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Optimization of resource storage location for managing flood emergencies

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ABSTRACT

Strategic infrastructure plays a key role in the functioning of urban areas, especially when dealing with emergency response to natural disasters. Urban areas and their infrastructure are threatened by natural hazards, which is likely to be exacerbated by climate change and intense urbanization in the near future. The UK National Flood Resilience Review (2016) committed £2.3 billion to be invested to reduce flood risk, of which £12.5 million specifically for temporary defenses. At present, the state of the art does not provide a proven efficient methodology specifically designed to optimally invest these resources; in light of this, a consolidated urban planning spatial optimization methodology is originally used for allocating resource storing space and ultimately optimize flood emergency management. This study developed and applied a RAOGA (Resource Allocation Optimization Genetic Algorithm) to balance the particular trade-off between simultaneous minimization of response time and costs. The presented optimization framework balances several competing tensions that include: (1) the identification of, and the cost of using, possible sites (warehouses) to store flood temporary defenses; (2) the identification of strategic infrastructure location; (3) transport optimization for moving emergency response resources into place. The methodology is applied to a regional case study (Yorkshire, UK) as proof of concept. Such a framework has the potential to lead a new generation of mathematically-based emergency response planning, targeted to policy makers dealing with urban planning and emergency management.

Keywords: Spatial optimization, Infrastructure resilience, Temporary flood defenses, Genetic algorithms

INTRODUCTION

Climate change and urbanization

Climate change's effects are increasing frequency and intensity of adverse weather events, with a heavy impact on urban areas and their infrastructure (IPCC, 2014; Jaroszweski et al., 2010). Worldwide, urbanization further exacerbates the impact of weather on the society: a higher density of population in urban areas increases the risk of an extreme weather event due to the higher number of people potentially involved.

Flooding is one of the most frequent and detrimental hazards intensified by climate change, which is expected to worsen in the future (Dawson et al., 2016). Protecting people living in flood prone areas should be a priority of local authorities, by enhancing urban resilience. Lifelines underpin all urban and human activities, thus protecting critical infrastructure networks means protecting societies. Disaster risk management is the most advanced procedure to achieve such a goal. However, the high-level of complexity of the matter requires sophisticated techniques that still need to be improved and developed.

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Flood defenses

Flooding is a worldwide problem; flood prone countries like the USA, Japan and the Philippines are periodically hit by catastrophes like recently happened with Hurricane Harvey (Blake & Zelinsky, 2018), devastating floods in the Philippines (Cabrera & Lee, 2018) and Japan (Shakti et al., 2018). While many examples can be found in Europe (e.g. Germany, Italy, Spain), the UK has recently been hit by a series of major flood events which led to significant infrastructure disruption. For example Storm Desmond in 2015 caused the collapse of critical infrastructure networks in Lancaster (UK) (Ferranti et al., 2017); Somerset, Cumbria and Yorkshire are other regions particularly affected in recent years with multi-million economic losses due to devastating flood events (Great Britain Cabinet Office et al., 2016).

Commonly implemented permanent flood defenses consist of levees, reservoirs, weirs, groynes, sea walls, dams, retention ponds and diversion canals. While temporary flood defense systems are devices that can be removed after their use and then used again when needed in the same location or somewhere else. They involve demountable plastic or metal barriers, water pumps and bags or containers filled with sand or water. They are a very adaptable and versatile tool thanks to their portability; on the other hand, their failure rate is around 25%, although it can be reduced with an efficient advanced planning.

The UK government set up the National Flood Resilience review (Great Britain Cabinet Office et al., 2016) to provide guidelines to better protect the country from future flooding and extreme weather events. In particular, the UK government allocated £2.3 billion in a 6-years program (2015-2021) to strengthen the country's flood and coastal defenses. Within this funding allocation, £12.5 million are meant to be invested in temporary flood defenses and other emergency response equipment, such as portable generators and mobile water pumps (Salagnac, 2007).

Despite increasingly sophisticated approaches to flood risk analysis and management, no framework exists to optimize the location of temporary defenses to protect key infrastructure to achieve the greatest reduction in flood risk whilst minimizing costs.

AIM AND OBJECTIVES

Given the strategic importance of critical infrastructure and the funding allocated to its protection by the UK Government (Great Britain Cabinet Office et al., 2016), this research aims to respond to the need of developing enhanced management of flood emergency response resources.This research proposes and demonstrates a methodology to optimize allocation of temporary flood defenses since, at present, the state of the art does not provide a proven efficient methodology specifically designed to optimally invest these resources, in the hope to potentially lead a new generation of mathematically-based emergency response planning, targeted towards policy makers dealing with urban planning and emergency management.

The research question this study aims to address is: what is the best strategical choice for stocking emergency response resources? A spatial optimization framework that uses a Genetic Algorithm (GA) has been adapted to suit this spatial optimization problem to find the best strategical position of warehouses for temporary flood defenses stocking. A case study concerning the Humber Estuary (Yorkshire, UK) is presented as proof of concept.

METHODOLOGY

Multi-objective spatial optimization

Multi-objective optimization has been widely applied in urban planning to find optimal configurations of infrastructure in situations with multiple conflicting objectives. Liang et al. (2004) and Berardi et al. (2009) are examples of application in sewers network design, while many other applications has been implemented for water distribution (Bieupoude et al. 2012), transport networks (Shimamoto et al. 2010) and land use allocation (Cao et al. 2011).

The optimization framework presented here is based on a Genetic Algorithm (GA). GAs belong to the wider family of Evolutionary Algorithms, which are processes that mimic natural evolution (hence their name) in the sense that only the fittest solutions survive in the iterative process (Dowsland 1996). GAs have already been used in land use multi-objective optimization (Cao et al. 2012), and their computational efficiency has been evidenced in several different studies (Caparros-Midwood et al. 2017, Sidiropoulos and Fotakis 2009). In particular, they outshine other traditional approaches, like Simulated Annealing (Sidiropoulos & Fotakis, 2009; Loonen at al., 2007) or Tabu Search, in finding global optima (rather than jamming in local optima) (Reeves 1995) with shorter run times (Mitchell 1998).

Resource Allocation Optimization Genetic Algorithm

The proposed Resource Allocation Optimization Genetic Algorithm (RAOGA) is an iterative process that evolves a set of initial solutions (Generation 0) to their optimal state (Generation N), thanks to the genetic operators "Selection", "Crossover" and "Mutation" (Python-based). Each generation is created from the previous one on the concept of Pareto-optimization (Goldberg 1989): a solution is defined optimal if it is not worse than any other in all the objectives and it is strictly better in at least one. Equation 1 shows a mathematical formulation for a minimization problem.

$$\begin{cases} f_m(s^1) \leq f_m(s^2)\ \forall\ n = 1, 2, \dots, \mathrm{M} \\ f_m(s^1) < f_m(s^2)\ for\ at\ least\ one\ m \in \{1, 2, \dots, M\} \end{cases} \tag{1}$$

Where s^1 and s^2 are two potential solutions and f_m are the M objective functions.

Fig. 1 shows the workflow of the genetic algorithm: after an input processing phase, the GA generates an initial population (Generation 0), whose fitness is evaluated with respect to the multi-objective optimization functions. The best elements of this population, thanks to the evolutionary operators, generate a child generation, whose fitness is evaluated again. The best elements of the child generation and the best elements of Generation 0 will constitute Generation 1. This iterative process is repeated until the maximum number of generations N is reached. This maximum number of generations is the result of a convergence calibration of the framework; this number can vary depending on different factors like the dimension of the case study area, the number of assets that are part of the problem and the chosen spatial resolution.

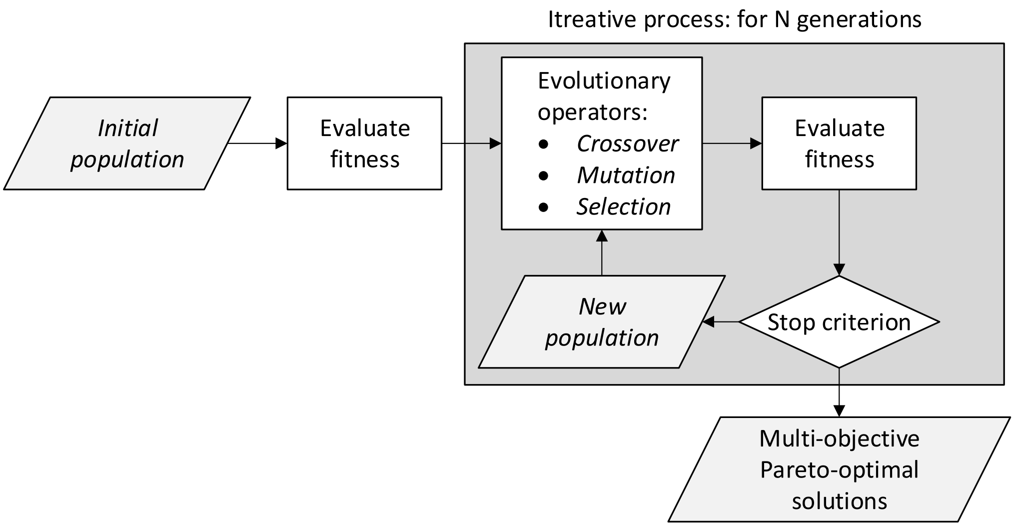


Figure 1. Flowchart of the Genetic Algorithm.

Objective functions definition

The RAOGA aims to find the optimal position of warehouses for emergency resources stocking. A series of strategic infrastructure hotspots (like energy, health, transport and telecommunications) are identified as priorities for flood protection in emergency situations (Great Britain Cabinet Office et al., 2016). The RAOGA inspects solutions with different number of warehouses (from 1 to *N*, being *N* defined by the user): this allows the optimization framework to inspect both centralized solutions (with one or few warehouses) and distributed solutions with a higher number of warehouses.

Two are the objectives to be optimized: 1) the minimization of emergency response time (which is translated as the minimization of travel times between warehouses and the strategic infrastructure hotspots to be protected) and 2) minimization of costs. These two objectives are conflicting, since minimizing one necessarily means to maximize the other. The proposed optimization framework optimally balances such a trade-off minimizing the two objective functions f_{dist} and f_{cost}.

Objective function 1: f_{dist}

A proposed warehouse plan for the entire case study region, *W*, is composed by a set of proposed warehouse sites w each with an ij location in the study area. The GA minimizes the f_{dist} function (Equation 2) depending on the shortest path *P* between warehouses sites w_{ij} and targets t_{ij} over the road network *R*; and such a shortest path distance is evaluated in terms of travel times.

$$f_{dist} = Min(P(w_{ij}, t_{ij}, R),\ \forall\, t_{ij}\ \forall\, w_{ij}\ \in \mathrm{W}) \quad (2)$$

The shortest path distance is evaluated with the function shortest_path_length of the Python module NetworkX (Hagberg et al. 2008).

Objective function 2: f_{cost}

The GA minimizes the f_{cost} function (Equation 3) basing on the average annual rental price p_{ij} of each site w_{ij}.

$$f_{cost} = Min(\textstyle\sum_1^Q p_{ij}\ \forall\, w_{ij}\ \in \mathrm{W}) \quad (3)$$

The annual rental price per square meter is the result of a market analysis of the Yorkshire area (UK) for the year 2017 (Estate Gazette, 2018).

CASE STUDY

Case study area

The case study area selected as proof of concept is the Humber Estuary and the surroundings of Kingston upon Hull (UK) because it is a well-known UK flood prone area with a good availability of input data (Fig. 2).

The RAOGA was applied to locate warehouses in order to minimize the transport time of flood emergency resources from the storehouse to strategic infrastructure assets to be defended during emergencies. The case study area is modeled with a 100m resolution, with 134 locations of potentially endangered strategic infrastructure assets. The modeled road network counts more than 15 thousand edges and the potential sites where to build warehouses are more than 20 thousand. Moreover, the number of warehouses to be part of the solution is not fixed, and it varies in a range from 1 to 6.

The input of the optimization framework is a series of raster (.tiff files) and vector (.shp files) datasets that represent the physical constraints and elements of the region. Such input datasets are representative of different layers through which the physical reality of the analyzed region is represented in the model (Fig. 2).

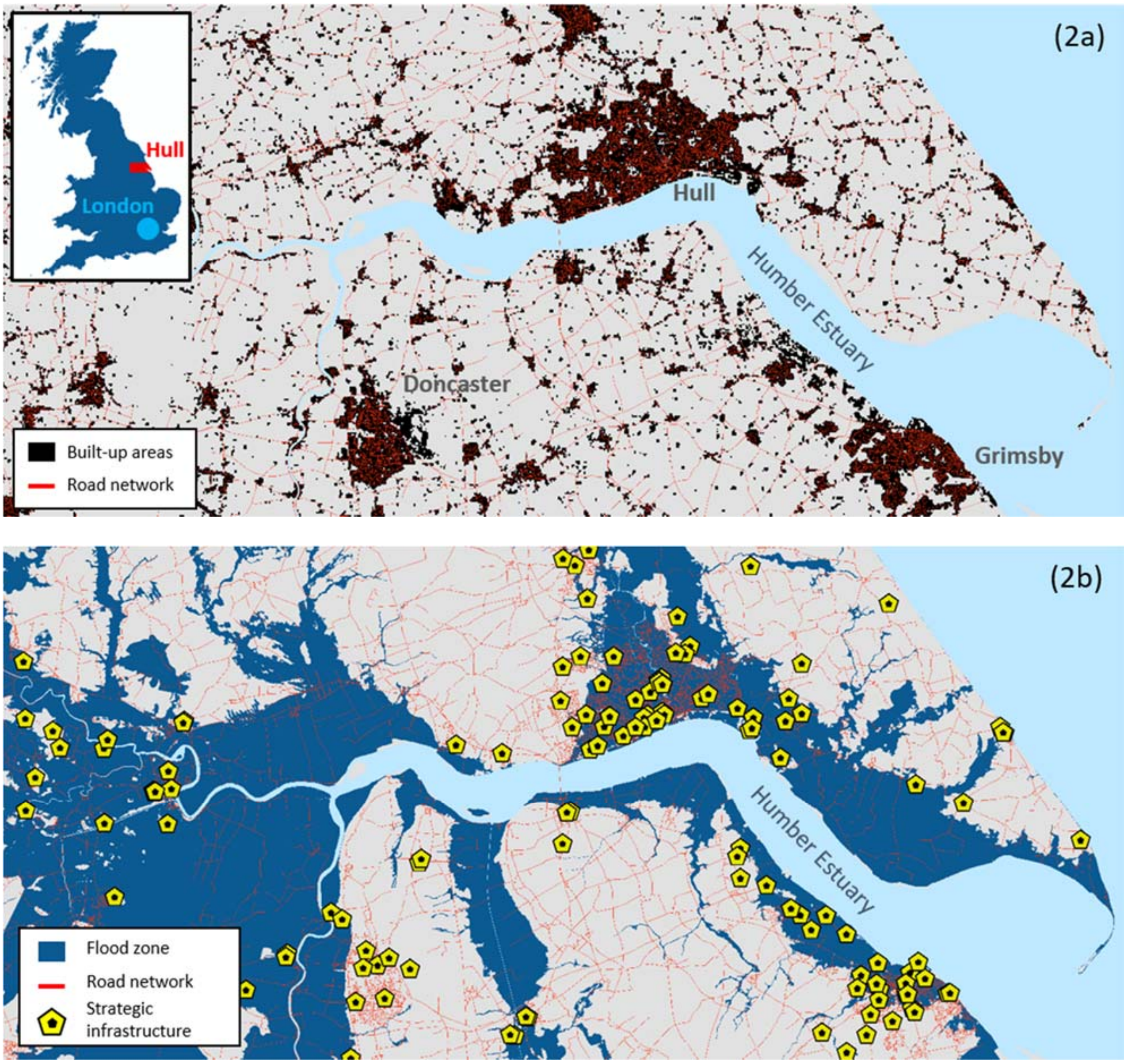


Figure 2. Input datasets of the RAOGA. The optimization framework reads a series of raster (.tiff) and vector (.shp) files that represent several physical features of the analyzed study area, i.e. built-up areas and the road network (2a) together with a flood zone layer and the strategic infrastructure assets to be protected (2b)

Following the raster and vector datasets input phase, the framework elaborates an availability layer using the information contained in the input files. This available raster dataset is formed by cells available for positioning warehouses of potential solutions.

Results

Fig. 3 shows the first output of the optimization framework after 200-generations. A plot of Pareto-optimal solutions that optimally balance the trade-off between the two conflicting objectives represented by the two functions f_{dist} (on the x-axis) and f_{cost} (on the y-axis), respectively expressed in minutes and British Pounds.

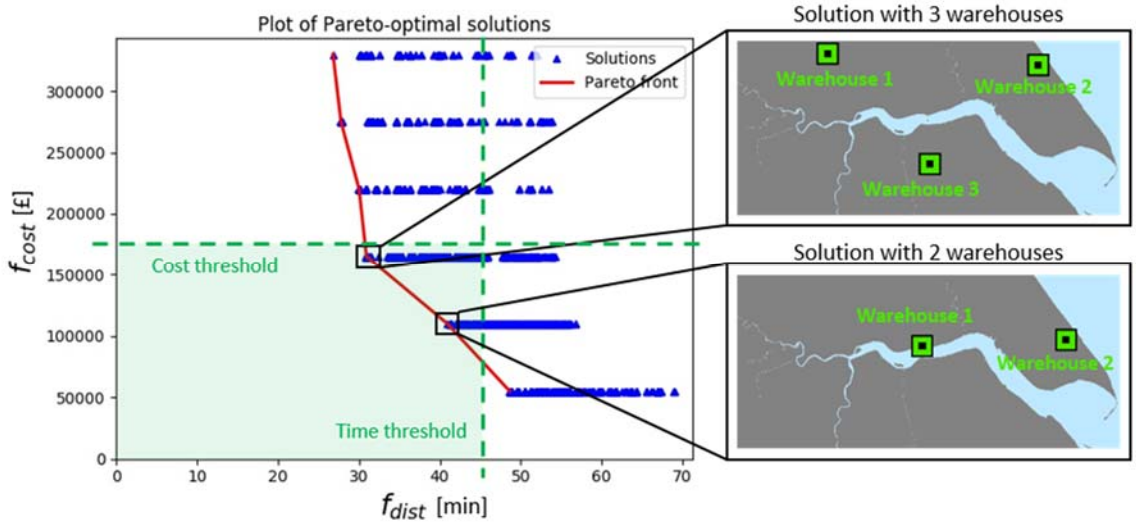
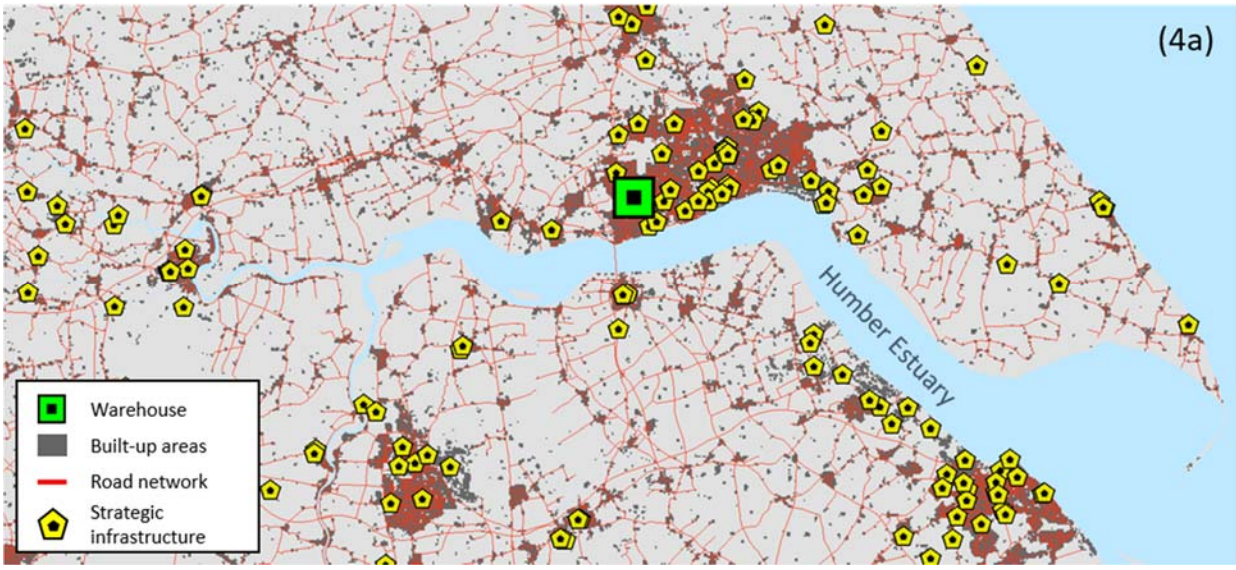


Figure 3. Output data produced by the RAOGA. The graph shows all the inspected solutions and their fitness concerning the two objective functions. The solutions that optimally balance the trade-off between the two conflicting objectives form the Pareto-front. Each solution lying on the Pareto-front correspond to a spatial warehouse plan.

The values on the x-coordinate (Fig. 3) represent maximum distance (expressed as travel time on the road network) between a single warehouse and the furthest strategic infrastructure hotspot to be protected. The values on the y-coordinates, instead, represent the cumulative cost of the proposed spatial plans. Every blue triangle in Fig. 3 represents a potential solution that corresponds to a spatial warehouse plan. The ones lying on the red line (the Pareto front) are the solutions that optimally balance the trade-off "minimization of costs" vs "minimization of response time".

The GA also produces other outputs that are respectively georeferenced raster datasets (.tiff files) with the indication of the geographical position of the proposed warehouses and, as an alternative, GIS point-shape files (.shp) with the coordinates of the spatial plans. Fig. 4 shows the spatial plans that optimally balance the trade-off: "minimization of response time" vs "minimization of costs".



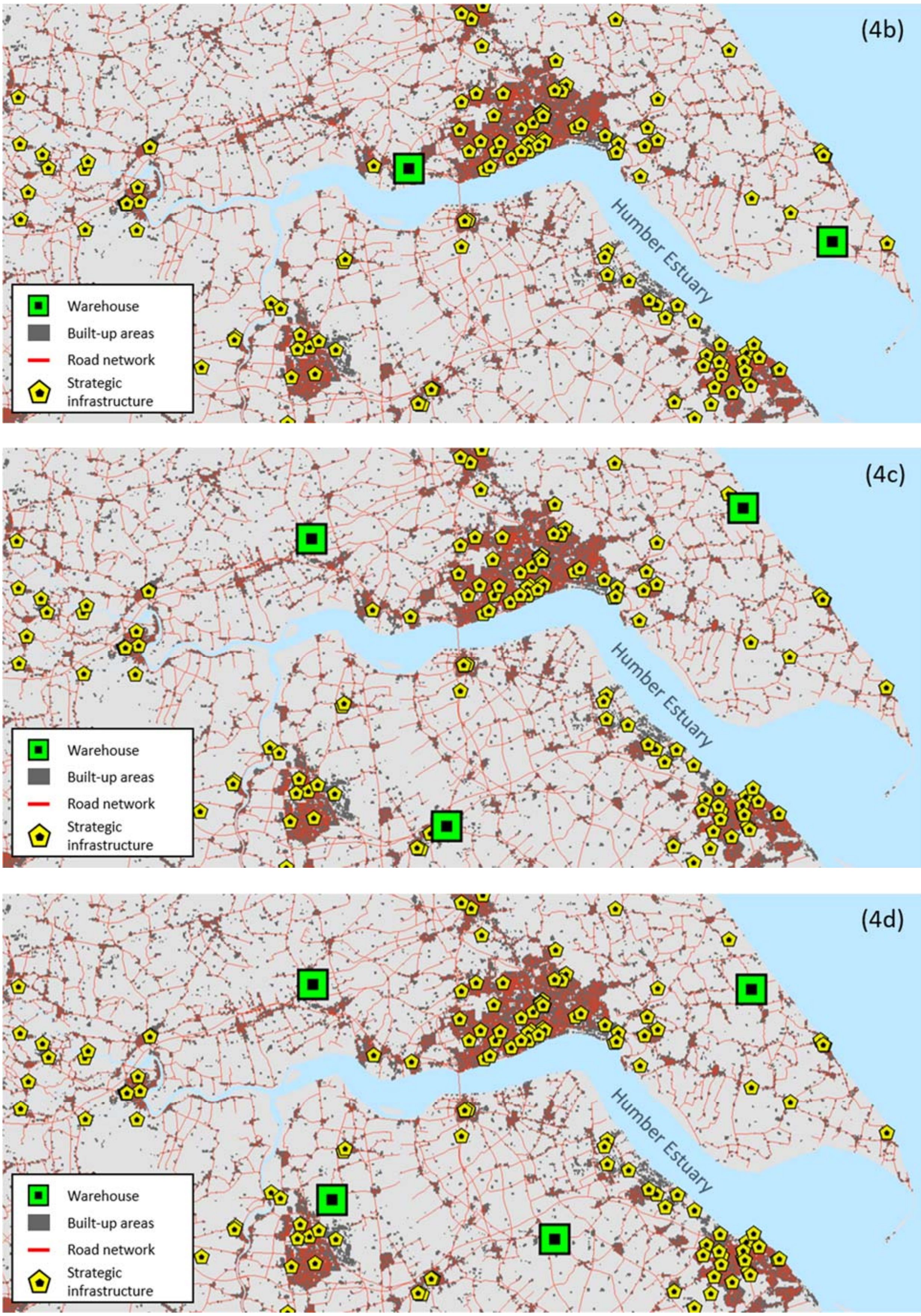


Figure 4. Spatial plans that lie on the Pareto-front (i.e. optimally balance the trade-off: “minimization of response time” vs “minimization of costs”). Solutions with 1 warehouse (4a), 2 warehouses (4b), 3 warehouses (4c) and 4 warehouses (4d).

Fig. 4a shows the optimal centralized solution (solution with 1 warehouse), near to the geometric centroid of the area. The cost of a single warehouse is estimated as £55k, on the basis of rental annual prices per square meter in Yorkshire (UK) (Estate Gazette, 2018) and the travel time associated to this solution is 49 minutes. This means that 49 minutes is the travel time required to reach the farthest at risk strategic infrastructure asset from the proposed warehouse position. Similar considerations concerning costs and travel times can be made also for the other solutions showed in Fig. 4 and they are summarized in Table 1.

Table 1. Cost and travel times associated to the solutions on the final Pareto front.

	N. of warehouses	f_{cost} [£]	f_{cost} [min]
Figure 4.a	1	55,000.00	49
Figure 4.b	2	110,000.00	41
Figure 4.c	3	165,000.00	31
Figure 4.d	4	220,000.00	30

DISCUSSION AND FUTURE RESEARCH

The Pareto front of Fig. 3 returns six optimal solutions that balance the trade-off "minimization of response time" vs "minimization of costs". That means that each of these six solutions outperforms the others in at least one objective; however, we are interested in the simultaneous optimization of the conflicting objectives, so it may be useful to define thresholds beyond which there is improvement in one objective, but not significant improvement in the other. Such thresholds are indicated in Fig. 3, identifying a green area of the graph that is the solutions' field of interest for this particular case study. Above the economic threshold there is still improvement in both the objectives, but in the face of a significant increase in costs, there is no significant decrease of travel times. This is important as local authorities and flood management agencies always have a fixed maximum budget to invest and they cannot afford to overinvest resources if there is no correspondent significant benefit in terms of security level.

On the other hand, also a threshold on the time of response is interesting as it relates to a certain level of service. This has repercussions on the safety level that local authorities want to set and guarantee. Such thresholds are not a priori implemented in the framework, since all the produced solutions are optimally balanced; it is up to the user to establish the thresholds according to several contingent considerations like financial means and required level of response time in emergency operations.

As can be noticed in Fig. 2b, strategic infrastructure assets are scattered all over the case study area. Even if it could be rather easy to determine where to place a single warehouse (around the geographic centroid, like in Fig. 4a), localizing optimal locations becomes less intuitive for solutions with a higher number of warehouses. This decision process is even less intuitive when considering complex spatial plans and two conflicting objectives (i.e. simultaneously making economic considerations) and considering travel times instead of geometric distance. Fig. 4b and 4c (respectively solutions with two and three warehouses) present solutions that both have warehouses localized East and West of Kingston upon Hull (the major built-up area), rather than having a single one serving the surrounding region. This output suggests that crossing the city is more time-consuming than reaching the assets of the area from outside. This is a first non-intuitive conclusion, since a high number of strategic infrastructure assets are concentrated in this area and having a warehouse among them could appear a good option. The proposed optimization framework shows that that is true only when considering a single warehouse, while optimal solutions require stocking positions outside the city when considering multiple storehouses.

Whilst the result for a single warehouse in the region of interest may seem intuitive, solutions for more warehouses are more complex and less readily identifiable. These are the most valuable to stakeholders and decision makers, which could benefit from the information provided by the proposed methodology when planning emergency response strategies.

The optimization framework provides a series of different kinds of useful information: not a mere geometric distance based spatial optimization, but a trade-off balance based on network analysis (involving speed and travel times) and on economic considerations. Although planners know that having numerous warehouses on the territory allows lower travel times and that a scattered arrangement of stocking positions optimizes response time, it is still difficult to numerically quantify advantages or disadvantages of different spatial plans. The present research, thanks to its mathematically-based results, allows scientific-supported considerations when comparing different solutions to the allocating problem.

The RAOGA provides answers in terms of performance of the solutions, i.e. it clarifies how much a spatial plan is better or worse than another in terms of costs and travel times. For example, it allows to appreciate how much the security level of the area (expressed in minutes to reach the endangered strategic infrastructure assets) is enhanced when considering an additional warehouse. It also allows more sophisticated observations; in fact, it becomes easy to understand how much the performance in terms of travel times is worsened when cutting the cost of a certain percentage for instance. Or, on the other hand, how much would it cost to increase the response time performance by a desired percentage. In light of this, the present methodology aims to provide mathematical based information to be a support to emergency response planning decisions by local authorities.

Future research

A first relevant assumption of the optimization framework is the definition of available cells (potential solutions); as described in the case study presentation, a potential warehouse location must satisfy a series of requirements coming from the input data defining the case study area (e.g. a cell is declared “available” if: i) it is within the borders of the case study area and on mainland, ii) it does not overlap a surface water cell, iii) it is outside the flood zone area, iv) it is closer than 500 meters to a major road etc.). Naturally, these requirements can be changed or modified according to the user’s needs or possible case study’s geographic peculiarities.

Moreover, travel times are evaluated on the basis of the free flow speed of the network edges; this implies that what is evaluated is a best case scenario, since traffic is not part of the equation and the possibility of traffic jams or delays caused by floodwater blocking certain routes is not factored in yet.

Possible room for future research concerns the consideration of i) flood disruption (or partial-disruption) of the road network; ii) the analysis of a larger region and; iii) the ranking of the benefits in terms of the importance of strategic infrastructure assets etc.

Many countries have similar datasets to those used here, which enables the framework to be transferable and flexible in terms of the values and optimization criteria (i.e. objectives) used.

CONCLUSIONS

Strategic infrastructure networks are fundamental for the normal functioning of urban areas and for emergency response to natural disasters. The UK National Flood Resilience Review (Great Britain Cabinet Office et al., 2016) committed £2.3 billion to be invested to reduce flood risk and coastal erosion, of which £12.5 million has been set aside specifically for temporary defenses. At present, there is no methodology able to identify optimal strategies to invest these resources, therefore this paper proposed an optimization framework aimed at the balancing a particular trade-off in emergency response planning: the simultaneous minimization of costs and response time when planning the stocking position of the afore-mentioned temporary flood defenses. A consolidated urban planning spatial optimization methodology has been applied for allocating resource storing space and ultimately optimizing flood emergency management.

The presented optimization framework balances several competing tensions that include: the identification of, and the cost of using, possible sites (warehouses) to store flood temporary defenses, the identification of strategic infrastructure location and transport optimization for moving emergency response resources into place. The methodology has been applied to a regional case study in the UK.

The optimization framework outcome comprises Pareto-fronts of optimal solutions, where each solution consists in a spatial plan that shows the best geographical positions for warehouses (in terms of costs and travel times) for storing emergency management resources. Each plan has an associated cost that allow simultaneous spatial, security and economic considerations.

Such information is meant to be the base of a mathematically-based emergency response planning on behalf of policy makers dealing with urban planning and emergency management. The methodology has been designed to be flexible and versatile, and it could be applied to different areas, as well as different parameters can be adjusted to model different scenarios or emergency situations.

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