Development of an Adaptive Solution to Increase Infrastructure System Resilience Based Upon a Location-Allocation Methodology

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Abstract

Infrastructure systems are critical to the normal functioning of our modern communities, enabling access to essential resources and services, and also providing a platform for social and economic growth. These systems are currently being subjected to a multitude of challenges and must therefore adapt to ensure the needs of society can continue to be met. Perhaps the most problematic of these challenges is climate change. The high level of uncertainty within long-term climate projections means that they cannot reliably be used as a basis for informed decisions to permanently alter existing assets or change the design of infrastructure assets (through alteration to design codes, for example). Therefore, we need new tools to ensure our infrastructure systems are resilient using adaptable approaches, which do not require accurate long-term climate scenarios to inform decisions. This paper develops a modified Location-Allocation modelling approach, which can provide an adaptive solution, utilising deployable resources, to increase the resilience of infrastructure systems. Specifically, this approach can be applied to indicate the optimal location to store resources so as to ensure a baseline level of service to our communities, either through the protection of critical assets (e.g. mobile flood defences, grit storage) or the provision of a temporary service (e.g. electricity generators). The approach we have developed is based upon a modified Location-Allocation analysis, which determines an optimal location for one, or more, resource sites to provide supply to a given set of demand points (e.g. hospitals, community centres). The novel contribution of the work, is to the development of a methodology to assign weighting to assets with only qualitative attributes within the Location-Allocation methodology. We use ArcGIS to undertake the analysis and apply our methodology to a real-world infrastructure case study and natural hazard threat.

Keywords: Infrastructure system; Resilience; GIS; Location-Allocation; Climate Change

Introduction

In 2017, there were 276 recorded natural disasters, displacing over 18.7 million people and causing approximately 144 billion (US$) of damage (Ritchie and Roser, 2019). The number of natural disasters and their cost has been steadily rising over recent decades; every society is "*becoming more vulnerable to these disasters day by day*" (Palliyaguru and Amaratunga, 2008). It has been estimated that approximately 25% of the world's landmass and nearly 75% of the total population is at risk (DFID, 2006).

In 2014, for the first time in history more people lived in cities than in rural areas across the globe (Dunn et al, 2016; UN, 2014). By 2050, the UN expects 68% of the world's population to be living in urban areas (equating to approximately 6.3 billion people) (UN, 2018). However, many of the world's cities are located in areas threatened by floods, storms, earthquakes and other natural hazards. These natural hazards not only endanger our society, but they can significantly damage the local economy of the affected area, and in some cases this can propagate to the economy of the region or entire country creating devastating consequences (Barnes et al, 2019).

It is the underpinning infrastructure which can be a deciding factor on whether or not a hazard becomes a disaster (UNU, 2016). When infrastructure systems, including transport or electrical networks, are impacted the threat of a humanitarian disaster arises. For example, roads are used to mobilise immediate aid relief to affected communities, but if the road is made impassable by the hazard then entire regions can become inaccessible, escalating the impacts of the hazard. The development and maintenance of infrastructure must be understood as a core component of disaster risk reduction.

There is little that society can do to prevent hazards from happening (i.e. there is little society can do to change the likelihood of natural disasters), therefore within the risk management community, there has been a move from solely reducing exposure or likelihood of a hazard event towards also improving resilience (Birkmann, 2006). This is improved resilience is generally achieved through the use of planning and construction guidelines (for example, US building codes or Eurocodes), which state that all infrastructure assets must be designed to a given level of safety. Infrastructure systems are currently being subjected to a multitude of challenges – from a changing climate, to increasing population demands and economic austerity. Whilst, the current individual assets (or components) are designed to building codes they have long lives and therefore many existing components were not designed to cope with these ever increasing external pressures. For example, the UK still relies heavily on infrastructure that was designed and constructed in the Victorian era, which was not designed for such a large population and constructed at a time when climate change was an unknown design factor.

In many cases, current solutions to increase the resilience of infrastructure systems are based on an *ad hoc* procedure. This is mainly due to the current high levels of uncertainty regarding long-term climate projections, meaning that they cannot be reliably used as a basis for informing decisions to permanently alter current assets (e.g. through the construction of permanent flood defences). Making the wrong investment decision can be very costly and government investments in the wrong areas can have devastating consequences (Atkins, et al. 2017). Within this current *period of flux* we cannot simply do nothing, nor can we base decisions upon such uncertain models, we therefore require alternate more adaptive solutions to increase the resilience of our infrastructure.

In this paper, we develop a new modelling approach which can provide an adaptive solution, utilising deployable resources, to increase the resilience of infrastructure systems, through the protection of individual assets, when subjected to natural hazard events. Using this solution there is no requirement for costly permanent alterations to existing infrastructure and the issues with climate model uncertainty can be overcome by altering the quantities (or type) of stored resource which are accessed by all asset sites. We term the methodology 'adaptive' as one solution can be applicable to a range of hazard scenarios of differing spatial locations and intensities, rather than the construction of permanent flood defences, for example, which can only protect one specific area. This solution is aimed at either the mitigation phase (for example, when storing demountable flood defences) or emergency response phase of disaster management (for example, when storing emergency supplies/kits). We base our methodology on *Location-Allocation* (LA) analysis, where the goal of the problem is to assure timely emergency relief, as well as reducing the resource deployment costs. The novelty of our contribution lies in the investigation of a set weighted metrics for assets requiring access to the resource site, which do not have a direct quantification (e.g. they have qualitative metrics, rather than quantitative). In this paper, we apply our developed methodology to a case study, which considers the protection of electrical substation sites in the UK from flood hazard, through the identification of the 'best' location(s) to store demountable flood defences. However, the methodology could equally be applied to consider the placement of grit storage (to ensure ready access to major transport routes) or for emergency supply storage to be accessed in the aftermath of a hurricane (ensuring those that have remained in place have quick access), for example.

Location-Allocation Analysis

The origin of LA problems can be traced back to Cooper (1963), and in their most general form, aim to find locations for one (or more) central facilities and an allocation of each point to these facilities, so as to optimise a given objective function (Scott, 1970). At the time of their origin, LA analysis was limited to relatively small problems, due to the restrictive computational power; for example, a simple problem could be to determine the location of a new hospital site, so that it can be accessed quickly and easily by a series of surrounding communities. Today, LA problems are normally considered to be "*complex and multi criteria decision* problems" (Saeidian et al., 2016), and a more complex problem could be to quantify the minimum number of hospital sites required so that all communities, within a large geographical area, have access within a 20 minute drive under 'normal' traffic conditions. It is clear that these problems can have many potential solutions and often require optimisation techniques in order to solve, the most commonly used methodology being those of Hillsman (1984) and Densham and Rushton (1992).

Regardless of their complexity, all LA problems can be summarised by four main components (ReVelle and Eiselt, 2005): (1) *demanders*, who require a quantity of resource; (2) *facilities*, a number of storage locations for the resource which need to be allocated a physical location; (3) *boundaries*, a spatial boundary for the problem; and (4) *limits*, a set of measures that can be used to limit the assigned location of facilities (e.g. limiting the distance that facilities can be from the demanders).

Using these inputs, the LA methodology is suited to the application of a wide range of locational based problems. It is also worth noting that in the case of identifying the optimal location this analysis is not necessarily the same for all types of facilities/assets. For example, the optimal location for a hospital will not be the same as that for a power station. The LA analysis allows for a different emphasis to be placed upon a range of parameters when identifying the resource location (e.g. proximity to highways or location of high population density). Alternatively, the LA analysis approach can be modified to account for demand/asset sites with different levels of "priority". For example, there could be one pumping station in a water distribution network that would cause more consumers to be without water if it was impacted by a hazard, therefore this station could be deemed more "important" to protect. All of these problems can be solved by controlling the four parameters stated previously within a modelling framework.

A large amount of current research focuses on the optimisation of resource distribution within an emergency management context, or other aspects of disaster response. These studies include, Zhang, et al. (2012) who located resources to minimise their total time needed for dispatch and Tzeng et al. (2007) who developed an emergency relief model for use by decision makers. Duhmael et al. (2016) considered an LA problem in post-disaster operations, accounting for the impact of supplies distribution over the population, considering restrictions including human and financial resources. Paul and MacDonald (2016) developed an LA modelling framework focusing on the location of distribution centres for emergency resources for events when there is little to no forewarning. Other studies have considered LA models for improving the spatial planning of public health services (Polo et al. 2015) and the optimising health-care facilities in highly developed cities (Zhang et al. 2016). More recently, Allahbakhsh et al. (2019) developed a crowdsourced game which "*employs wisdom and intelligence of the crowd*" to solve LA problems.

Location-Allocation Analysis within GIS

The LA analysis tool within ArcGIS has been used to offer solutions to a range of different problem types, enabling researchers to answer specific types of questions. Each problem type consists of three main components: (1) *demand points* (potentially with an assigned weighting), M; (2) a given number of *candidate facilities*, N; (3) a *subset of the candidate facilities*, P. The problem is to choose the subset of the candidate facilities, P, from the total number of candidate facilities, N, such that the sum of the distances (either weighted or unweighted) from each demand point, M, to each closed P are minimised. The problem can quickly become computationally inefficient, even with relatively small numbers of facilities and demand points and it is not possible to consider all of the possible combinations. Therefore, optimisation techniques are required to identify solutions.

Within ArcGIS the location-allocation tool starts by generating an origin-destination matrix of the shortest paths between all of the facilities, N, and the demand point, M, locations in the network. The shortest paths are determined by applying Dijkstra's algorithm (Dijkstra, 1959). This matrix is then edited using the Hillsman editing process (Hillsman, 1984) which is a largely universal heuristic and its inclusion allows the tool to solve many types of Location-Allocation problems. The tool then follows the heuristic method set out by Densham and Rushton (1992), which generates a set of semi-randomised solutions and applies a vertex substitution to refine and form a set of good solutions. A metaheuristic then combines this group of good solutions to form better solutions. When no additional improvements are possible, the metaheuristic then returns the best solution found. It is this combination of an edited matrix, semi-randomised initial solutions and a vertex substitution heuristic which causes ArcGIS to quickly return near-optimal results (ESRI, 2019a)

Using these inputs virtually any LA problem can be solved within an ArcGIS framework and there are several problem types which exist. For example, the *minimise facilities* problem type aims to place the fewest number of facilities in order to cover the whole of the customer area. Whereas, the *maximise attendance* problem type assumes that the further people have the travel to reach your facility the less likely they are to use it and often requires the input of additional public transit facilities in order to determine the most suited location (ESRI 2019b). There are many studies, within current literature, which have utilised the LA functionality with ArcGIS, for example Yeh and Chow (1996) considered an approach to planning public facilities and Garcia-Palomares et al. (2012) considered the location of stations for bike-sharing programs. In this paper, we use the *maximise coverage* problem type which best to the location of facilities which aims to cover the maximum number of asset sites within a given time radius.

APPLICATION TO CASE STUDY: OVERVIEW AND APPLICATION

For the case study presented in this paper, we have applied an adapted LA methodology to consider the optimum location to position demountable flood defences in order to minimise the distance to National Grid substation assets, which have an associated flood hazard. Unlike permanent flood defences, the demountable defences can be deployed to any substation asset and we apply the analysis to identify the 'best' single and multiple (of two or three) locations to store the demountable flood defences. From discussion with the National Grid, it is known the spreading the demountable defences to more than three locations is not feasible (due to the quantity of defence held at each site and also transport considerations, as the barriers are moved using heavy transport vehicles). In this paper, we focus on the accessibility to each substation asset, rather than the quantity of defence required by each site. We initially consider the storage location of the flood defences using an unweighted model, before considering how to assign weighing to assets with a qualitative quality (e.g. flood risk) rather than quantitative (e.g. number of consumers served). It is worth noting that within the analysis we do not consider the flood risk to each road and assume that these will be operational when the demountable defences are deployed to each substation site (in the pre-disaster phase).

We have considered the placement of flood defence locations in this paper by using an adaptation of the LA methodology available in ArcGIS, combined with the Closest Facility (CF) tool. We required detailed datasets for the substation asset locations, flood risk maps and also a fully connected roads dataset for England and Wales.

The National Grid own, and manage, 472 substation sites location in England and Wales and their location data was obtained directly from the National Grid (National Grid, 2019). This was then combined with Environment Agency flood maps (for Risk of Flooding from Rivers and Sea within England

and Wales (EA, 2019)) in order to associate a flood risk with each substation, using a GIS framework and simple attribute selection. This analysis concluded that there were 130 substation sites which intersected with a flood boundary (approx. 27.5% of the total number of substation sites) (Table 1).

Table 1 – Showing the number, and percentage, of National Grid substations which intersect with Environment Agency flood maps for England and Wales.

Flood Risk Category	Flood Risk Likelihood Range	Substation Sites with Corresponding Flood Risk		
		Number	Percentage (of total 472 sites)	Percentage (of the 130 sites at risk)
Very Low	Chance of flooding less than 1 in 1000 each year	5	1.0%	3.9%
Low	Chance of flooding between 1 in 100 and 1 in 1000 each year	86	18.2%	66.2%
Medium	Chance of flooding between 1 in 30 and 1 in 100 each year	21	4.5%	16.2%
High	Chance of flooding greater than 1 in 30 each year	18	3.8%	13.8%
Total		130	27.5%	---

We also used data from the Ordnance Survey, specifically the National and Local Roads dataset, to generate a full dataset of roads within England and Wales (Ordnance Survey, 2019). In order to reduce geoprocessing and computational effort to a reasonable level, the dataset needed to be modified and adapted to reduce its excess complexity and detail (there were more than 3 million roads/polylines within the raw dataset). We achieved this by minimising the number of minor roads within the network through the exclusion of roads that were not within a 5km buffer of each substation location (Figure 1). It is assumed that the major highways (motorways and A-roads) will be used to transport the demountable flood defences to the closest junction to the substation location, and then the minor roads (B-roads and local roads) will be used for the final section of travel. We also merged these minor roads and the major highway network into one coherent layer in order to further reduce complexity and technical issues. The challenge at this stage was to integrate and connect the whole dataset at the national scale, to ensure the connectivity of the whole network. There were cases when roads did not intersect at the exact junction or in some cases one road overshot another. This was overcome by using the *extension* and *trimming* tools within GIS. The resulting network must be fully connected in order to correctly apply the LA methodology and CF tool.

In our case study problem, we do not want to identify the exact longitude and latitude co-ordinates of the optimal resource storage locations, rather we wanted to find the point on the major road network which should form the connection to the storage locations. From discussion with the National Grid, it is known that the resource location will be closely connected to the major network to ensure a rapid deployment. This assumption was also made, as the spatial boundary for this analysis is defined as the land boundaries of England and Wales, which includes too many potential storage locations (e.g. industrial estates, brownfield sites) to maintain reasonable computational effort. Therefore, to keep the study to a manageable size, we spread 5,000 individual points at regular intervals over the major road network and considered these to be potential storage locations. This number was chosen to balance the computational effort alongside accuracy, and results in points 7km (approx. 4 miles) apart. These individual points were required in the analysis, as the LA tool within ArcGIS requires that optimal resource locations be attributed to a point, rather than a section of polyline.

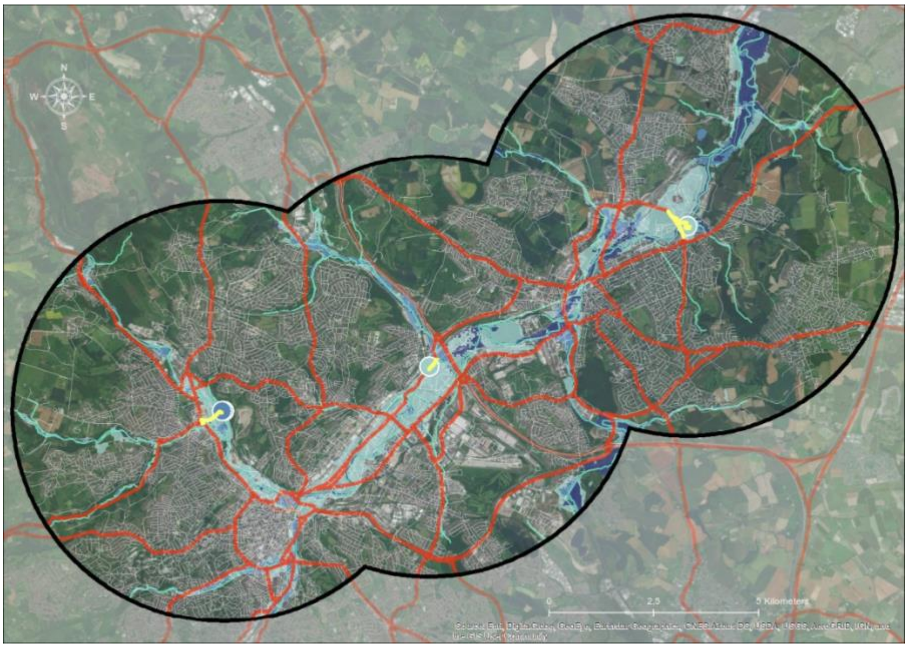

Figure 1 – The locations of three substation sites (blue circles), where the major roads are shown throughout (red lines) and the minor roads within a 5km buffer (grey lines) in order to reduce the computational effort of the analysis. The shortest path taken on the minor roads to the major routes are also highlighted (yellow lines). The basemap used was obtained from ESRI (2020).

We employed the LA tool within ArcGIS to determine the best single and multiple locations (either two or three locations) for the demountable flood defences, utilising the *maximum coverage* problem type to achieve this. We did not use a time impedance cut-off within the analysis, as all substation sites require access to resource and the priority within our analysis was to maximise the coverage of substations from the selected resource locations. We also did not use the LA tool to identify the optimal number of resource locations required to access all substation sites within a minimum time. It is not practical to store the demountable flood defences in more than three locations, due to the quantity of resource to be stored at each site.

It is worth noting that several of the assumptions, regarding data, have been made to reduce the computational effort of the analysis (e.g. the use of 5,000 potential storage locations and consideration of minor roads within a 5km buffer of each substation only). This is largely due to the scale of the problem, as the majority of LA problems in literature tend of focus on small geographic areas/regions and can therefore be analysed with more detailed, higher quality datasets.

Application to Case Study: Non-Weighted Analysis

We initially conducted a non-weighted analysis, where each substation location had equal demand, or "pull", on the potential resource storage locations. We conducted this analysis for one, two and three potential storage locations and optimised the algorithm to minimise the distance to each substation location. It is worth noting that in this analysis we only considered substation sites at flooding risk to require a quantity of resource (we removed all other substation sites from the analysis). The results of this analysis are shown in Figure 2 and quantified in Figure 3.

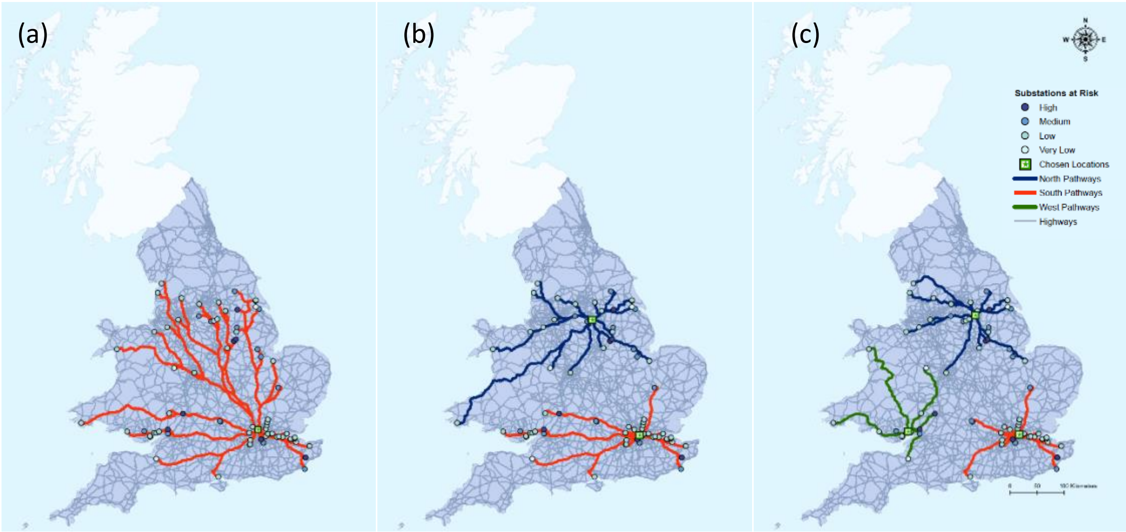

Figure 2 – The locations of the resources (star), when (a) only one location is considered, (b) two locations and (c) three locations are considered. Also showing the shortest path (in terms of average travel time) between each substation site (dots) and their closest resource location (red, blue and green lines) (ESRI (2020b)).

From Figure 2(a) it can be seen that the optimum location for one resource site is close to London. The addition of another resource site does not significantly alter this location, but introduces a location around Doncaster (Figure 2(b)). It is also interesting to note that with the addition of a third resource storage site, these first two locations did not significantly alter and the site is introduced around Cardiff (Figure 2(c)). The distance from each substation site to the resource storage location is shown in Figure 3, where the distance to the "high" flood risk substations is also indicated (dropped lines). From this figure, it can be seen that for one resource location the maximum travel distance is 390km, which reduces to 280km (28% reduction) when an additional location is added and to 178km (54% reduction from one location, 36% reduction from two locations) for the third location. This equates to approximately one hour travel time saved when using two storage locations and a further 30 minutes of time saved by using three locations, compared to only one storage location. The distance to the furthest high risk flooding site also reduces as more resource storage locations are added, from 390km for one location to 198km for two locations and 178km for three locations.

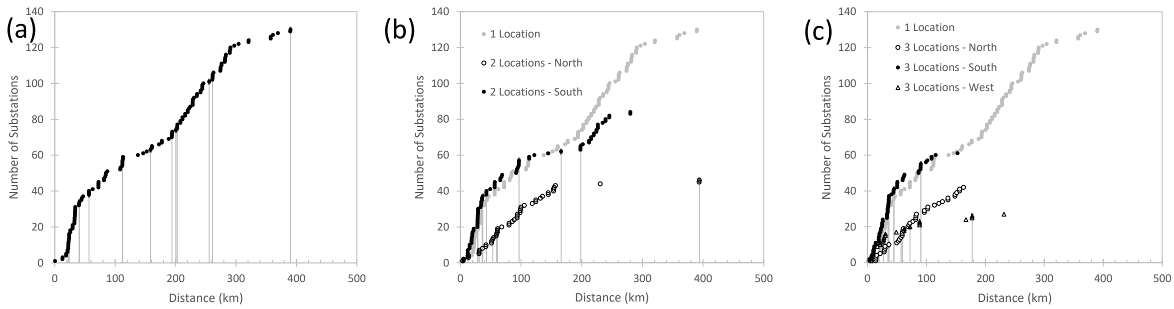

Figure 3 – The distance from the resource location(s) to each supported substation site, for (a) one, (b) two and (c) three resource locations. Also showing the location of the substations classified with High flood hazard (dropped lines).

Application to Case Study: Weighted Analysis

Within an LA methodology there is an opportunity to weight assets/sites requiring access to the resource location. This weighting can be achieved by considering the population of a community or the economic outputs of industrial areas, for example. In these cases, the weighting can be applied directly to the assets (e.g. the exact population or economic data can be used). However, when weighting assets that do not have a direct quantification further thought is required. How do you apply a quantified weighing to asset sites that are at low flood risk compared to those a high risk? Do you double the arbitrary weight applied? Or should the relationship be cubic?

In this paper, we have identified three potential methods to assigning weights to assets where direct quantification is not possible. These are shown in Figure 4 where we consider a liner, power-law and logarithmic trend to the weightings. To consider the difference made in each case, arbitrary weighted numbers were chosen which conformed to these three trends and for each case we used three sets of weightings (i.e. we have nine sets of weighing to apply in total). It is worth noting that the "Very Low" flood risk sites are always allocated a weighting of one and we use the trends to assign weights to the other three flood risk categories.

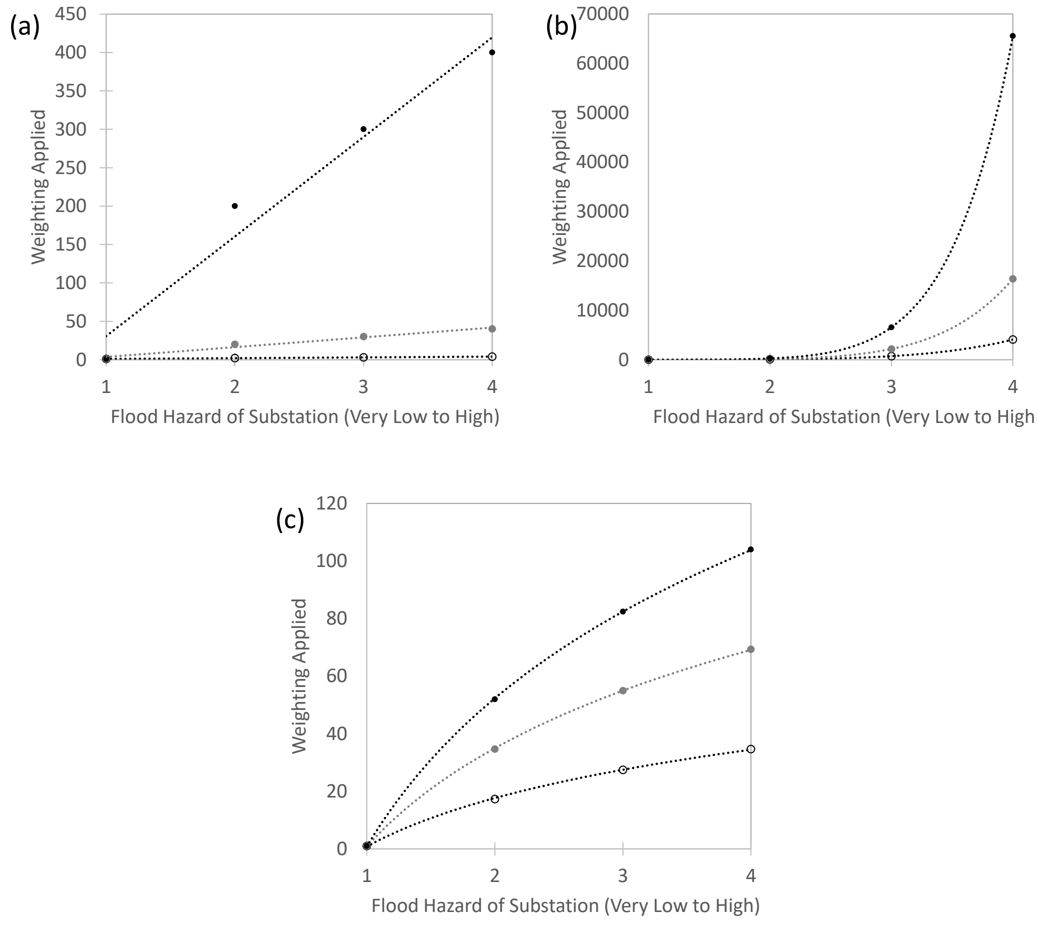

Figure 4 – Showing the weightings applied to the substations, for (a) linear, (b) power law and (c) logarithmic trends, where (1) indicates Very Low, (2) Low, (3) Medium and (4) High substation flood hazard.

The results of the applied weightings found that it was the relationship between the weightings (e.g. linear or power-law) which caused a change to the optimal resource location, rather than the arbitrary values chosen. For example, the same results were achieved for linear weightings of 1, 2, 3, 4 and 1, 200, 300, 400 applied to the very low, low, medium and high flood risk substations, respectively.

Therefore, to keep the number of results shown in the paper to a manageable size we have shown the results for one weighting only in each of the three trends. These are shown in Table 2 in terms of the distance change from the un-weighted optimal resource location (identified in Figure 2) to the new weighted optimal resource location. The maximum change observed occurs when two storage locations are considered for the power-law weightings (of up to 54km, which equates to approximately one hour of driving time). However, for the majority of locations it can be seen that there is little to no change. For example, no change in optimal resource location is observed for one storage location for both the linear and logarithmic weightings. To investigate the cause of this change we need to consider the spatial distribution of assets, along with the spatial distribution of assets within different flood risk categories.

Table 2 – Showing the change in resource location with the weightings from Figure 3 applied. It is worth noting that the same results were achieved for each value of weighting within the same distribution type, therefore only the results of one analysis have been shown.

Weighting Applied	Number of Storage Locations	Movement of Resource Location (from non-weighted)		
		Location 1	Location 2	Location 3
Linear	1	0km		
	2	8.5km	14.5km	
	3	5km	2.2km	0km
Power-Law	1	8km		
	2	19.3km	54km	
	3	13.6km	21.1km	52.5km
Logarithmic	1	0km		
	2	0km	14.5km	
	3	5km	0km	2.2km

To achieve this, we use the Average Nearest Neighbour analysis as developed by Ebdon (1977). The Average Nearest Neighbour value is a "*measure of how clustered, or dispersed, a spatial layout is based on the average distance from each node to its nearest node*" (Dunn 2014). In this case, the substation sites form the "nodes" in the analysis. The results of this analysis have been shown graphically in Figure 5, where it can be seen that all substations with associated flood hazard conform to a clustered layout. This is also the case, but to a lesser extreme value, for all substation assets at risk of flooding with the exception of the Very Low category, which displays a dispersed pattern of assets. However, it should be noted that there are only five nodes associated to the Very Low flood risk category (Table 1).

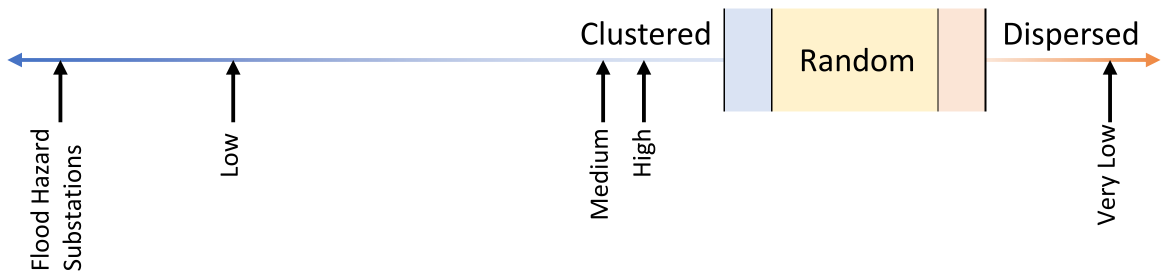

Figure 5 – Showing the results of the Average Nearest Neighbour analysis for all substations within a flood hazard area and those for each individual flood risk category. The "Random" section (yellow) occurs when the obtained p-value is between +-0.10 and indicates a random dispersal of nodes throughout the area. Whereas, a score between 0.05 and 0.10 indicates either a clustered layout (blue) or dispersed layout (red), and a score less than 0.05 is classed as significant (ESRI, 2019c).

This is likely to be the reason behind the lack of change of optimal storage location when weightings are applied to the network. All substation sites display a clustered pattern and it is highly likely that each of these clusters (or group of assets) contains approximately the same number of substation assets associated to each flood risk category. As such, each cluster has the same "pull" on the resource site to be located, causing the same overall result. In order to determine if this is the case we construct several small scale tests to investigate this phenomena.

We use a clustered layout and a uniformly distributed with area layout, both generated using the algorithms presented by Dunn and Wilkinson (2017). In these synthetic layouts, we use 50 nodes and assess how the location of the nodal risk (e.g. high risk to very low risk) alters the change in one resource location when different methods of assigning weightings to the nodes are considered (e.g. linear, power-law and logarithmic). We maintain the same proportion of high, medium, low and very low risk nodes as for the real-world layout, as shown in Table 1, and we assign each node as risk rating using two methods: (1) on a geographically linear scale (high risk nodes are located on the right spatial boundary and the risk decreases towards the left spatial boundary), and (2) randomly. As in the previous analysis, we then calculate the resource location initially using a non-weighted analysis (for a comparison baseline) and then apply a linear, power-law and logarithmic scaling. The results of this analysis are shown in Figure 6 and Figure 7 and quantified in Table 3.

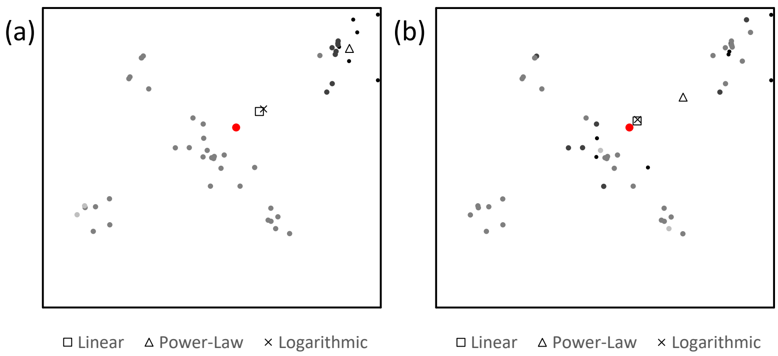

Figure 6 – Showing the location of the resource location for the un-weighted (red dot), linearly weighted (square), power-law weighted (triangle), and logarithmically weighted (cross) analysis, when the nodes are located in a clustered layout, with weightings assigned (a) geographically and (b) randomly.

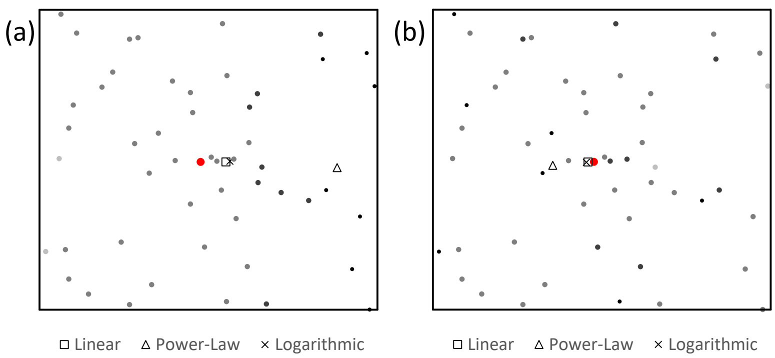

Figure 7 – Showing the location of the resource location for the un-weighted (red dot), linearly weighted (square), power-law weighted (triangle), and logarithmically weighted (cross) analysis, when the nodes are located in a uniform with area layout, with weightings assigned (a) geographically and (b) randomly.

Table3 – Showing the change in distance for the resource location for the Uniform with Area and Clustered nodal layouts when the high-very low risk nodes are placed either linearly (from the right spatial boundary to the left) or randomly within the spatial boundary, for three different applied weightings.

Weighting Applied	Movement of Resource Location (from non-weighted)			
	Uniform Area (Linear Placement)	Uniform Area (Random Placement)	Clustered (Linear Placement)	Clustered (Random Placement)
Linear	44.9	10.3	52.2	19.0
Power-Law	242.8	73.3	256.1	113.2
Logarithmic	52.0	13.3	61.2	21.5

Considering only the clustered layout (which is similar in properties to that of our real-world problem), there is little movement of the resource location when the weightings are applied linearly or logarithmically, for both methods of assigning the location of the nodal risk factor. This lack of movement is also displaced by the uniform with area nodal layout, meaning that it is not the location of the nodes which governs this result, but rather the method used to assign the weightings. In both nodal layout cases, it is the power-law distribution which results in the most movement of the resource location from the unweighted analysis. With the greatest change being observed when the risk factor of nodes is assigned based on a linear scale (from the right spatial boundary to the left), compared to the random layout.

In our real-world case study, the asset sites form a clustered nodal layout, as do the sites for only high and medium flooding risk (Figure 4). The results achieved correspond to those shown in the synthetic nodal layouts, namely that it is the location of the high and medium degree nodes which governs the resource location. The weighting scale also has a bearing on the change in resource location, with the power-law distribution having the most impact.

Considering the findings from Section 4.3.1, we also consider the optimal location of the resource location accounting for the high and medium flood risk substations (as these were shown to have the most impact to the analysis) (Figure 8).

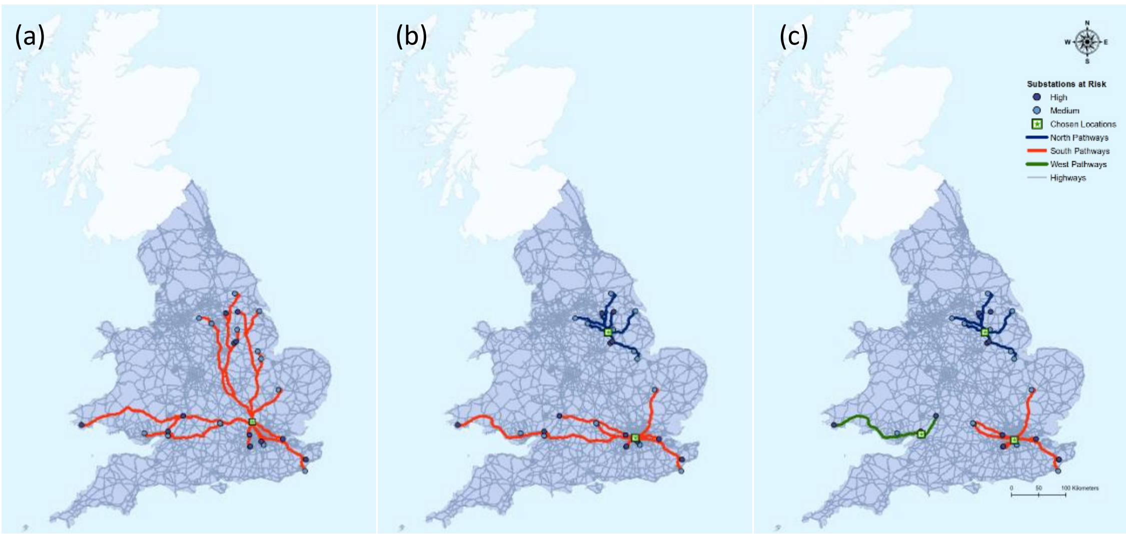

Figure 8 – Showing the location of the medium and high flood risk assets in England and Wales and the locations of resources (star), when (a) only one location is considered, (b) two locations and (c) three locations are considered. Also showing the shortest path (in terms of average travel time) between each substation site (dots) and their closest resource location (red, blue and green lines) (ESRI (2020(b)).

In this case, we only consider the high and medium flood risk asset sites (and remove those with low and very low risk from the analysis) and apply weightings to these two risk categories only. To achieve this, we use proportional weightings where the value applied to the high risk asset sites is a power to the 2, 3 and 4 of the arbitrary weighing applied to the medium risk sites. The results of the analysis are shown in Table 4.

Table 4 – Showing the change in resource location with the weightings applied to the Medium and High flood hazard substations only, the substations with Very Low and Low flood hazard remained in the analysis, but had a weighting value of one only.

Weighting Applied	Number of Storage Locations	Movement of Resource Location (from non-weighted)		
		Location 1	Location 2	Location 3
High = Medium^2	1	8.0km		
	2	19.3km	34.5km	
	3	13.6km	21.1km	31.2km
High = Medium^3	1	8.0km		
	2	19.3km	54.0km	
	3	13.6km	21.1km	52.5km
High = Medium^4	1	15.8km		
	2	19.3km	54.0km	
	3	13.6km	21.1km	52.5km

From the results shown in Table 4, it can be seen that applying weightings to the medium and high risk flood asset sites always results in a change in the optimal resource storage location. All three applied weightings show approximately the same results, with very minor differences. Comparing the results to those shown in Table 2, show very similar results to those for the analysis including all asset sites at flood risk and a power-law weighting. Thereby, further demonstrating that it is the location of the high and medium flood risk substations which govern the optimal resource location in this case study.

CONCLUSIONS

In this paper, we have developed a modified LA tool for modelling adaptable solutions for infrastructure systems, specifically accounting for the weighting of assets with only qualitative characteristics. Within today's changing climate and the, often large, uncertainty related to this adaptable solutions, similar to that presented in this paper, present an alternative solution to potentially costly and wasteful permanent solutions to ensure the resilience of our critical infrastructure systems. The methodology presented in this paper, is one methodology by which this can be achieved by infrastructure owners and operators to increase the resilience of their systems. We have specifically developed a methodology for determining the optimal placement of these deployable resources so they can reach sites within a minimised time/distance. The methodology also allows for each asset site to have a different "pull", or demand, on the location of resources. The developed methodology has been applied to the analysis of demountable defence locations for the National Grid, but could equally have been applied to other areas, for example: the storage of grit facilities (considering the maximum amount of road to be covered from each site) or the optimal storage location for electricity generators (considering the historic location of power outages). Within this current *period of flux* adaptable solutions offer the best investment in order to increase the resilience of our critical infrastructure networks.

We have investigated the weightings which should be applied to the assets when direct quantification (e.g. population supported or economic output) is not possible. In order to achieve this, we applied linear, power-law and logarithmic trends to the weightings used, finding that it was the power-law trend which caused the greatest change in the optimal resource placement (with a change of up to 54km). We also investigated the nodal configuration and the impact that this has to the placement of the resource locations; concluding that it is the location of the high and medium flood risk sites and not the nodal configuration which causes the greatest change in resource placement. These are both new investigations in the field of LA analysis, which can significantly alter the placement of resources, therefore must be considered in any future analysis.

This research has shown that infrastructure owners and operators must carefully consider the placement of their key resources (to either be deployed in the mitigation or disaster response phase) and that (1) the number of key resource locations used, and (2) the classification of medium-high risk asset sites, can have a large impact on subsequent travel times (and therefore risk). In relation to (1), there must be careful consideration of the number of resource storage sites used. The more sites, the lower the travel time (and therefore the lower the risk); however, this requires the resources to be divided over each site, potentially increasing the risk depending on the amount of resource available/required. For (2) infrastructure owners and operators must carefully consider, and classify, their medium to high risk assets, as when using the weighted analysis these can have a profound impact on the storage location of the emergency resources. Errors in this classification could lead to unacceptably lengthy journey times to access the emergency resources. In both cases, this methodology allows for infrastructure owners and operators to calculate the level of risk of their asset sites in terms of travel time from the resource storage location to their asset location and to form their conclusions about what is acceptable for their systems/circumstances.

Further work in this area should consider the quantity of resource to be stored at each resource location and "disrupting" resource location when multiple locations are used. "Disrupting" resource locations could be used to simulate the change in travel time/distance when the closest storage location becomes compromised (either by hazard or lack of resources). Further work should also consider the combination of additional GIS layers (e.g. population, road traffic, electrical demand), within the weightings assigned to each asset site as appropriate for individual infrastructure systems, to improve the robustness of the model outputs.

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