agency, 2016).

Electricity Northwest, the region's electricity distribution company, provided a database detailing all of their assets amounting to over 3000 different assets. Distribution infrastructure has three types of substation, grid, primary and secondary. Grid and primary feed into large areas and consequentially have a large impact on the region if flooded the location of these substations is shown in Figure 3, which shows the geographical locations of the grid and primary substations. From Figure 3 it is clear that most of the substation assets are located in areas of risk, i.e. close to the coast, rivers etc. Comparing the asset locations with the flood risk map from the EA indicated that some assets are in a flood risk area already and this number will only increase up to 2100.

2.0 Methodology

The methodology undertaken was to identify all the suitable substations in the selected study area, the local distribution company Energy Northwest provided a spatial dataset with the sizes and locations of all their assets. The size threshold was set at 30 m, all substations with an perimeter greater or equal to this was selected, this resulted in a list of 388 substations that could potentially require flood defenses during extreme events.

The methodology presented in this paper, that combines flood inundation and economic analysis involves multiple steps to produce an annual cost due to flooding. This cost can be viewed as a revenue stream of damage avoided if flood defense investment takes place. The revenue stream will continue for the whole of the defense lifetime and will likely increase over time due to higher costs of flooding with increased mean sea-level. The costs of building and operating the defenses can be offset from this revenue stream, giving a net present value for flood

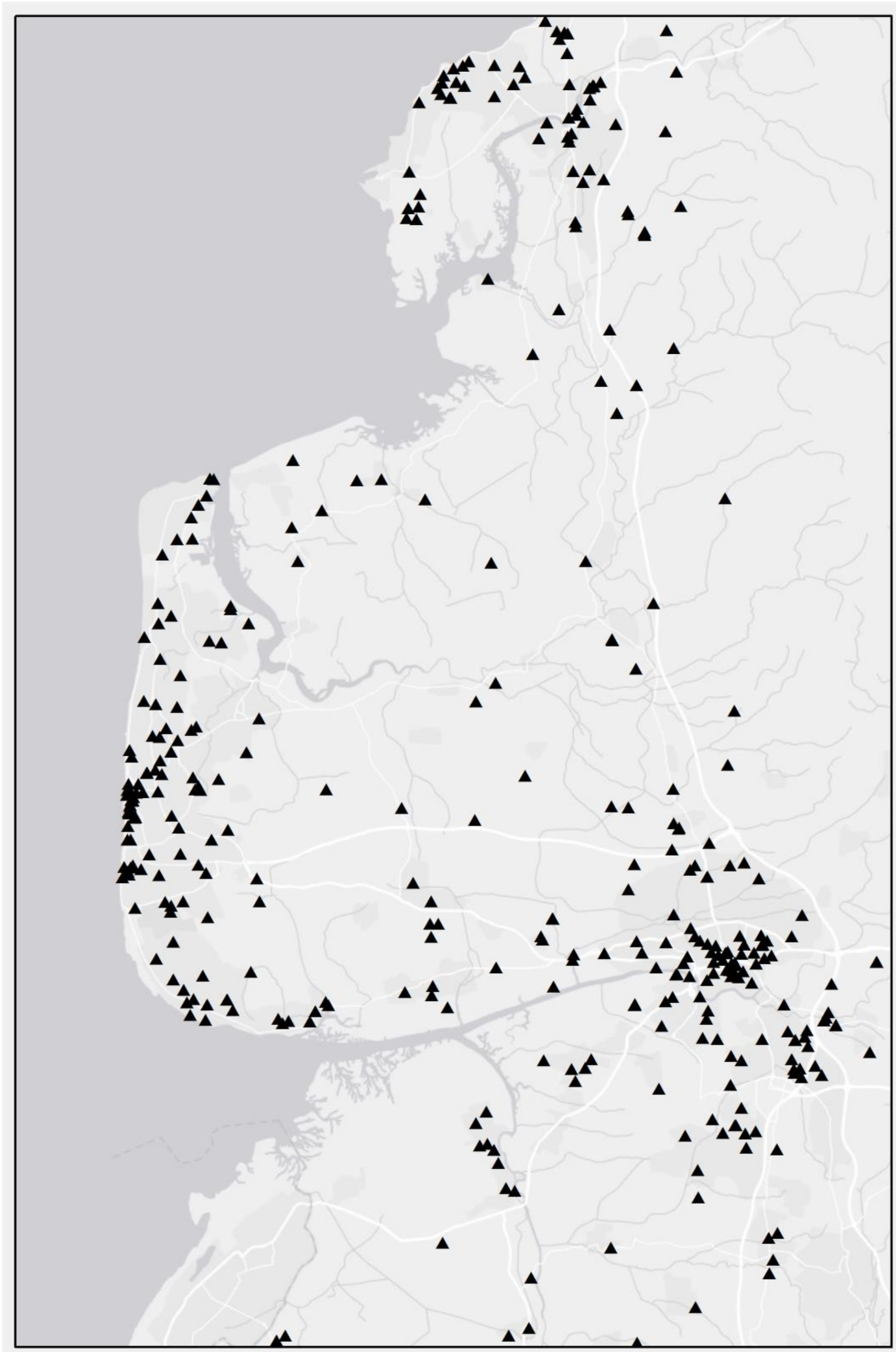

Figure 3: Black triangles denote the location of the 388 grid and primary substations in the study area (defined as having a perimeter greater than 30 m).

defense investment decisions. This means that a SLR projection value is required for every year of the defense life span starting from the potential investment point. In this study the defense life span is 50 years so investment decisions can only be assessed 50 years before the end of the SLR projection, which in this case is 2100. However, longer SLR projection datasets and defenses with a shorter life span can be used to increase the investment decision time horizon.

2.1 Storm Surge Data

To simulate these extreme events, Environment Agency data was used, this consisted of 16 extreme water levels at 2 km intervals around the UK coastline. The water levels correspond to a given probability of exceedance, e.g. 1 in 1 year, which is the water elevation that has the probability of occurring on an annual basis or 1 in 100 years which is the water level that has the probability of being exceed of 1% in any given year. The full list of probabilities available are:

1. 1 in 1 year
2. 1 in 2 years
3. 1 in 5 years
4. 1in 10 years
5. 1 in 20 years
6. 1 in 25 years
7. 1 in 50 years
8. 1in 75 years
9. 1 in 100 years
10. 1 in 150 years
11. 1 in 200 years
12. 1 in 250 years
13. 1in 300 years
14. 1 in 500 years
15. 1 in 1000 years
16. 1 in 10,000 years

This dataset provides the data required to simulate a wide range of potential extreme events in the present day. With increasing mean sea-levels, the impacts of these extreme events will be greater. The United Kingdom Climate Projections 2009 (UKCP09) gave a maximum plausible sea level rise of 1.8 m under their H++ scenario. To investigate the impact of this possible range of sea level rise 21 intervals of sea level rise were simulated for each of the 16 extreme events provided by the EA data.

The method used to simulate coastal flooding follows the same methodology as (Prime et al., 2015) where extreme water levels with a given probability of occurrence are combined with a synthetic storm surge curve and a predicted high tide to create a storm tide of a specific likelihood. This produces a synthetic storm surge that peaks at the desired extreme water level and rising and falls in a way that is appropriate to the location around the UK. A SLR parameter can also be added across all water elevation values to simulate the storm tide in the future based on SLR projections. In Prime et al. (2015) this described process was only completed for one extreme water level likelihood and one sea-level rise projection. However, for this study the process was applied across all 16 likelihoods, from 1 in 1 year up to 1 in 10,000 years and all 21 sea-level rise intervals giving 336 discrete (16x21) scenarios to simulate.

For this study, the present-day sea defenses will be incorporated in the flood inundation simulations and assumes that these defenses will not be upgraded over the time period of this study. This work will be examining up to the year 2100, it is recognized that this is a long time for power generation and transmission. Historically this amount of time has shown a large amount of change and it is likely that in this time period large changes may occur, for example more local generation from solar panels etc. This work has assumed that there is relatively stationarity in the electrical grid in that all the 388 substation sites will continue to be needed and will be worth defending from extreme events in the future.

2.2 Flood Inundation Simulations

To simulate the impact of coastal flooding a flood inundation model was used. Previous studies have used a SLOSH model to estimate storm surge damage to coastal settlements, (Genovese and Green, 2015). (Barnes et al., 2017) used the CLARA model for storms in coastal areas and estimated damage values. However, for this work the model chosen was LISFLOOD-FP. LISFLOOD-FP was first formulated by (Bates and De Roo, 2000) in order to provide a computationally efficient two dimensional hydrodynamic flood inundation model. LISFLOOD-FP is a freely available 2D finite difference model based on a storage cell approach. It has been continually developed since its inception, improving computational runtime and accuracy and has been used successfully in coastal flooding applications, including flood assessment within the study area. LISFLOOD-FP has also been tested on multiple occasions, and was found to have a good fit between the predicted and observed flood inundation extent making it suitable for this study (Smith et al., 2011).

LISFLOOD-FP was run for each of the 336 simulations with the horizontal resolution of the domain set at 50 m. This is comparatively coarse for flood inundation, but the large number of simulations meant that the computation cost of running a given simulation had to be reduced from several days (as for a 5 m resolution used by Prime et al., 2015) to around an hour. LISFLOOD-FP then provides the maximum water depth experienced throughout a given simulation at each of the 338 locations that correspond to an identified substation. This results in 336 levels of flooding (which might be zero) for each substation. Figure 4 shows an example flood inundation output from a simulation for the study area.

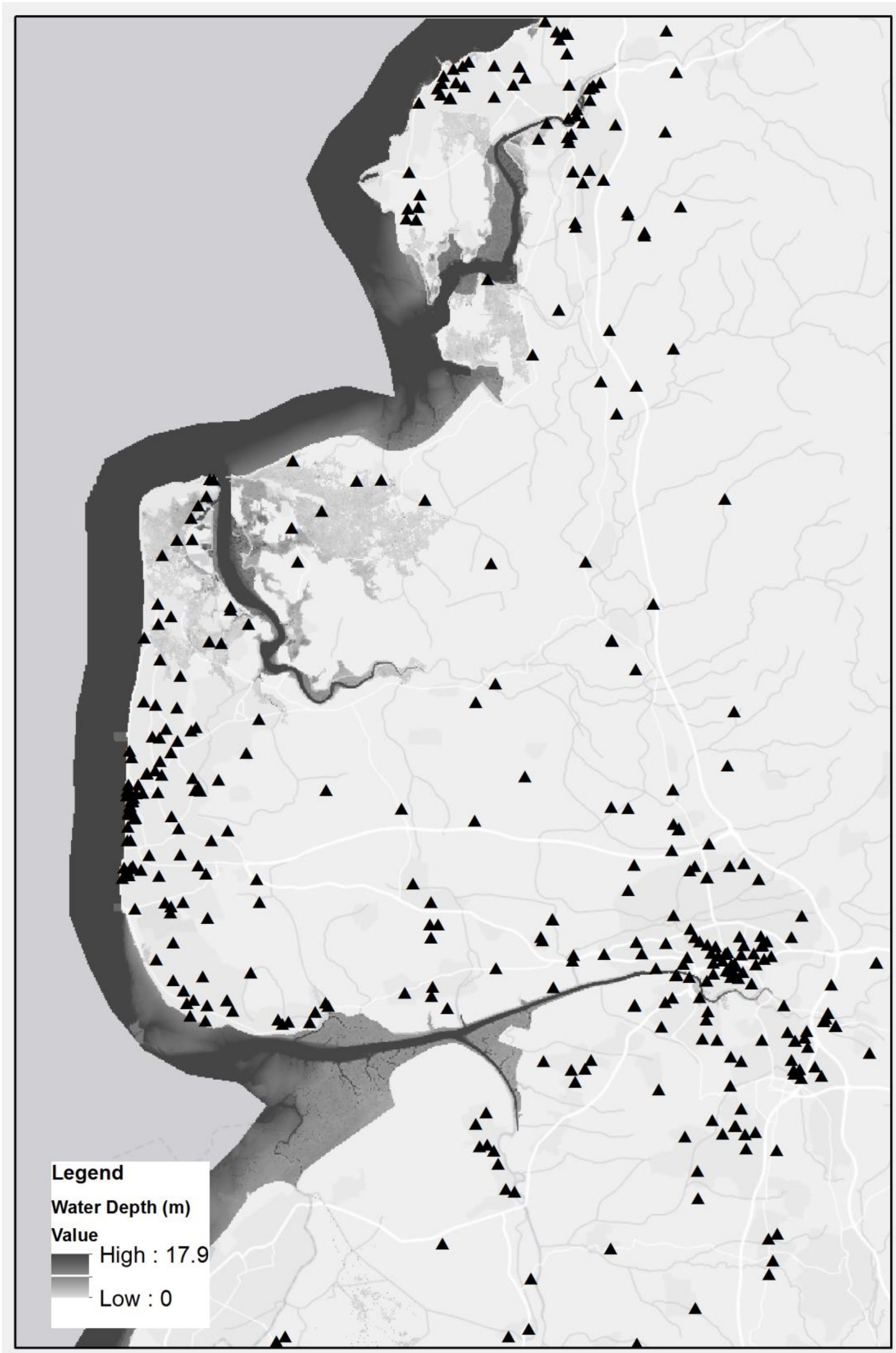

Figure 4: Example inundation output for study area, scenario shown is a 1 in 200 year 0.5% annual probability event with 0.5m of SLR realized.

2.3 Calculating Economic Damages

To determine the impact of a flood inundation scenario a monetary cost needs to be derived. This is achieved using a depth damage (DD) curve (Penning-Rowsell et al., 2014). A depth damage curve shows the relationship between floodwater depth and the relative clean up and repair costs. Beyond the scope of this study, other costs can be added to the curve, that also take into account disruption and compensation paid to consumers as well as the cost of not transmitting electricity when the substation is damaged. This curve was provided by the Flood and Coastal Erosion Handbook 2014 (Penning-Rowsell et al., 2014). This publication details many different depth damage curves for different infrastructures, different types of residential housing and also different types of arable land. It also provides curves for different forms of flooding, from the type of water (salt water or fresh) to the length of duration (short or long). Short duration is classified as a few days, typical of a storm surge. Whereas long is classified as being over several days, typical timescales of river flooding. For this work the short duration salt water curve for substations was used (Figure 5) this also shows the curves used to as part of the sensitivity analysis where each monetary value on the short duration salt water curve was increased by 30% and decreased by 30%. The resulting curves will also be used within the analysis to see how sensitive the results are to the monetary damage costs.

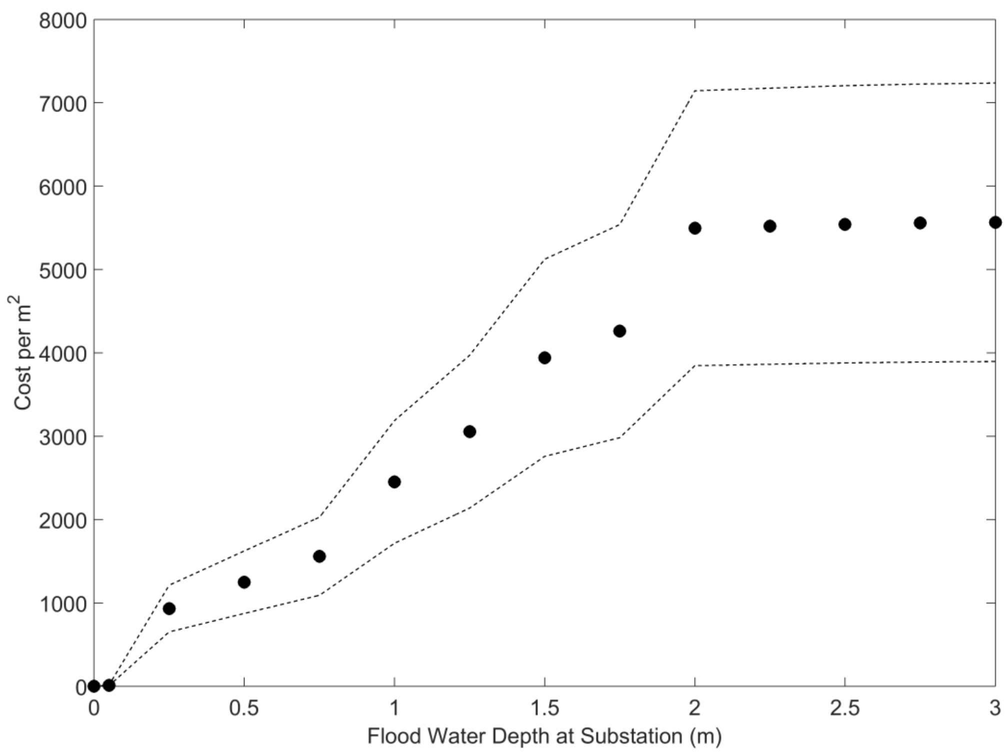

Figure 5: Depth damage (DD) curve for salt water short duration flooding. Black circles show the cost in flooding in £ per m^2 for different flood water depths. The dashed lines show the plus and negative 30% values used in the sensitivity analysis (Penning-Rowsell et al., 2014).

For each substation and for each simulation the cost of flooding can be calculated using this curve. Data provided by Electricity Northwest allowed the area of each substation to be calculated and used in calculating economic damage. Following the methodology used in Engineering Technical Report 138 provided by the Energy Networks Association all substations sites should have a freeboard of 0.3 m from flooding so this amount was added to each flood water depth (Energy Network Association, 2009).

2.4 Estimated Annual Damage/Vulnerability

Once the cost for each combination of storm likelihood and sea-level rise has been calculated at every grid cell that corresponds to a substation site, the estimated annual damage (EAD) at each site can be derived. EAD is the annualized cost of the damage due to flooding for all the storm likelihood flood events. Figure 6 shows the process in deriving Estimated Annual Damage (EAD) from the flood water depth value at each substation site location for each of the 336 flood inundation simulations.

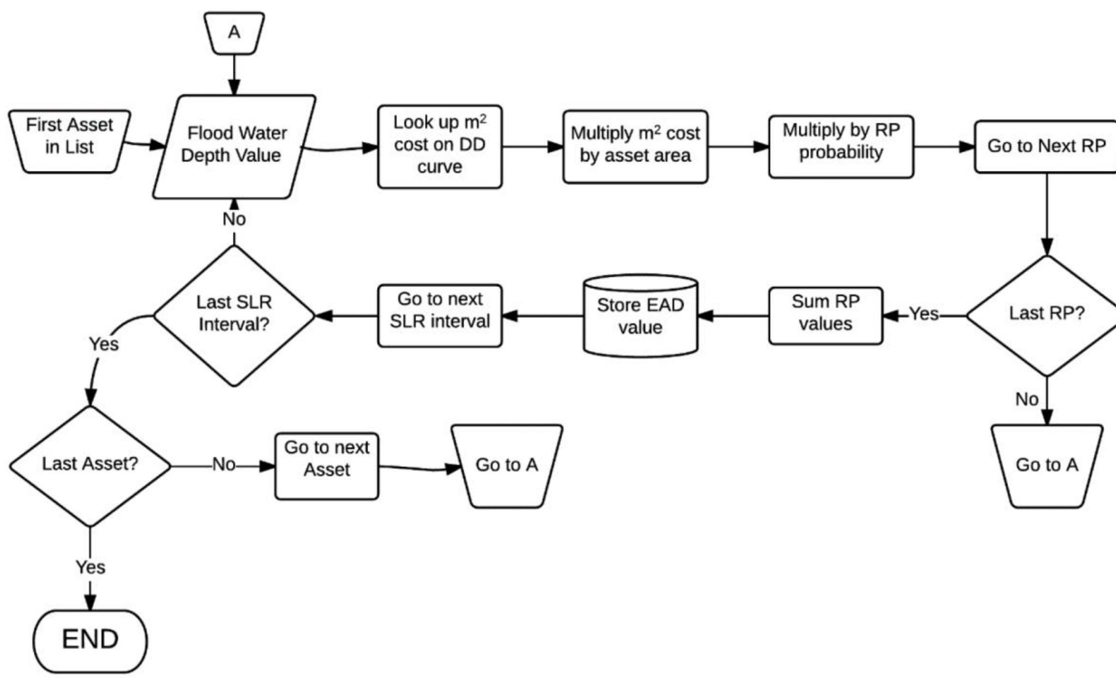

Figure 6: Flow chart showing the process in calculating EAD for each grid cell containing an infrastructure asset.

EAD is calculated by multiplying the monetary impact of each of the storm likelihood events for each asset by its probability of occurrence. For example, a 1 in 200-year recurrence interval has a probability of 0.005 or 0.5%. These values are then summed for each of the 16-recurrence interval at each SLR projection. The output from this is 21 values of estimated annual damage (EAD) ranging from 0 m of SLR (present-day) to 2 m of SLR (H++ scenario). This process is repeated for each of the 388 grid cells that correspond to a substation asset shown in Figure 3.

An example of one of these EAD versus SLR relationships for substation number 67 is shown below in Figure 7.

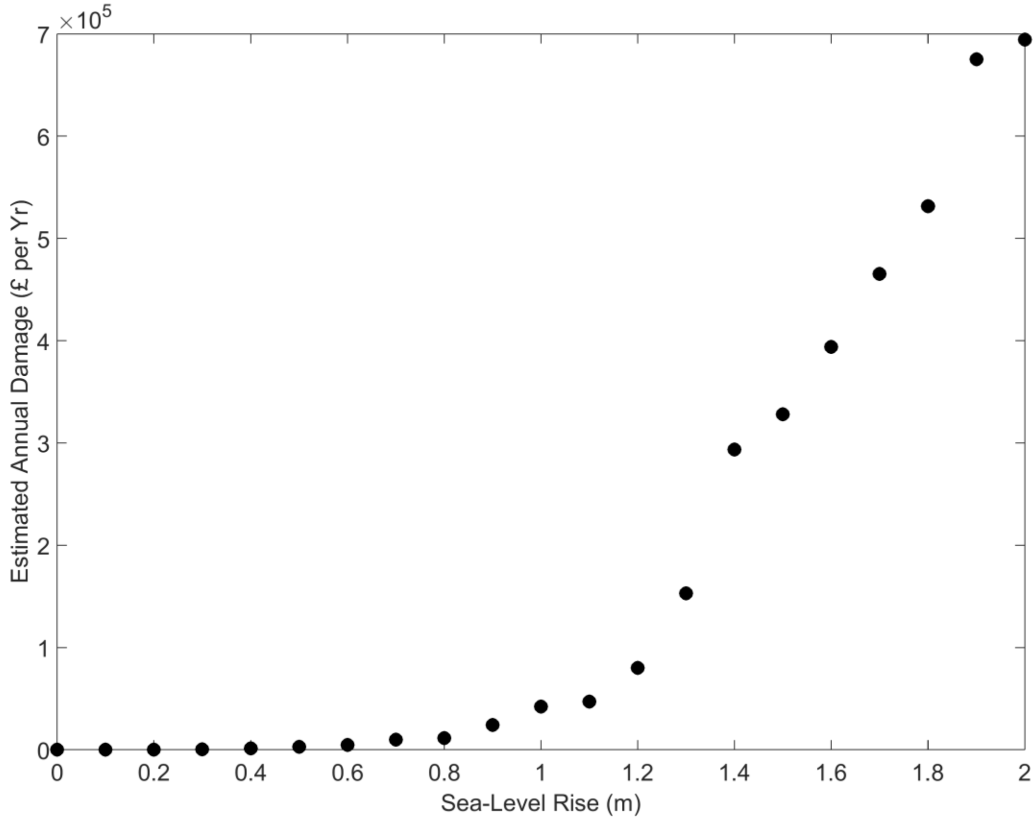

Figure 7: Changes in EAD for substation number 67 in study area. Black dots show the increase in EAD in relation to the increase in mean sea-level.

Figure 7 shows the EAD at each SLR interval for a substation, for this particular site it is clear that there would be no flooding damage across all extreme events up to around 0.6 m SLR, after that it would only be for very unusual large storms. From around 1.1 m of SLR it is clear that flooding and damage would be much more likely and it can be seen that there is a threshold or tipping point in EAD where it significantly increases relative to SLR between 1.3 m and 1.4 m for substation 67. Once the SLR to EAD relationship for each asset is calculated the EAD of the asset as a result of coastal flooding can be projected into the future using any given SLR projections.

2.5 Sea-Level Rise projections

The sea-level rise projections used in this study are from the UKCP09 (Lowe et al., 2009) high emission scenario regional relative sea-level rise projections for the study area. The majority of large UK key infrastructure providers use UKCP09 within their climate adaptation reports (Duffield and Macgregor, 2012; National Grid, 2010) therefore using this dataset for this study will be acceptable to most investment managers within these industries.

The data is provided in the form of a 5th, 50th and 95th percentile SLR value for every year up from 2010 to 2100. Global sea-level rise projections could also be used, but consideration needs to be made due to the fact that sea-level rise varies spatially around the world so the global values may not be appropriate. As the projections are relative, they also take into account glacial isostatic adjustment (GIA) where the land is still adjusting to the removal of the weight of ice sheets present during the last glacial maximum. This land movement can be positive (uplift) or negative (subsidence) and varies spatially around the world.

As the 5th and 95th percentile SLR projections are equidistant from the 50th percentile, a suitable distribution to fit to these projections would be a normal or Gaussian. Figure 8 shows an example of this normal or Gaussian distribution for the year 2100.

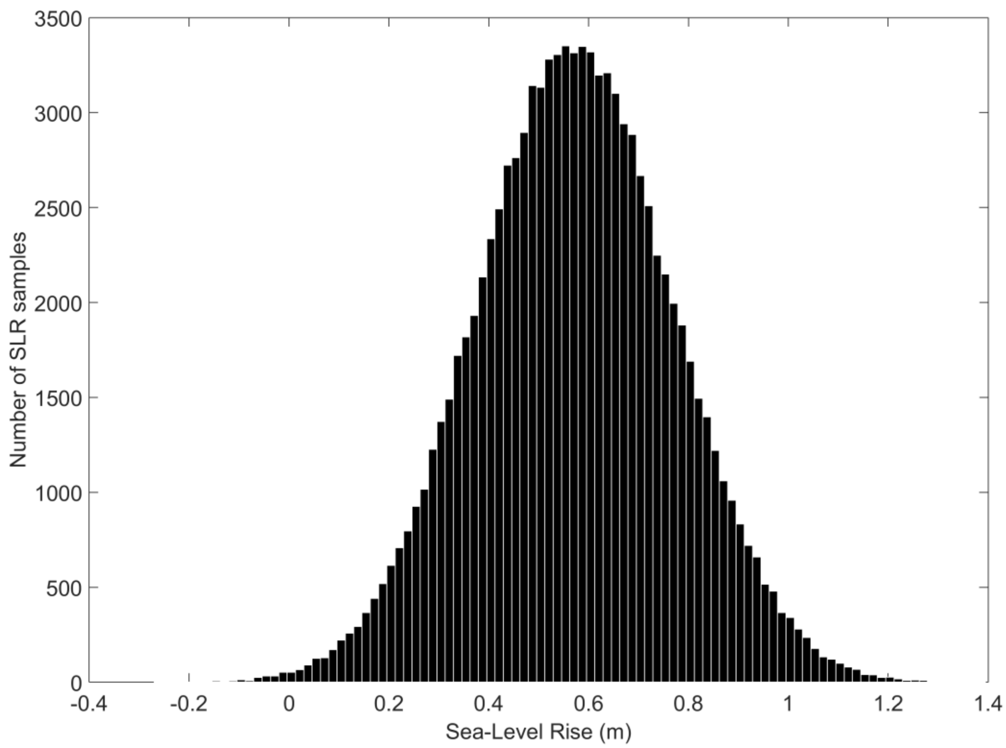

Figure 8: Sea-level rise distribution for the year 2100 based on a normal probability distribution.

The 91 normal distributions available from the UK Climate Projections 2009 (UKCP09) for each of the years from 2011 to 2100 can be drawn to provide a possible sea-level rise "pathway" from 2010 to 2100. Each of the annual normal distribution provides a potential SLR value, e.g. on average this would be 0.6 m for the year 2100 but if sampled multiple times, one in twenty (95th percentile) would be over 1.2 m. This process was repeated 100,000 times across all the annual distributions giving 100,000 potential SLR "pathways" up to 2100. The SLR values from these pathways were converted into EAD cost using the EAD against SLR curve that has been produced for each substation site. For SLR values between the

0.1 m intervals, the EAD value was interpolated from the surrounding data points. Thus, for each substation site, this results in 100,000 values in EAD that reflect the SLR projections produced by UKCP09. These annual EAD values represent the damage averted if flood defenses were present and therefore represent "revenue" generated by investing in flood defenses.

As well as using a normal probability distribution, other distributions could potentially be used. Being able to capture the lower probability but higher impact events would help to potentially identify which assets are vulnerable to these lower probability sea-level rise projections. As can be seen from Figure 9, the 95th percentile SLR value is approx. 1 m. However, the H++ scenario that is part of UKCP09 has a value of 1.8 m, which (while there is no probability attached to this value) recent research projects a 95th percentile value of 1.8 m for global sea-level rise in 2100 (Jevrejeva et al., 2014). While this is a global SLR projection, the UK experiences SLR values that are comparable to global projections. A log-normal probability distribution is able to capture this as a tail in the probability distribution. Figure 9 shows a log-normal distribution based on the same UKCP09 SLR projections for 2100.

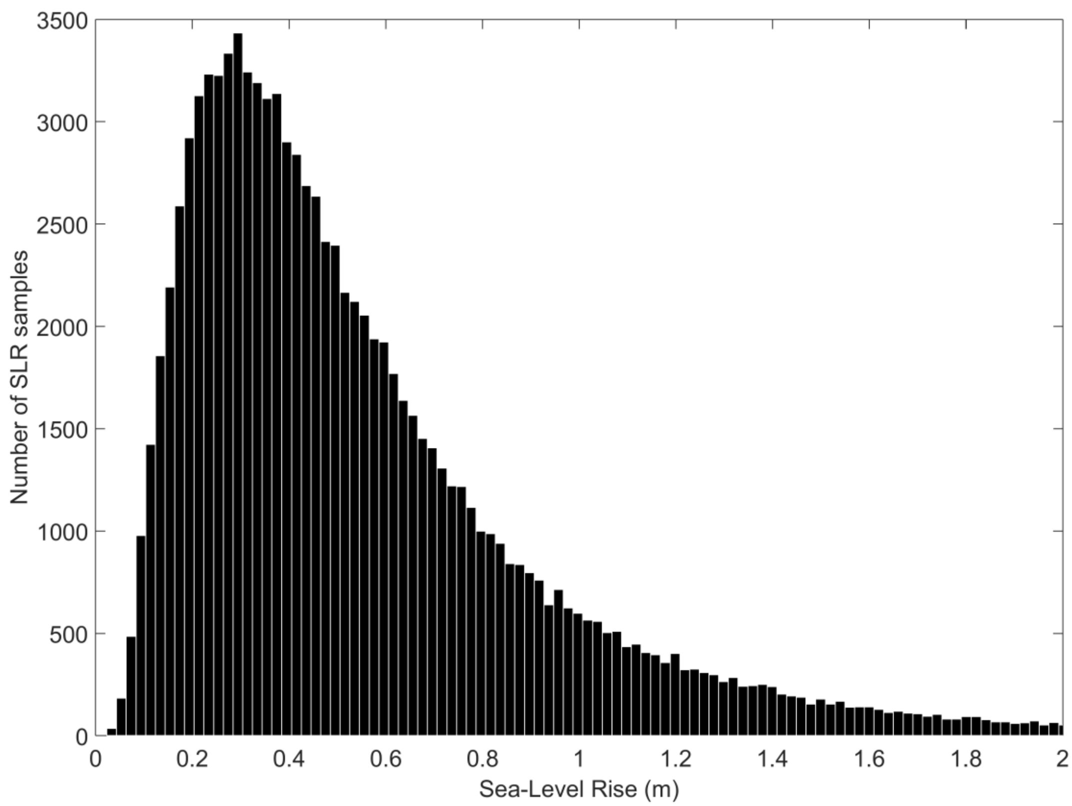

Figure 9: Sea-level rise distribution for the year 2100 based on a log-normal probability distribution.

Comparing the results using both sets of probability distributions will show what effect the lower probability high values of SLR have on the vulnerability of energy assets up to 2100.

2.6 Defense Investment Cost

There are many different defense types that could be utilized to defend substation sites, these range from permanent defenses, temporary barriers and flood proofing the substation buildings. There are also demountable defenses where defense walls are slotted into pre-mounted posts. However, like temporary defenses this requires a site visit to erect the defenses before the extreme event occurs (e.g. due to a storm surge warning). For this study, demountable defenses were the defenses selected to protect all 338 studied sites, future work could assess the benefits of using different defense types.

The demountable defense installation cost was calculated by using the perimeter of the asset as the length of defense needed and multiplying that cost by the £ per m for the demountable defenses used in this study. The £ per m varies depending on the maximum modelled flood water depth (the max depth experienced over all simulations) at the asset site. The cost of operating and erecting the defenses was also added to the investment cost. Equation 1 shows the method in calculating the total investment cost for installing and operating demountable defenses for each asset.

$$DIC = (P \times M + EAO) \qquad (1)$$

where:

- DIC = Defense Investment Cost
- P = perimeter length of asset
- M = £ per meter to build defenses (dependent on max flood water depth)
- EAO = Estimated Annual Operational Cost (see equation 2)

Calculating the cost per meter to erect the defense to protect against an extreme event and multiplying that by the perimeter of the asset produced the operational cost for a given extreme event. This value for each asset is then multiplied by the probability of occurrence for each recurrence interval and summed, giving an Estimated Annual Operating cost (EAO). Equation 2 shows this in more detail.

$$EAO = \sum_{t=1}^{n} P \times N \times RP \qquad (2)$$

where

- EAO = Estimated Annual Operational Cost
- P = length of perimeter of asset
- N = £ per metre to erect defenses
- RP = probability of each recurrence interval expressed in decimal
- n = number of recurrence interval values

The cost to install and erect defenses has been calculated for each site and can be compared with the benefits that building the defenses brings in reducing the EAD cost to zero. It is assumed that the defense totally protect the substation sites during the extreme events and no damage due to flooding occurs.

2.7 Net Present Value

The net present value for investing in demountable flood defenses, is calculated by comparing the cost of building and operating the defenses over the projected defense lifetime with the amount of damage cost that has been averted by having the defenses in position. The costs and benefits of the defenses also need to be discounted to the present day to allow for a direct comparison.

However, it is not as simple as this as there is large uncertainty in the amount the sea levels will raise by. This will have a large impact on the outcome, as higher increases will result in more benefits realized by the defenses therefore making them more cost effective sooner. Conversely if minimal sea level rises occur then building defenses may have been unnecessary and the resources used to build and operate the defenses were wasted. This study has used two different methods in calculate the net present value of investing in flood defenses for each substation site. The first is net present value classic (NPV classic), where the decision on whether to invest today is taken based on the most likely outcome of SLR, i.e. the 50^{th} percentile of each annual sea-level projection. The second method is net present value flexible (NPV flexible), where the uncertainty surrounding the sea-level rise projections is utilised to determine if there is value in deferring the investment of defenses for a defined period, in this case 10 years. This allows more information to be gathered, better or more confident sea level projections to be made and used. This can be repeated in 10-year intervals to see when it is likely based on current projections that the decision to invest in flood defenses would be made. The first stage in this process is to decide what rate to apply to future costs and benefits to discount the present day to allow them to be compared.

2.8 Discount Rate

Using annual SLR projections up to 2100 to allow the estimation of EAD revenue also requires that EAD to be discounted to the present day. This allows comparison with the defense costs and any defenses costs that occur in the future, such as operation costs over the defense life span or deferred building of defenses. To do this a discount rate is used, for this study the UK Government Treasury Green Book for infrastructure projects was used to provide the percentage term. This term varies depending on the number of years that have passed, for example the first 30 years is set at 3.5%. This discount rate is applied to all future revenue from the flood defenses or EAD and also to the capital costs and costs of operating and building the defenses.

2.9 Calculating Net Present Value (classic)

To calculate classic NPV the cash flows in and out of the project need to be discounted and compared. For flood defenses the revenue or cash flow in is the EAD accrued for each year over the defense life span based on annual SLR projections. The NPV calculation uses the mean annual SLR projection. The cash flow out is the initial cost of building defenses and the annual operational costs. All cash flows are discounted to the current time interval and compared. If the costs exceed the revenue generated then building defenses is not cost effective, but if the revenue is greater than costs then the investment is cost effective. Basing the revenue on the mean or 50th percentile SLR projection does not take into account the uncertainty in SLR projections and under-estimates the impact of crossing the threshold in EAD where large changes in EAD are present for small changes of SLR (Figure 8). If these thresholds occur at lower probability SLR values, then the $NPV_{classic}$ will be suboptimal for a given asset.

$$NPV_{classic} = (PV_{ci} - PVI_{inv} - PVOpEX) \quad (3)$$

$$PV_{ci} = \sum_{t=1}^{L} \frac{EAD}{(1+r)^t} \quad (4)$$

$$PVI_{inv} = \frac{DIC}{(1+r)^1} \quad (5)$$

$$PVOpEX = \sum_{t=1}^{L} \frac{EAO}{(1+r)^t} \quad (6)$$

where PV_{ci} is the discounted revenue over the defense life based on annual 50th percentile SLR projections, PVI_{inv} (Initial Investment) is the discounted cost of installing the defenses in year 1 and PVOpEX is the discounted operational cost of the defenses over its lifespan. r is the discount rate, L is the lifespan of the defenses in this case 50 years, DIC is the defense investment cost and EAO is the estimated annual operational cost. It has been assumed that there are no or negligible maintenance costs for the demountable defenses over the course of its lifetime. The operational projected annual cost is represented by the cost of deploying the barriers in response to a given extreme event.

2.10 Real option analysis

Real option analysis is an extension of financial option theory (Black and Scholes, 1973; Copeland et al., 2005; Cox et al., 1979; Dixit and Pindyck, 1994). The main feature of financial option theory is that financial assets are valued under uncertainty. While financial options are written as an explicit contract, real options need to be recognized and specified. A financial option is an option that when purchased grants its owner the right but not the obligation to buy/sell a financial asset after a specified period of time. This is comparable to a company that makes strategic investments having the right but not obligation to take advantage in investing in the future. Real options are embedded in plans, projects or investments. An example of this is the ability to postpone or defer an investment to await the arrival of key information. Real options can also be used to value real assets under uncertainty (Farrell, 2012; Kjærland, 2007).

To derive real option valuation three methods may be used. These include (i) stochastic differential equations, (ii) dynamic programming and (iii) simulation models. Under specific conditions an option can be valued using a stochastic partial differential equation (PDE). The solution of the PDE provides the value of the option as a direct function of the inputs. The Black-Scholes equation (Black and Scholes, 1973) is considered the seminal work on option valuation theory. Dynamic programming is an approach based on splitting the whole problem into two basic constituents, the immediate decision and a function that summarizes the consequences of all future subsequent decisions starting from the immediate decision. An example of this approach is the binomial lattice (Cox et al., 1979). Finally, the approach used in this study is simulation models where thousands of likely paths of underlying asset evolution are generated by Monte Carlo sampling (Boyle, 1977). For each path, the optimal investment strategy is determined, and the option return is calculated. The option value is estimated as the average of the option returns for all paths, which will identify which substations would benefit from flood protection and when between the present-day and the end of the investment decision time horizon.

2.11 Real Option Valuation: Net present value flexible

Using simulation modelling this study values the Real Option (RO) to defer or invest; these are decided with the following decision rules and option valuation adapted from Pringle et al 2015:

Option	**Condition 1**	**Condition 2**	**Condition 3**
Defer Investment	$NPV_{max} > 0$	$NPV_{flexible} < 0$	$NPV_{classic} < 0$
Invest Now	$NPV_{max} > 0$	$NPV_{flexible} > 0$	$NPV_{classic}$ < or > 0

Table 1: The different conditions that need to be met to enable the option to invest or defer flood defense investment to be exercised.

- Option to defer: Provides the right to postpone the investment for a set period of time, rejecting the revenue for this deferred period and await the arrival of new and better information the reduces the SLR uncertainty
- Option to Invest: The conditions are favorable at the current time to invest in flood defenses

where NPV_{max} is defined as the difference between the discounted maximum revenue that can be generated for each asset based on the mean of the maximum SLR value for 2100 and the discounted capital and operational costs of investing in defenses.

$NPV_{classic}$ defined in section 2.8 uses the 50th percentile annual SLR projections up to 2100 to produce the revenue which is discounted and compared with the discounted capital and operation costs.

$NPV_{flexible}$ is the flexible NPV value that consists of the $NPV_{classic}$ with the addition of the option value.

$$NPV_{flexible} = NPV_{classic} + Option\ Value \tag{7}$$

The option value is the mean value of all the Option Returns (OR) calculated from the Monte Carlo EAD pathways. These consist of 100,000 potential SLR pathways for each substation sampled from the 91 annual SLR distributions. The option return (OR) for a single EAD pathway is calculated as follows:

$$OR = [(Revenue\ Expected\ to\ Earn - Costs) - (Revenue\ Deferred - Costs)] \tag{8}$$

$$OR = \left[\left(PV_{fi} - I_{inv} - OpEX\right) - \left(PV_{mi} - I_{inv} - OpEX\right)\right] \tag{9}$$

$$PV_{fi} = \sum_{t=D+1}^{D+L} \frac{EAD}{(1+r)^t} \tag{10}$$

$$PV_{mi} = \sum_{t=1}^{D} EAD(1+r)^t \tag{11}$$

$$PVI_{inv} = \frac{DIC}{(1+r)^D} \tag{12}$$

$$PVOpEX = \sum_{t=1}^{L} \frac{EAO}{(1+r)^t} \tag{13}$$

where PV_{fi} is the discounted revenue over the defense life span if it is executed after the deferral interval, PV_{mi} is the discounted deferred revenue over the deferral interval, PVI_{inv} is the discounted construction costs after the deferral interval and PVOpEX is the discounted operational costs over the defense life after the deferral interval. Further, r is the discount rate, DIC is the defense investment cost, EAO is the estimated annual operational cost, D is the deferral interval (in this case 10 years) and L is the defense life span (50 years).

This process is repeated at each time interval to show the changes in options to invest or defer at set intervals based on regional SLR projections.

The methodology has been summarized in the flow chart in figure 10 showing the process for calculating the flood damage benefit and defense investment cost.

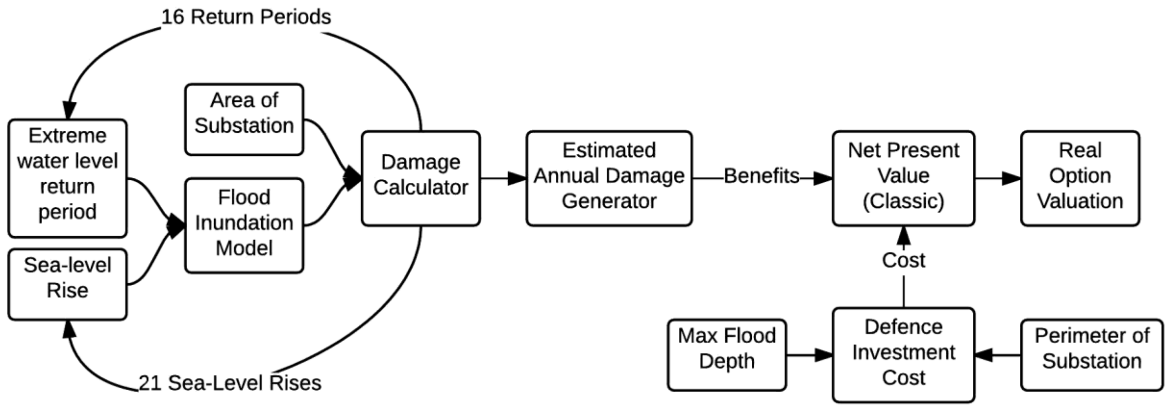

Figure 10: Schematic showing the process used to calculate benefits/revenue and costs for input in real option valuation analysis.

3.0 Results

For each of the 388 substations, a classic NPV based on DCF methodology has been calculated for every time interval up to 2050 (Table 2). Any substation that has a positive value would go ahead with flood defense investment. However, this approach does not value any flexibility in the management process. Additionally, the flexible NPV has been calculated using the Real Option Valuation methodology with the number of substations taking options to invest or defer calculated for each time interval up to 2050. The option to invest or defer investment in flood defenses has been considered using the decision rules in Table 1. Table 2 shows the results of the economic analysis, both NPV classic and both NPV flexible options.

Scenario	Option	2010	2020	2030	2040	2050
$NPV_{classic}$	Invest	4	4	6	6	7
$NPV_{flexible}$	Invest	6	7	10	15	21
$NPV_{flexible}$	Defer	46	45	43	38	35

Table 2: Numbers of substations that would be invested in based on DCF NPV and Real Option Valuation methodology.

Comparing the results of the DCF and real option valuation methodology shows that using real option analysis, investment in flood defenses would go ahead for 2 additional substations in 2010, 3 in 2020, 4 in 2030, 9 in 2040 and finally 14 in 2050. Table 2 shows that a small number of substations (6) generate enough revenue from EAD at the present day to cover the cost of building and operating flood defenses in 2010. This is due to the NPV flexible taking into account the more unlikely levels of SLR that could be realized over the defenses lifetime. This rises to 21 by 2050 with the biggest increase of 6 being seen between 2040 and 2050. In 2010 46 substations exercise the option to defer investment which by 2050, has reduced to 35 as more substations exercise the option to invest rather than defer.

Substation Number	Year Invest Option Taken
24	2030
25	2040
26	2050
30	2010
40	2020
58	2010
59	2050
67	2040
104	2040
105	2010
106	2040
107	2010
108	2010
222	2010
350	2030
351	2050
352	2050
355	2040
356	2050
357	2030
384	2050

Table 3: The year when a substation would exercise the option to invest in flood defenses based on the decision rules in Table 1. Any substation that does not take the investment option has been removed.

Table 3 presents the year a specific substation would exercise its option to invest based on the decision rules of Table 1. The invest option would be exercised when the $NPV_{flexible}$ value or $NPV_{classic}$ is greater than zero. There are 6 substations that would invest in flood defenses in the present day, whereas the majority of additional substations that exercise the option to invest by 2050 do not do so until 2040/2050. This is likely due to a threshold being reached in SLR where the increase in revenue from EAD at this point in time justifies the investment in building and maintaining flood defenses at the relevant substations. 2050 is the furthest this methodology can assess based on the operational life of defenses being assessed and the length of the regional SLR projection dataset, to extend the time horizon a longer SLR dataset would be required or defenses with a shorter life span.

Using model simulation real option analysis also allows the percentage chance of the $NPV_{flexible}$ being positive (and therefore exercising the option to invest) to be calculated. The real option value is based on the mean option value calculated across the 100,000 SLR pathways. Instead of using the mean option value, the percentage chance of the option value ever making the $NPV_{flexible}$ positive can be calculated instead. By calculating the percentage chance, it is possible to identify assets that would be invested in if a low probability high impact SLR pathway are realised. Table 4 below shows the percentage likelihood for flood defense investments for all assets up to 2050 (to simplify the table, any asset that remains at zero percent in 2050 has been removed).

Substation Number	2010	2020	2030	2040	2050
24	0	0.04	93.22	100	100
25	0	0.02	2.37	53.88	100
26	0	0	0.13	3.83	48.77
27	0	0	0.01	0.17	3.92
30	100	100	100	100	100
40	0	92.8	100	100	100
43	0	0	0	0	0.44
58	100	100	100	100	100
59	0	0	0	0.14	93.66
67	0	0	3.26	99.42	100
70	0	0	0	0.01	20.37
100	0	0	0	0	0.09
101	0	0	0	0.01	15.04
104	0	0	0.2	47.45	100
105	100	100	100	100	100
106	0	0	15.08	99.71	100
107	100	100	100	100	100
108	100	100	100	100	100
222	70.47	100	100	100	100
350	0	27.29	100	100	100
351	0	0	0.01	1.73	93.38
352	0	0	0.02	3.05	97.81
354	0	0	0.01	0.29	7.81
355	0	0.06	10.49	82.83	100
356	0	0	0.04	8.34	99.97
357	0	0.68	100	100	100
384	0	0	0.03	15.04	99.78

Table 4: Percentage chance of a substation asset receiving flood defense investment.

Table 4 shows a larger number of substations that could potentially exercise the option to invest in this case there are 27 assets that have some percentage chance of the revenue from EAD to exceed the cost of building and operating the defenses. The additional 7 substations are the ones with percentage chances less than 50%, of these one has a chance of 48.77% in 2050 it may be worth considering this substation for investment. The other substations have percentage chances ranging from 0.1 to 20% indicating they are only likely to be considered for investment under unlikely high end SLR projections or over a longer time period that the current regional SLR projections do not cover.

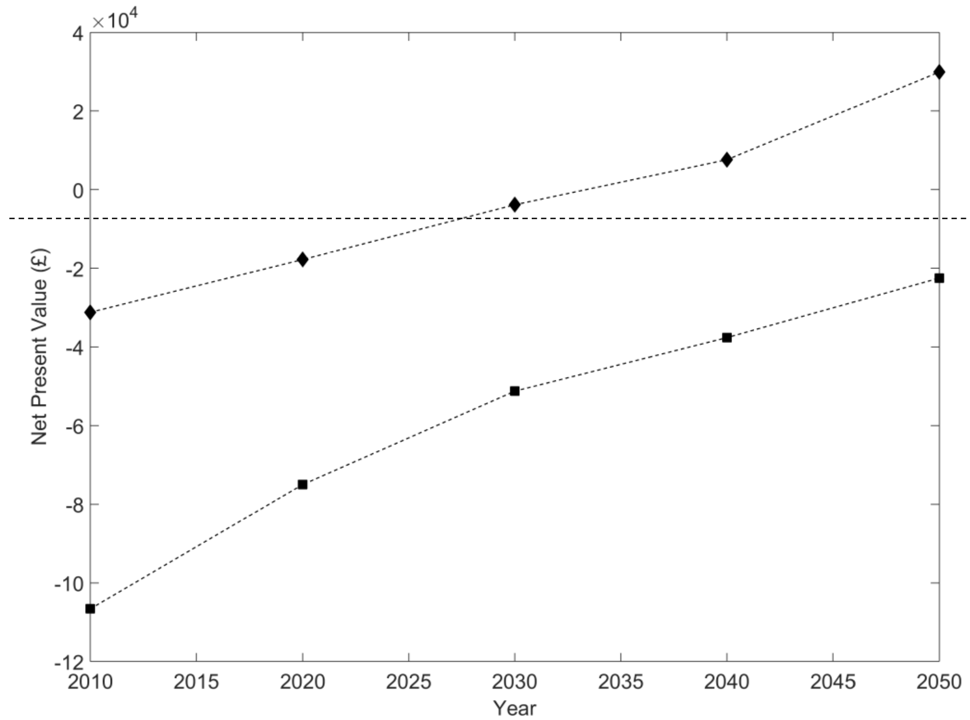

Figure 11: $NPV_{classic}$ values (black squares) and $NPV_{flexible}$ values (black diamonds) at ten-year intervals up to 2050 for substation 67. The horizontal dashed line is at zero where the NPV becomes positive and investment would take place.

Figure 11 shows the $NPV_{classic}$ and $NPV_{flexible}$ values for substation 67, in which the $NPV_{classic}$ increase up to 2050 but remains negative so investment would not proceed at any point before 2050. The $NPV_{flexible}$ values do become positive in 2040, where the option to invest would be exercised. The real option valuation analysis has found extra value in the management flexibility, which while negative in 2010 to 2030 is still greater value than the corresponding $NPV_{classic}$ value.

Figure 12 below shows the results of the sensitivity analysis that has been performed by varying two key parameters to see their impact on the outcome of the real option valuation method. The depth damage curve has been increased and decreased by 30% (Figure 5) along with the discount rate provided by the UK Treasury. Finally, changing the probability distributions of SLR used from a normal to a log-normal has also been investigated.

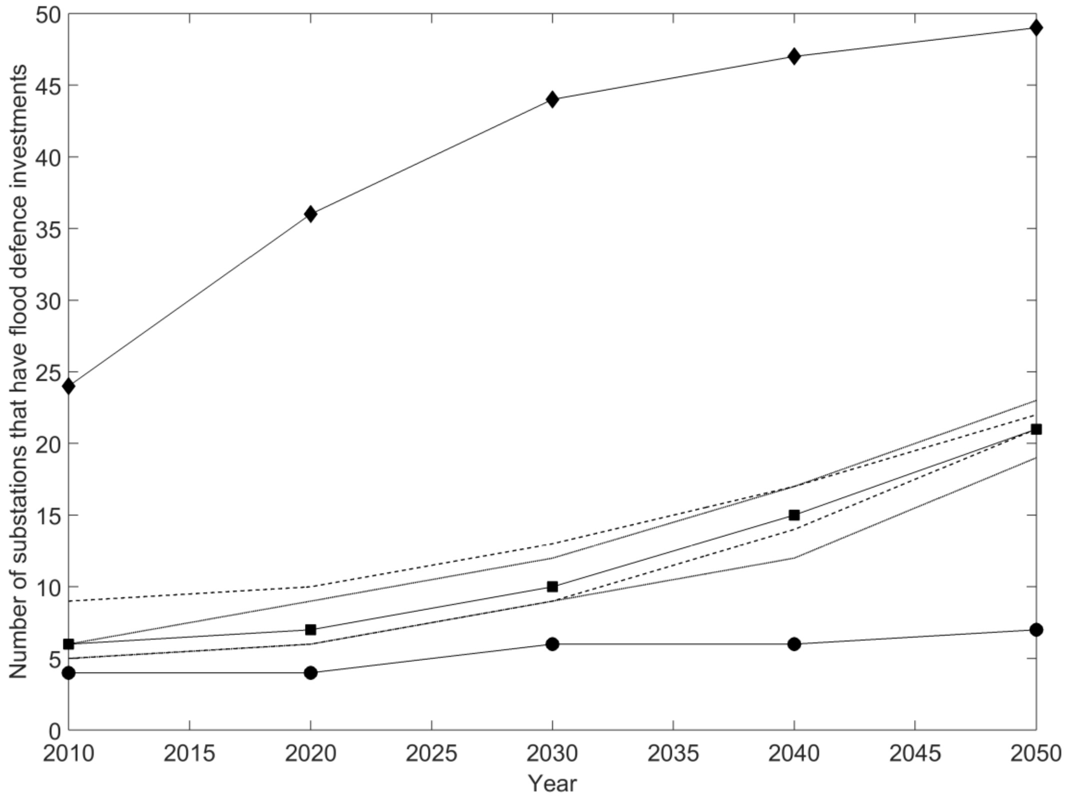

Figure 12: Number of substations undertaking flood defense investments up to 2050. For DCF methodology (black circles) and real option valuation methodology (black squares). The effect in varying the depth damage curve (dotted lines), discount rate (dashed line) and log-normal probability distribution (black diamonds) is also shown.

Figure 12 shows that varying the depth damage curve or discount rate by +/-30% does not have a large effect on the outcome of the analysis, the trend and values are largely the same and always provide more investment opportunities than DCF methodology. Assuming SLR projections have a log-normal distribution has a large effect with increases of 18 in 2010 to a maximum of 34 in 2030 reducing to 18 again in 2050. The reason for large increase is due to the higher levels of SLR that are more likely to occur over the defense's life-span giving increased revenues of EAD making taking the option to invest in defense investment more likely.

The real option valuation methodology specifies using the mean option value from the 100,000 SLR pathways, but sensitivity analysis was also performed to see what the impact of using a different percentile from the mean would have the results (Table 5).

Option Value Percentile Used	2010	2020	2030	2040	2050
25th	5	7	11	14	20
50th (Mean)	6	7	11	15	22
75th	6	7	11	15	22

Table 5: Number of substations taking the option to invest, for different percentiles of Option Value based on the SLR pathways

Table 5 shows that there is little sensitivity to the percentile of option value used with a small reduction in substations taking the investment option for the 25th percentile, a reduction of one in 2010, 1 in 2040 and 2 in 2050.

Overall sensitivity analysis has shown that the only variable that significantly affects the results is the use of a log-normal probability distribution of SLR that makes sampling a higher value for future SLR more likely, making more substations more likely to exercise the option to invest due to the resulting higher EAD revenues over the defense lifetime.

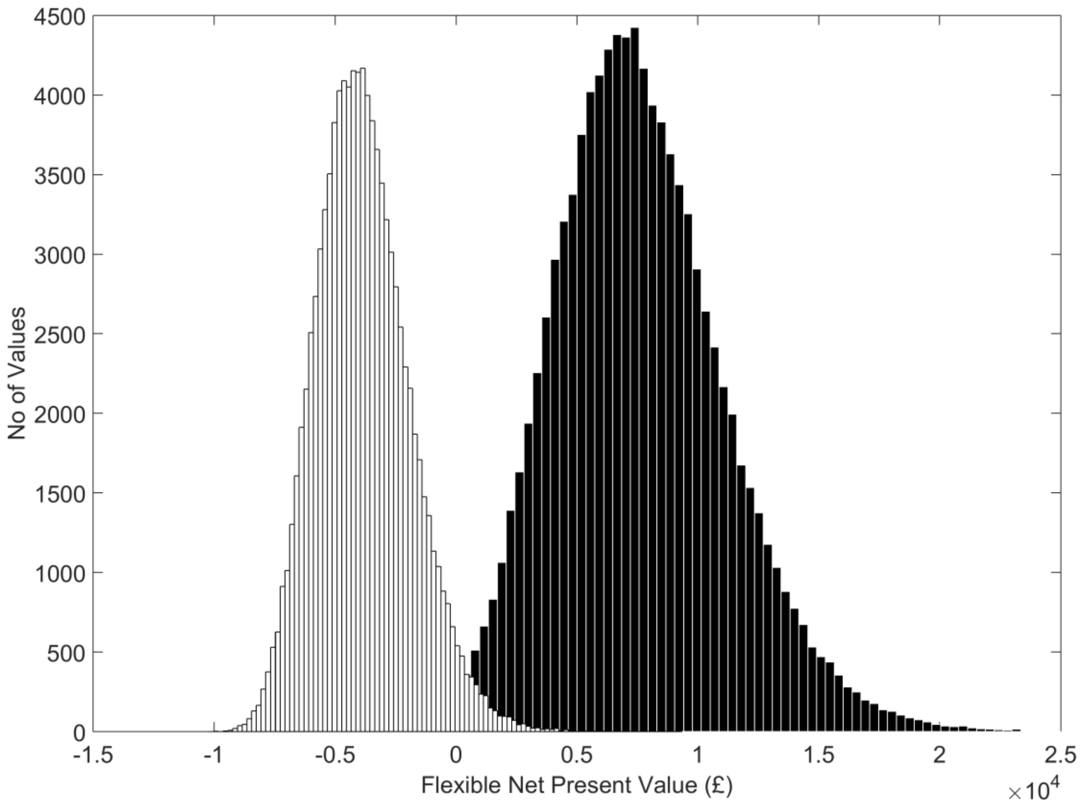

Figure 13: Flexible net present value distribution for substation 67 in 2030 (white bars) and 2040 (black bars).

Figure 13 shows the distribution of $NPV_{flexible}$ across all 100,000 pathways. In 2030 for substation 67 only the upper bars of the histogram are over zero meaning only under low probability high future SLR pathways would the decision to invest be taken here. By 2040 this has changed where the majority of the distribution is over zero with only a minority of the lower probability low level SLR resulting in the decision to invest not being taken. For the analysis, the mean value of the distribution at each time interval has been used.

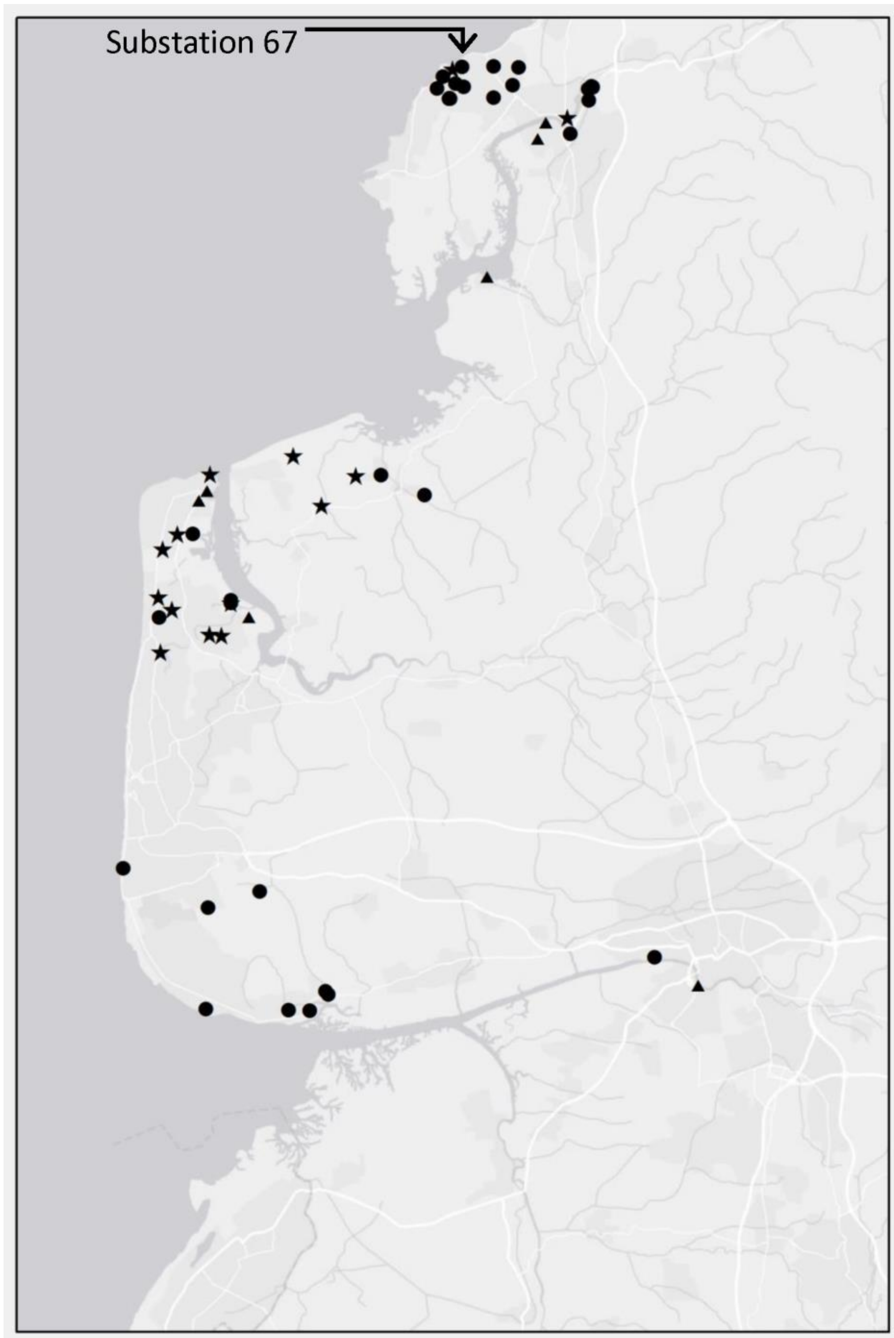

Figure 14: Map showing locations of substations in 2050 that would invest in flood defenses under DCF methodology (black triangles). Substations that have been identified in addition to these that would exercise the option to invest (black stars) and the option to defer investment (black circles) have also been identified.

Figure 14 shows the locations of the substations in 2050 that would be invested in based on DCF methodology (black triangles) it also shows the substations that exercise the option to invest (black stars) and also the option to defer investment (black circles). Comparing with Figure 3 it can be seen that these substations are very spatially variable with small areas of the map having large numbers of both invest or defer options present. Invest options are predominantly concentrated in the Fleetwood area with a few substations on the banks of the Lune river near Heysham also exercising the invest option (Figure 2A). Defer options are also present in these locations, particularly concentrated around the north of Heysham showing that these assets may potentially in the future exercise the option to invest. Finally, some defer options are also present on the north side of the Ribble estuary and river indicating that this is an area that may be at risk beyond 2050 (Figure 2A). Investments based on DCF methodology are concentrated in Fleetwood close to the River Wyre and also in Heysham close to the River Lune (Figure 2A).

4.0 Discussion

The previous section provides results from the flooding and economic analysis methodology, which we will now discuss in more depth. We have found that relying on DCF methods to decide whether to invest in flood defenses will end up with suboptimal decisions being made where some projects that would benefit from defenses will be missed. This is due to the DCF methodology not taking the uncertainty of future conditions into account as well as the flexibility of management decisions to respond to them.

This study has conducted a sensitivity analysis by varying the three key parameters, Firstly, the depth damage curve that changes a flood water depth into a monetary value. Secondly, there is the discount factor discounting future values to present day ones. Finally, there is the probability distribution used to sample SLR values for a given year. It was found there is some sensitivity to all parameters. Changing the depth damage curve +/- 30% caused a maximum change in the number of invest options of +/- 2 substations. Changing the discount factor by +/- 30% also showed some sensitivity with a maximum change of +/- 3 substations. The most significant sensitivity in the results is the assumed probability distribution for SLR values. Changing from a normal to a log-normal distribution that captures the low probability high-end values of projected future SLR shows a maximum increase of 34 substations in 2030. A recent global SLR projection study put the 95th percentile probability of SLR at 1.8 m in 2100 (Jevrejeva et al., 2014), which is a closer match to the log-normal distribution used within this study, showing that using log-normal probability distributions may be more suitable than a normal probability distribution. Another benefit for the decision to use log normal distributions is that the Black-Scholes option pricing formula also assumes a lognormal distribution. Sturm et al. (2017) has noted that using Black-Scholes on natural systems with log normal distributions gives identical values to Monte Carlo simulations predicated on certain assumptions similar to the work as undertaken for this study. The latest regional relative SLR projections have been used as a sectoral standard reference, but these were produced in 2009 and are not up to current knowledge regarding SLR.

Similar results to this study have been made in (Sturm et al., 2017) which while it examined drought, also looked at distributions at the intersection of nature and humans. (Sturm et al., 2017) demonstrated that for asymmetric human cost overlay functions on even non-lognormal natural distributions generates data that mimics options even when there is no choice, and that valuing the costs at the mean of the natural distribution gives lower values than using the entire distribution (Sturm et al., 2017). This is comparable to the methods followed for NPV flexible (Monte Carlo analysis) and NPV classic (valuing costs at the mean). This is the likely explanation of the results observed.

The trends in both $NPV_{classic}$ and $NPV_{flexible}$ are one of increasing value up to 2050. Most substations that are under assessment within the study always stay negative. This is due to the low EAD revenue if flooding is minor or zero EAD revenue if the substation never floods, regardless of the SLR considered. The benefits brought in building demountable flood defenses never exceed their cost of construction and operation. Some substations at the present day have positive $NPV_{classic}$ values. Figure 14 shows that a lot of these are located close to major rivers, and care must be taken with these locations due to the low horizontal resolution of the flood model (50 m) which may cause the flood water depths to be over-estimated. This can be resolved by using an input dataset with higher spatial resolution. At the time of running the inundation model it was too computationally expensive but recently a newer version of the flood model has been released which reduces the computation cost potentially allowing higher resolution domains to be simulated. A good comprise between 5 m and 50 m is likely to be a 10 m horizontal resolution which will provide much more detail than the 50 m grid while having a large reduction in the computational cost when compared with the 5 m grid.

Figure 13 shows the distribution of option value for substation 67 in 2030 and 2040, the mean value of the distribution is what is used in the calculation of $NPV_{flexible}$. To see if the outcome is sensitive to the percentile used the 25th and 75th percentiles of option value were considered alongside the 50th in calculating the $NPV_{flexible}$ value. It was found that using the 25th percentile value resulted in the option to invest being exercised in one less substation in 2010, one less in 2040 and two less in 2050, whereas the 75th percentile had the same results as the mean. The results show little sensitivity to the percentile used, so only the 50th percentile needs to be considered within the real option analysis.

However, considering the full distribution of $NPV_{flexible}$ values can be beneficial as it can highlight additional substations that will require investment if a low probability SLR projection is realised. It also highlights substations that can just miss the option to invest, such as substation 26 where a percentage chance of 48.77% of the pathways result in investment in 2050 meaning that it would exercise an option to defer. If it was over 50%, so more pathways result in investment than defer then it would reach the threshold required for it to be invested in, warranting a closer analysis. Likewise, other percentage chances on the order of 1% where only 1 in every 100 pathways result in the option to invest being taken show that taking the option to defer is the right one based on the SLR projections used.

As expected, from inspection of the data, the substations at risk overlap to some degree with the Environment Agency's flood risk map (Figure 2C) but as this map only covers present-day flood risk for a single extreme event it is unable to highlight which assets would have the investment decision to invest in flood defenses made or deferred particular with the increasing uncertainty of SLR over time.

The methodology outlined in this paper has shown it is able to integrate physical risk from marine flooding with economic considerations of resilience within a flexible real option analysis methodology that only an interdisciplinary model would be able to provide. It also enables timely and cost-effective investment in building flood defenses that allow energy infrastructure to remain resilience to extreme events in the face of a changing climate.

5.0 Conclusions

This work has focused on the economic impacts of future sea-level rise on coastal energy infrastructure. Although a UK case study is presented the approach could be applied to energy infrastructure in coastal region. Investment is required to maintain the standard of flood protection to important electricity distribution and transmission infrastructure in the face of climate change, or potentially improve it. To date, the impacts of sea-level rise and coastal flooding - and the possible adaptation responses - have been studied using very different approaches, such as very detailed site-specific engineering studies and global macroeconomic assessments of coastal zone vulnerability. This paper offers a real option analysis framework that values the investment potential of flood defenses around electricity infrastructure at local spatial scales for a large region. The results have shown that tipping points in the EAD curves result in thresholds being present, most notably in 2030 where the number substations exercising the option to invest more than doubles by 2050. The analysis has been found to be insensitive to the underlying cost curve that converts flood water depth into cost and also the discount rate used to discount future revenues to the present-day. It is however very sensitive to the probability distribution used to sample annual SLR projections for each SLR pathway to 2100. A log-normal distribution appears to fit global SLR projections well, but for the regional SLR projections a normal SLR projection maybe more appropriate due to the 25th and 75th percentile values being an equidistant from the mean.

As demonstrated, the work undertaken has given an indication of where and when these investment resources should be deployed. Knowing which assets are vulnerable and require investment now and which are likely to be vulnerable and require investment in the future ensures an optimum allocation of available resources. Thus, the authors believe that both the methods and results presented in this paper will help to inform management policy on deciding where it is cost effective to invest in flood defenses and where it is cost-effective to defer investment. It allows a more flexible policy procedure than the policy informed from discount cash flow methods alone.

The outputs from this analysis can also be fed into a decision-support tool, such as the one described by Knight et al. (2015). This would allow stakeholders to access economic data for areas of interest, while also providing flood water depths for each of the extreme events under different SLR scenarios. EAD and defense costs for each substation site would also be available, along with information about which investment option is taken and when. This study has effectively demonstrated the essential need to combine physical environment and economic modelling to provide effective decision-support for climate change adaptation and optimized investment for building infrastructure resilience.

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