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Optimisation of Temporary and Demountable Flood Protection for Infrastructure Resilience

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ABSTRACT

Infrastructure systems provide crucial services to human settlements. Extreme weather events, especially flooding, can disrupt these vital services. Temporary and demountable flood protections (TDFPs) are increasingly used to protect infrastructure assets and provide resilience. Budget constraints mean that TDFP are typically deployed to multiple sites from a single warehouse. Identifying optimal locations to maximise coverage and minimise costs is a complex spatial problem not yet tackled in the literature. To address this, a Spatial Resource Allocation Optimisation (SRAO) framework, using a genetic algorithm (GA), has been developed. The SRAO framework is applied to a case study in the Humber Estuary (UK) where 133 strategic infrastructure assets serve over 400,000 people in the floodplain. Eight scenarios assess how cost, TDFP availability, transport and asset prioritisation for protection influence warehouse size and sites. The SRAO identifies optimal strategies that, relative to other strategies, reduce annual costs by 40%–50% and deployment times by 60%–70%. Furthermore, 8 'hotspot' sites appear in over 60% of optimal solutions; these can be considered robust to model uncertainties and scenario assumptions, providing decision-makers with locations performing well under varied conditions. The methodology benefits local authorities, infrastructure operators and emergency management agencies, reducing costs and improving resilience for communities.

1 | Introduction

Infrastructure networks such as telecommunications, power systems, banking and finance, transportation, water supply, government and emergency services deliver crucial social and economic services (Dawson et al. 2018). Their continued operation is therefore fundamental to community and urban resilience. However, risks to people, buildings and infrastructure are increasing as a result of new development and increased frequency and severity of natural hazards from climate change (United Nations, Department of Economic and Social Affairs Population Division 2019; Global Commission on Adaptation 2019).

Flooding is one of the most significant hazards for human settlements and infrastructure systems (Koks et al. 2019; CCRA3 2022; Dodman et al. 2022). Flood management typically focuses on reducing risks to people and the initial direct impacts of flooding. Yet, the impacts of flooding on infrastructure can lead to substantial disruption, with many people not realising they are indirectly vulnerable to flood impacts (Merz et al. 2021); for instance, a flooded electricity substation in Lancaster (UK) in December 2015 affected more than 100,000 people (Royal Academy of Engineering 2016), while Arrighi et al. (2021) report indirect impacts from disruption to transport networks in Florence (Italy).

Resilient infrastructure better anticipates future shocks and improves actions to resist, absorb and recover from shocks and stresses (National Infrastructure Commission 2020). Proactive investments in resilience reduce the need for costly emergency responses and repairs, minimise resource consumption and lower emissions associated with rebuilding and recovery efforts (Baral and Shahandashti 2022). In the context of flood management, providing high levels of flood protection to all infrastructure assets would be extremely costly and may not be practical for many sites. This economic reality has led to increasing interest in more flexible protection approaches. Temporary flood protection comprises removable flood protection products that are wholly installed at the outset of a flood event and removed completely when flood levels have receded, while demountable flood protection systems require installation of barriers into pre-installed guides or sockets within a pre-constructed foundation (Environment Agency 2011). Temporary and demountable flood protection (TDFP) are usually cheaper than permanent structures and can be deployed and then removed, stored and re-used when and where needed. These characteristics led the UK National Flood Resilience Review (Cabinet Office, Department for Environment, Food, and Rural Affairs 2016; Ball et al. 2012; Hewett et al. 2020; Booth and Gleed 2024) to recommend the use of TDFP to improve the resilience of infrastructure to flooding.

Despite these advantages, a substantial compromise of the flexibility offered by TDFP is the lead time to deploy and erect them. TDFP strategies are therefore most effective where several hours of advance warning can be provided, such as tidal surges, coastal flooding and slower-onset river flooding. They are generally unsuitable for rapid-onset events such as flash floods where warning times may be measured in minutes rather than hours (Woolhouse 2017). Planning and logistics are therefore as crucial as structural design to ensure their effective use. TDFP are increasingly used in town centres because they provide a balance between managing flood risk and enabling river access and amenity for most of the year. However, their use for infrastructure protection has been limited for a number of reasons (Shirvani et al. 2021; Nofal and van de Lindt 2020; Environment Agency 2011):

- Sufficient warning time is required for the TDFP to be fully deployed.
- Temporary barriers are bulky and require sufficient storage space, which costs money.
- The storage site, and the route between storage and infrastructure assets, must remain accessible at all times.
- Infrastructure assets are distributed, so either multiple storage sites are required, or individual sites may need to serve multiple assets across a region.

Regional flood risk managers need to balance costs, such as the location and size of TDFP storage warehouses, while maximising the coverage of protection provided to as many dispersed infrastructure assets as possible. The number of possible strategies to store and deploy TDFP grows combinatorially with the number of infrastructure assets, making it impractical to solve precisely how best to balance competing objectives. To address this, a Spatial Resource Allocation Optimisation (SRAO) methodology has been developed (Lopane et al. 2023) and used here to identify optimal strategies to store and deploy TDFP resources. Specifically, this paper demonstrates how the SRAO can be applied to identify optimal locations for storing temporary flood protection to minimise cost and maximise accessibility to infrastructure assets. Following a thorough review of the literature, no previous development and application of a spatial optimisation algorithm to address this problem has been found.

After this introduction, the SRAO framework's formulation is described (Section 2), the approach is then applied to a case study in the Humber Estuary (UK) (Section 3), followed by discussion (Section 4) and conclusions (Section 5).

2 | The SRAO Framework

2.1 | Conflicting Objectives in the Location-Allocation Problem

Real-world decisions typically involve multiple, often conflicting, objectives that must be considered. In such circumstances, traditional single-objective optimisation approaches fall short, as they fail to capture the trade-offs inherent in multi-objective systems. Our work is situated within this context, where the goal is not to find a single optimal solution, but rather a diverse set of solutions that represent the best possible compromises across all objectives. This approach enables decision-makers to evaluate various options and consider the most appropriate balance of each objective.

In this study, we consider the problem of where to allocate storage space for emergency resources across a geographical area. Decision-makers must determine where to locate storage facilities and how many resources they need to hold (i.e., their size). This determines how rapidly resources can be deployed in response to emergencies across one or many infrastructure sites to provide the best possible coverage. The benefits of infrastructure protection must be balanced against the time required to deliver emergency resources to where they are needed, and the overall cost of the emergency resource allocation strategy. Having many storage sites provides better coverage and allows emergency resources to rapidly reach the places where they are needed, whereas a single site will be cheaper but more distant infrastructure may not be effectively protected. These two objectives—minimising deployment time and minimising costs—are inherently in conflict. Our optimisation framework is designed to explore this trade-off space and identify a set of non-dominated solutions, collectively forming the Pareto front (Figure 1).

A large number of optimisation algorithms are available (Gunantara 2018; Ojha et al. 2019; Sharma and Kumar 2022). Genetic algorithms (GAs) have been identified as the most effective method for resource allocation problems that need to balance multiple competing spatial objectives (Xiao et al. 2007; Sidiropoulos and Fotakis 2009; Caparros-Midwood 2015; Chandra et al. 2021; Liu et al. 2022). The SRAO framework developed here comprises six key components: (1) Initialisation: the algorithm begins by processing input data and generating an initial population of potential solutions. In GA terminology,

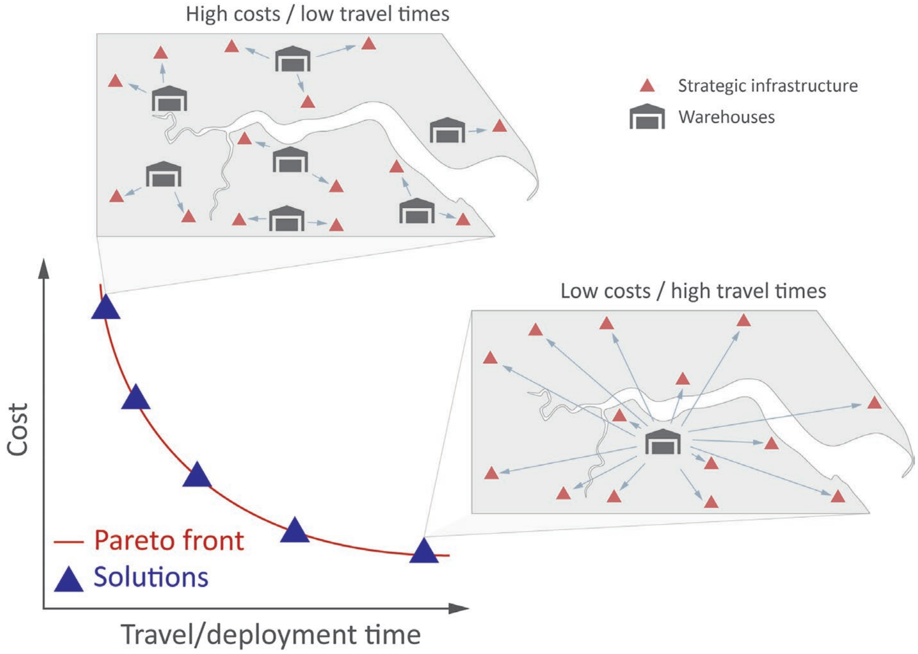

FIGURE 1 | Location-allocation problem and interpretation of Pareto front solutions.

a 'population' refers to a set of potential solutions (in this case, spatial plans for warehouse locations) that are evaluated and evolved through successive generations to identify optimal configurations. (2) Iterator: this component governs the iterative process of solution refinement through multiple generations. The Iterator includes (3) Evolutionary operators: genetic mechanisms such as selection, crossover and mutation to efficiently explore and evaluate the parameter space and (4) Constraints: problem-specific limitations or rules are enforced to ensure that only feasible solutions are retained and evaluated. (5) Multi-Objective Pareto Optimal Set: a set of non-dominated solutions is maintained to balance trade-offs among multiple conflicting objectives. (6) Output: the algorithm returns the final Pareto front or selected optimal solutions as the result of the search process (Figure 2).

2.2 | Initialisation

Both vector and raster datasets can be used as inputs to model the geographies and constraints of the case study area. This enables a wider transferability and scalability of the methodology to different locations and scales. A series of physical constraints are taken into account to model natural features (e.g., rivers) and practical constraints (e.g., distance from roads—see Section 3.2.1) to generate an availability raster where cells are defined as 'available' if they meet all the constraints. The outcome is a georeferenced GeoTIFF raster image used to generate a lookup table of available locations. Lookup tables are useful tools to improve the efficiency (and consequently reduce run times) of the whole framework primarily by reducing the variable dimensions (Figure 3a).

Distance along road networks is calculated using the Network Analysis Module using NetworkX (Hagberg et al. 2008). Distance is converted to travel times based on the free flow speed along the network according to the specified road classification and indicative speed provided by Ordnance Survey (2025). To improve the computational efficiency of the optimisation, a 'Distance Lookup' table for all journeys in the study area is pre-processed.

The SRAO is seeded with a combination of randomly and k-means generated initial spatial plans. Here, 20% of the population is randomly generated, such that warehouse locations can be assigned to any available grid cell. To avoid impractical plans that have warehouses located in directly adjacent or very nearby cells, warehouses must be at least 10 km network distance away from each other.

To improve the efficiency of the initialisation (Irfan et al. 2017), a k-means clustering process has been implemented to seed the algorithm with spatial plans that are spread out across the case study area. *K*-means clustering is an unsupervised machine learning (ML) technique aimed at partitioning a series of *n* data into *k* clusters. The SciKit-learn (Pedregosa et al. 2011; Buitinck et al. 2013) open-source Python module is used to perform a k-means clustering of all the available locations to find the centroids of these clusters. The number of k-means clusters calculated corresponds to the number of warehouses under consideration. For each cluster, the 50 nearest grid cells by travel time that are not subject to other constraints are then denoted as possible warehouse locations for the spatial plans generated in this initialisation stage. This ensures that the SRAO always considers strategies with warehouses spatially distributed according to distance, which in many situations reduces the number of generations required (Molla et al. 2022). An Initial Population of solutions is then generated in the Initialisation phase, corresponds to $\text{parents}_{g=0}$ in the Iterator phase described in Section 2.3. The population is made of individuals that represent singular spatial plans, and it represents the initial parent set from which subsequent generations are created.

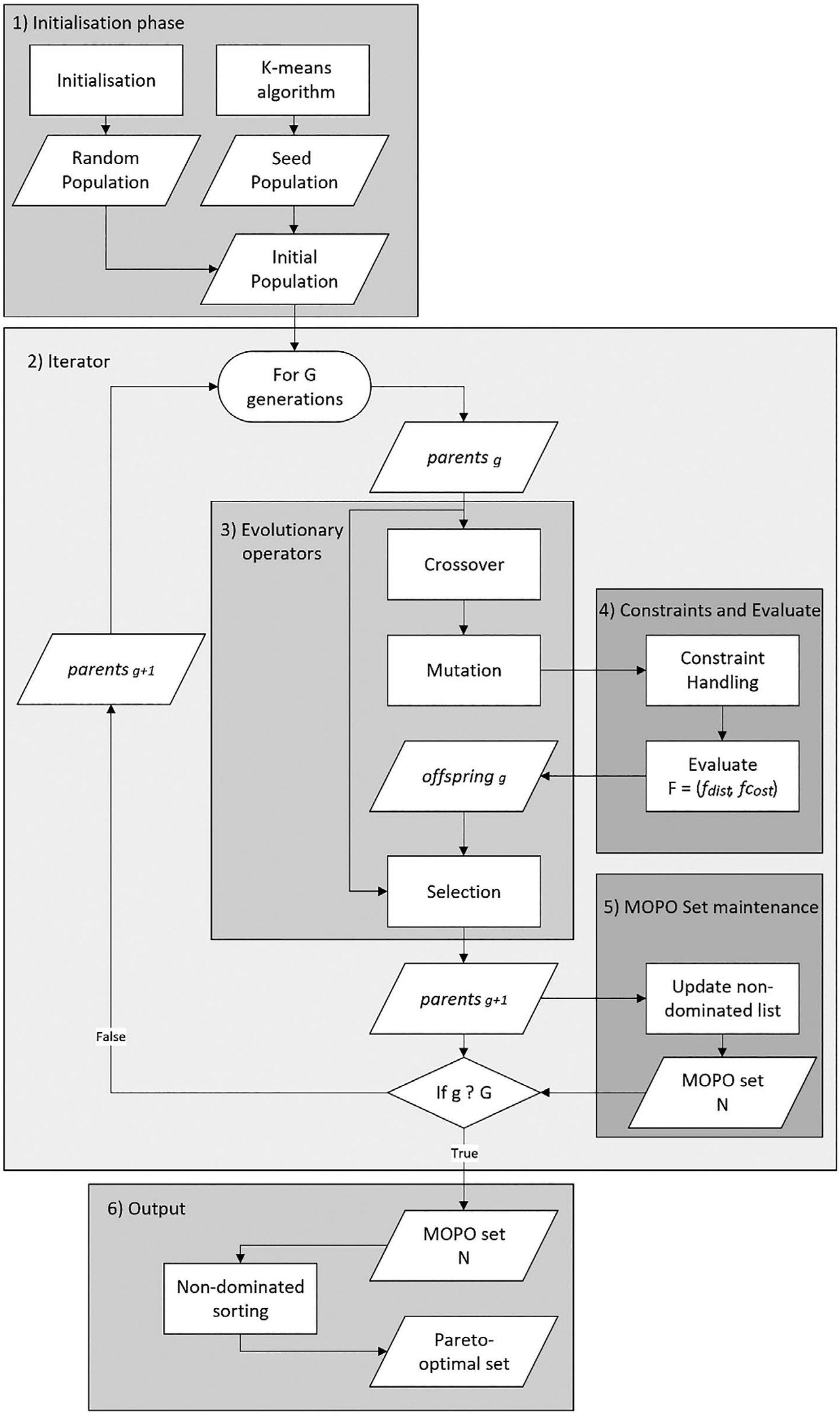

FIGURE 2 | SRAO framework flowchart. (1) Initialisation phase, (2) iterator, (3) evolutionary operators, (4) constraints and evaluate, (5) MOPO set maintenance and (6) output.

2.3 | Iterator

The iterator comprises three components: (i) the application of the evolutionary operators, (ii) the evaluation phase with the application of constraints and (iii) the Multi-Objective Pareto-Optimal set maintenance. These operations are repeated for a number G of generations. Each generation has a parent set (parents_g), with the Initialisation stage producing $\text{parents}_{g=0}$. The child set (offspring_g) is generated from parents_g by the application of the crossover and mutation evolutionary operators. The next generation, parents_{g+1}, is created by applying the selection evolutionary operator to offspring_g.

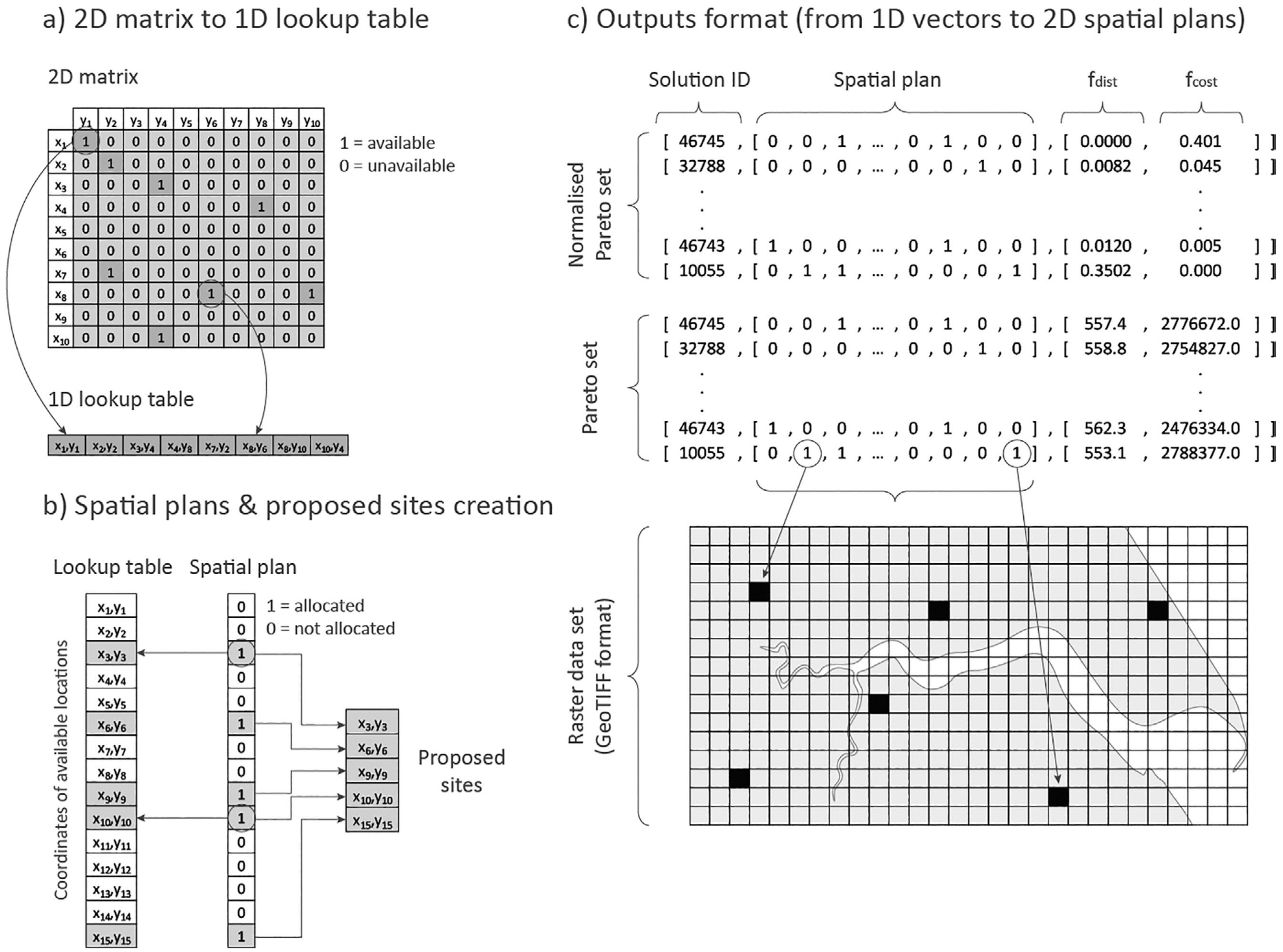

FIGURE 3 | (a) Lookup table creation from 2D matrix; (b) creation of spatial plans and proposed sites and (c) generation of solutions.

Each set of parents_g and offspring_g contains several spatial plans; each spatial plan is a potential solution S. To generate new solutions that efficiently explore the solution space and avoid converging on local optima (Rothlauf 2011), the evolutionary operators of crossover and mutation are applied to each spatial plan with a user-defined probability $p_{\text{crossover}}$ and p_{mutation} using the Mu-plus-Lambda strategy (Mitchell 1998). A two-point crossover operator (Figure 4a) has been applied which cuts two solutions, S^1 and S^2, in two points, cx_1 and cx_2, randomly chosen such that $0 < cx_1 < cx_2 < L$ (where L = length how of S^1 and S^2), and swaps the spatial plans' sections between, cx_1 and cx_2. The mutation operator (Figure 4b) is applied to those solutions on which the crossover has not been applied. In this process, a mutation of a randomly selected i, j location transforms the solution S into the new solution S'. Specifically, the mutation operator selects a random grid cell location and changes its value—if that location is empty (0), it assigns a warehouse (1) or if it already contains a warehouse (1), it changes it to empty (0). This operator has two advantages as it can improve the performance of a solution against one or more objectives and prevents convergence on local optima by introducing permutations at each generation.

Finally, the selection operator is applied to identify the best performing solutions from parents_g to provide a new set of solutions used in the next iteration: offspring_g. The Non-dominated Sorting Genetic Algorithm II (NSGA-II) (Deb et al. 2002) is applied to identify the best performing solutions against the optimisation criteria (see Sections 3.2.2 and 3.2.3 for more details on the optimisation functions). NSGA-II is more efficient at evaluating the Pareto front for multi-objective objective problems than other algorithms (Zhang and Fujimura 2010), and has been proven effective in other spatial problems (Jaeggi et al. 2008; Cao et al. 2011; Caparros-Midwood et al. 2017; Chai and Liang 2020; Lin and Hsieh 2022). The Iterator is repeated until the Pareto front, $\sum F(f_{\text{dist}}, f_{\text{cost}})$, does not change by more than 0.5% over 10 generations. Testing established that 50 generations was more than enough to observe convergence in the presented case study.

2.4 | Constraints and Evaluation

The nature of the evolutionary operators in the GA can create solutions that breach physical constraints. This can include allocating warehouses in places they could not be built (e.g., in the estuary), or allocating more or less resources than are available in a given scenario. This step ensures that only feasible spatial plans be considered within the resulting offspring_g solutions (see Figure 4c). Once all the spatial plans within the subsequent generation of solutions meet the constraints, they

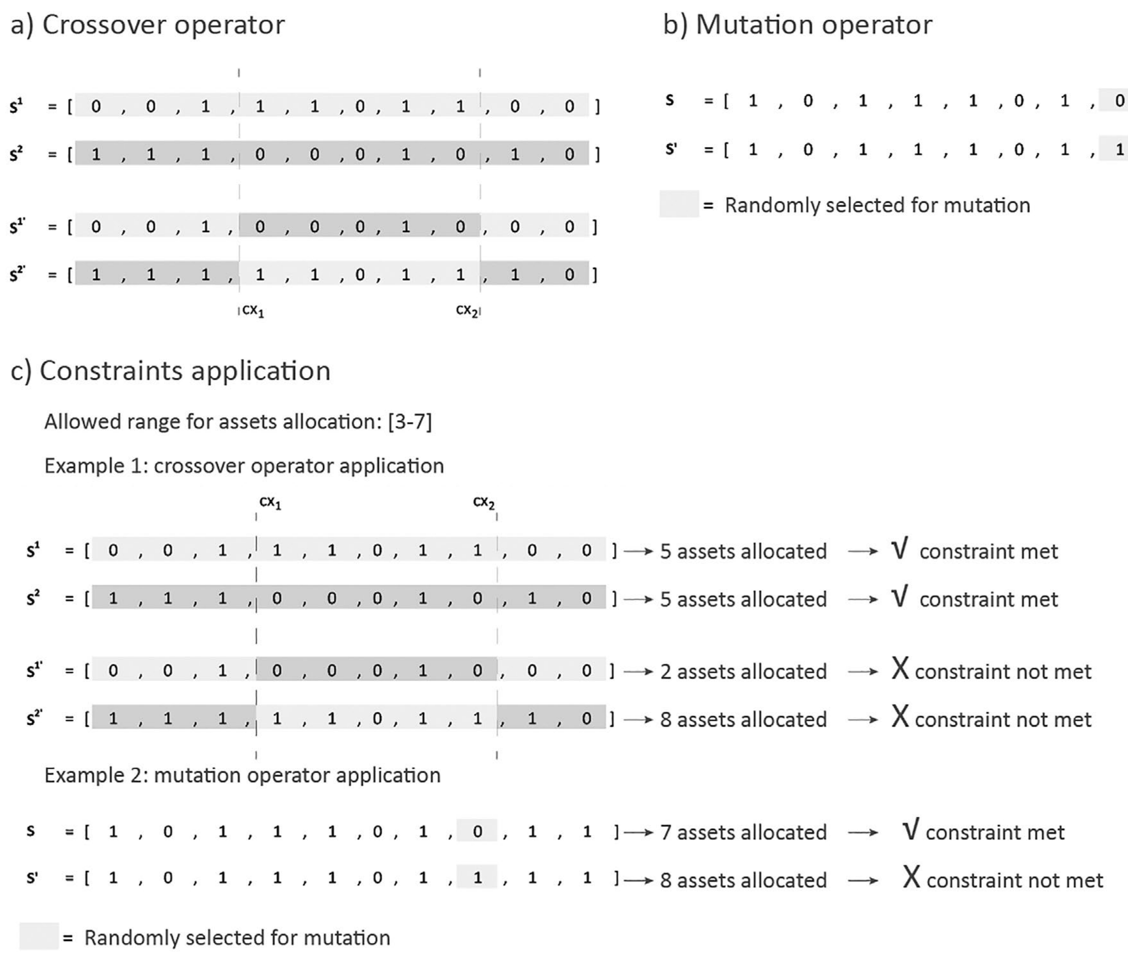

FIGURE 4 | Examples of application of (a) crossover operator; (b) mutation operator and (c) constraints after evolutionary operators.

are evaluated against the objective functions (see Section 3 for the functions used in the case study), and the best-performing ones are selected to form the next generation of solutions, $parents_{g+1}$.

2.5 | Outputs

The optimisation criterion for the output solutions is Pareto efficiency, which is widely utilised in engineering, urban planning and infrastructure optimisation (Vamvakeridou-Lyroudia et al. 2005; Fu et al. 2012; Shu and Durango-Cohen Pablo 2022; Shi et al. 2023). The main advantage of this approach is its independence from any a priori preference (in contrast with other methods like weighted sums). In a multi-objective optimisation problem, a solution is defined 'Pareto-optimal' based on the concept of domination (Goldberg 1989). A solution is optimal if it is 'non-dominated' by any other solution. Considering a minimisation problem, a solution S^1 is defined as 'non-dominated' by a solution S^2 if S^1 is not worse than S^2 in all objectives and it is strictly better in at least one objective:

$$f_n(S^1) \leq f_n(S^2) \, \forall n = 1, 2, \dots, N \tag{1}$$

$$f_n(S^1) < f_n(S^2) \text{ for at least one } n \in \{1, 2, \dots, N\} \tag{2}$$

where f_n are the N objective functions. After the application of a non-dominated sorting algorithm (Du et al. 2007; Mishra and Harit 2010), the previous equations are applied to all search results, S, to determine a set of non-dominated solutions. Such non-dominated solutions are selected and saved since they are equally Pareto-optimal and no other solution could provide an improvement of one objective without worsening the others.

The Output step produces a number of results to support decision-making. This includes the arrays shown in Figure 3c which provide the raw values of objectives for each solution. Plotting the objectives on a graph allows the Pareto front trade-off between different objectives to be visualised. A raster map showing the layout of each Pareto-optimal spatial plan is created as a GeoTIFF and vector file for GIS compatibility.

3 | Emergency Management in the Humber Estuary

The SRAO framework is applied to the Humber Estuary, on the East coast of England, the case study area spans the boundary between Yorkshire (North bank) and Lincolnshire (South bank). It has been chosen as a case study area because over 400,000 people live within a number of settlements, the largest of which is Kingston upon Hull (Coulthard and Frostick 2010; Hull City

Council 2015; Environment Agency 2016; Lonsdale et al. 2022). There are 133 Strategic Infrastructure (SI) sites, defined here as hospitals, electricity generation and distribution, gas storage and distribution, telecommunication, police and fire stations in the low-lying estuary floodplain.

The Humber Estuary experiences a temperate maritime climate; annual rainfall averages approximately 600–700 mm (Met Office 2019), with precipitation distributed relatively evenly throughout the year, though autumn and winter months typically receive slightly higher rainfall. The estuary's hydrogeological setting presents significant flood vulnerability: it is a low-lying coastal floodplain where five major rivers (Trent, Ouse, Derwent, Aire and Don) discharge into the North Sea, creating a complex interaction between fluvial and tidal flooding mechanisms. Much of the inhabited area lies below the high tide level and the region is particularly susceptible to tidal surge events from the North Sea, which can be exacerbated by storm conditions and high astronomical tides, as demonstrated by the 2013 tidal surge that caused widespread flooding (Environment Agency 2022). Additionally, the flat topography and impermeable clay-rich soils (Ellis and Atherton 2003) contribute to surface water flooding during intense rainfall events. These combined hydrogeological and climatic characteristics make the Humber Estuary one of the most flood-vulnerable regions in the United Kingdom, necessitating robust flood protection strategies for critical infrastructure.

3.1 | Flood Management Context in the Humber Estuary

The Humber Estuary has experienced several significant flooding events in recent decades that have shaped current flood risk management policy. In June 2007, Hull experienced severe flooding from surface water and overwhelmed drainage systems during intense rainfall, affecting approximately 8600 properties (Coulthard and Frostick 2010). This event highlighted vulnerabilities in the city's drainage infrastructure but was predominantly a pluvial (surface water) flooding event rather than tidal.

The most significant recent tidal flooding occurred on 5 December 2013, when a major storm surge affected the east coast of England. The surge coincided with high spring tides, resulting in record water levels of 5.8 m at the Hull Tidal Barrier—the highest ever recorded at this location (Hull City Council 2015). Floodwater breached defences at Albert Dock and other locations, demonstrating the vulnerability of SI despite existing flood protection measures. This event was comparable in magnitude to the catastrophic 1953 North Sea flood, though improved flood defences and warning systems prevented the loss of life experienced in the earlier event.

Emergency management during the 2013 surge involved coordinated multi-agency responses, with Hull City Council working alongside the Environment Agency, emergency services and volunteer organisations to evacuate residents from at-risk areas, deploy emergency equipment and coordinate relief efforts (Hull City Council 2015). The event demonstrated both the effectiveness of emergency response coordination and the limitations of existing flood defence infrastructure.

Current flood risk management policy in the Humber Estuary operates within a strategic framework developed following these events. Since January 2025, the Environment Agency leads the Humber 2100+ programme, a long-term strategy currently being developed involving several local authorities across the Humber catchment to manage tidal flood risk over the next century (Environment Agency 2023).

Significant investment has been made in permanent flood defence improvements, including the £42 million Humber Hull Frontages scheme completed in 2022, which upgraded approximately 7 km of tidal defences along Hull's waterfront to provide protection against a 0.5% annual probability flood event (equivalent to a 1 in 200 year return period) (Environment Agency 2022).

However, budget constraints and the distributed nature of SI across the estuary mean that permanent flood protection cannot feasibly be provided to all vulnerable assets. The National Flood Resilience Review (Cabinet Office, Department for Environment, Food, and Rural Affairs 2016) specifically recommended the use of TDFP as a cost-effective complement to permanent defences, particularly for protecting critical infrastructure assets. TDFP are recognised as an important component of the flood risk management strategy because they offer flexibility to protect multiple sites from a centralised resource base, can be deployed where permanent defences are impractical or cost-prohibitive and can be scaled up or down according to the predicted severity of flood events.

The SRAO framework developed in this study directly addresses the challenge identified in current policy: how to optimally locate and deploy TDFP resources to maximise infrastructure protection while minimising costs.

3.2 | Problem Formulation

The objective of deploying TDFP is to maximise the speed with which it can be deployed at the lowest cost. Here this is achieved through two fitness functions, f, which seek to minimise the time of travel from the storage site(s) to the infrastructure asset(s), f_{dist} and to minimise the cost of the TDFP storage, f_{cost}.

Recommendations by Cabinet Office, Department for Environment, Food, and Rural Affairs (2016) underpin some of the key assumptions of this analysis: (1) Sandbags are not considered, despite their affordability, as they provide a low standard of protection and very limited re-usability; (2) when assessing the suitability of temporary defences, the Environment Agency found that the category of SI protected is a 'less of a determining factor than the size of the site' (Cabinet Office, Department for Environment, Food, and Rural Affairs 2016). For this reason, SI assets are differentiated only on the basis of their footprint rather than their service and (3) TDFP cannot typically provide protection above 1.5–2 m flood depth, so here 1.5 m is used as the reference height of flood defences for the purposes of estimating storage space.

3.2.1 | Land Availability

The case study area has been discretised into a 500 m grid, and the definition of available cells for warehouses happens in the initialisation phase (see Figure 2). Locations are considered to be 'available' if they are (1) within the case study boundaries; (2) on dry land; (3) outside the flood zone; (4) not within protected green areas and/or parks and (5) within 500 m from a road suitable for a large lorry.

The flood zones used in this analysis are derived from DEFRA's 'Flood Risk Areas' dataset (see Table B1—Appendix B), which encompasses multiple flood sources including fluvial (river), coastal (tidal surge from the North Sea), and pluvial (surface water) flooding. These Flood Risk Areas, defined by the Environment Agency for main rivers and coastal waters and by Lead Local Flood Authorities for surface water, represent locations where there is believed to be significant flood risk according to the EU Floods Directive's definition of Areas of Potentially Significant Flood Risk (APSFR). This multi-hazard approach ensures that the spatial optimisation framework accounts for the full range of flood mechanisms relevant to the Humber Estuary, thereby providing robust warehouse location strategies that remain effective across different flood scenarios.

3.2.2 | Travel Time Objective

All the available locations for potential warehouses are potential origins for the journeys required to deliver TDFP to the destinations, which are the sites of existing SI assets. Therefore, while the destinations are predetermined by the case study, the origins are a variable the SRAO framework optimises in Section 3.3.

Distance and travel time are pre-processed for computational efficiency and calculated using the method described in Section 2.2.

The distance function f_{distl} accounts for the number of lorries available to transport TDFP to their destinations to calculate the time for TDFP to reach infrastructure assets:

$$f_{\text{distl}} = \frac{\sum_{i=1}^{SI} 2 \cdot TT_i}{L} \tag{3}$$

where L is the number of available lorries, SI is the total number of strategic infrastructure assets and TT_i represents travel time for each journey from an infrastructure asset i to the closest warehouse. This means that when there are fewer lorries, the travel time increases as lorries are required to make multiple journeys to cover all the infrastructure assets in the service area of a given warehouse.

3.2.3 | Storage Cost Objective

A range of factors influence the cost of building and operating a warehouse, including personnel costs, fleet costs and maintenance costs (Environment Agency 2011). The generalised formulation for cost is (Hendrickson 1989; Ramos 2017; Mishra 2021):

$$f_{\text{cost}} = W_{\text{h}} + R_{\text{s}} \tag{4}$$

where W_h is the cost associated to warehouses, and R_s is the cost associated to emergency resources. According to the conducted market analysis (see Figure A1), the average ground rent for a warehouse in the region is £55/m^2 (US\$75/m^2), but this does not reflect whether the location is urban, suburban or rural, nor does it include operational costs. Two continuous functions are used. The first is a linear function that uses this average rent value multiplied by warehouse area. The second is a logarithmic function which provides the best fit (lowest R^2 value) to the actual rent prices for warehouses in the region (Figure A1).

The generalised cost equation is decomposed into capital and operational costs (see Appendix A for more details on the cost function's formulation), to get to the final equations, respectively, for linear and non-linear formulations:

$$f_{cost} = \begin{cases} \sum_{i=1}^{W} f_i \cdot p_i + m_w + p_b \cdot l_{ab} + hp \cdot n_p \cdot n_h + p_t \cdot n_t + m_r & \text{linear} \\ \sum_{i=1}^{W} (\alpha \cdot \ln(f_i) + \beta) \cdot p_i + m_w + p_b \cdot l_{ab} + hp \cdot n_p \cdot n_h + p_l \cdot n_l + m_r & \text{non-linear} \end{cases} \tag{5}$$

where f_{cost} represents the total cost of warehouses and emergency resources; W is the total number of warehouses; f_i is the floor space of the ith warehouse (m^2); p_i is the annual rental price per square metre of ith warehouse; α and β are the parameters of the logarithmic equation (regression from Yorkshire rent prices); h_p is the hourly pay for personnel; n_p is the number of workers for strategic resources' deployment; n_h is the number of working hours for deployment and removal of temporary defences; p_l is the rent price of a single lorry and n_l the number of additional lorries to existing fleet; m_w represents the warehouses' maintenance costs; m_r represents the emergency resources' maintenance costs; p_b is the unitary price of demountable barriers (£/m) and l_{ab} is the total length of demountable barriers purchased. The annual rental price per square metre of each warehouse is scaled according to the rural, suburban or urban price differential. Consequently p_i assumes different values according to which scenario the user considers:

$$p_i = \begin{cases} p_{av} & \text{average rent price} \\ p_{av} \cdot \gamma_u + p_{av} \cdot \gamma_r & \text{urban} + \text{rural} \\ p_{av} \cdot \gamma_u + p_{av} \cdot \gamma_s + p_{av} \cdot \gamma_r & \text{urban} + \text{suburban} + \text{rural} \end{cases} \tag{6}$$

where p_i is annual rental price per square metre of ith warehouse, p_{av} is average rent price of the case study; γ_u is the multiplier for urban areas; γ_r is the multiplier for rural areas; γ_s is the multiplier for suburban areas. The multipliers γ_u, γ_r and γ_s have been assumed, respectively, as 2.0, 1.0 and 1.5; implying that urban locations cost twice as much as rural ones, with suburban values in the middle.

In the United Kingdom, specialised workers who deploy temporary flood barriers are full-time employees who are called during emergencies, even outside their normal working hours (Environment

Agency 2011) so n_p is assumed to be 0. However, these costs can be considered in different regions or for different scenarios.

Different types of TDFPs are available; Environment Agency's (2011) appendix provides prices for different typologies of TDFPs ranging from £12,000/100 m to £50,000/100 m according to height, material and storage system. The price, p_b, of the TDFP is a one-off, rather than annual, cost and can be set accordingly. For the purposes of this case study, it was assumed sufficient TDFP is available to protect all the infrastructure assets allocated to each warehouse by the optimisation algorithm. Purchase of additional new equipment was not required. Parameter p_l is assumed as £2520 (US$3400) for annual costs of truck and telehandler hire (Keating et al. 2015). Warehouse maintenance cost m_w is assumed to be 20% of the capital cost paid on top of the rent and includes property taxes, property insurance and CAM (common area maintenance).

3.2.4 | Prioritisation of Critical Assets When Budgets Are Constrained

To reflect a possible cap in available funding an additional criterion was applied to some scenarios. This criterion involves prioritising the protection of infrastructure assets based on their importance and the number of buildings they serve. Specifically, only the Top 3, 5 or 10 assets are protected for each infrastructure sector. This prioritisation is intended to ensure that the assets considered most critical receive protection when resources are limited. Here, criticality is determined by the number of buildings they serve, providing a proxy for the asset's importance in the infrastructure network. Where data on the number of buildings served by each asset could not be provided by utility operators, Thiessen polygons were used to estimate service areas. The sensitivity of optimal warehouse sites to the location of critical assets can be assessed.

3.2.5 | Scenarios

The SRAO was implemented in the Humber Estuary case study and eight scenarios summarised in Table 1 were evaluated. This allowed the sensitivity of the optimisation to important assumptions to be understood. Results for three of the eight scenarios (shown in Table 2) are reported in more detail to highlight key features of the different approaches (Figures 6–8).

TABLE 1 | Range of combinations of variables used in the scenario analysis.

SRAO variable	Scenario option
f_{cost}	• Linear • Logarithmic
f_{dist}	• Travel time • Number of lorries (L): 0.5, 1, 2, 3 per warehouse
Strategic Infrastructure (SI) prioritisation	• All SI are protected with equal importance • Only the Top 3, Top 5 or Top 10 SI assets per infrastructure sector are protected

3.3 | Optimal Locations for TDFP

The objective function values are calculated for each solution produced by the SRAO and plotted against each other. Figures 6–8a plot all evaluated solutions at each generation and the final Pareto front for a particular scenario. With each generation, the solution set gradually moves the Pareto front as solutions that perform better against the objectives are identified by the SRAO. Each of the solutions on the Pareto front is optimal in that for any given f_{dist} no better f_{cost} can be achieved and vice versa. A decision-maker can explore these solutions and consider the most appropriate trade-off between these two objectives.

Figures 6–8b–d show the spatial configurations of three optimal solutions, taken from the pareto front, for storing TDFP for different scenarios. In each case Solution (A) is from the top-left side of the front (generally higher costs and lower travel times), Solution (B) from the middle (a balance of cost and travel times) and Solution (C) from the bottom-right side (generally lower costs and higher travel times). The (A) solutions in Figures 6–8 have more warehouses as they prioritise asset coverage and lower travel times over cost. The Figures also show the warehouse size, average and maximum travel times to the infrastructure assets they serve. Some of the solutions show warehouses providing TDFP to assets on both sides of the estuary; this may seem unintuitive but is enabled by the Humber Bridge (Figure 5).

3.4 | Trade-Offs Between Costs and Benefits of TDFP Scenarios

Figure 9 shows the Pareto fronts for the selection of scenarios in Table 2. In almost all the scenarios, the Pareto fronts transition from very steep to very shallow. The former signifies part of the solution space where high investment in storage returns little benefit in terms of deployment time; the latter signifies a rapid loss of deployment time (to cover all infrastructure assets) for only modest reductions in cost. For all scenarios, the optimisation is able to identify solutions that substantially improve overall performance.

The Pareto fronts of Scenarios 2–5 in Figure 9 show the variations in terms of costs and travel times when varying the number of lorries. While the range of costs remains comparable, travel times are significantly decreased when the fleet is larger. This suggests that travel times are more of a driving factor in determining Pareto-optimal solutions for this particular region. The Pareto fronts of Scenarios 6–8 in Figure 9 represent scenarios that take a risk-based approach to prioritising investment by ranking the importance of the asset in terms of people served and targeting protection at those assets. When the Top 10 assets are protected, costs are only reduced by a little, and an estimation of 4% of households is not protected against flood disruption to infrastructure services. Costs are more substantially reduced if only the Top 5 assets

TABLE 2 | Summary of selected scenarios reported in detail.

Scenario ID	Scenario name	Cost function	Number of lorries	SI priority
1	L-Fix10-All	Linear	Fixed: 10	All the SI
2	NL-Var0.5-All	Non-linear	Variable: 1 lorry every 2 warehouses	All the SI
3	NL-Var1-All	Non-linear	Variable: 1 lorry per warehouse	All the SI
4	NL-Var2-All	Non-linear	Variable: 2 lorries per warehouse	All the SI
5	NL-Var3-All	Non-linear	Variable: 3 lorries per warehouse	All the SI
6	NL-Var1-Top3	Non-linear	Variable: 1 lorry per warehouse	Only Top 3
7	NL-Var1-Top5	Non-linear	Variable: 1 lorry per warehouse	Only Top 5
8	NL-Var1-Top10	Non-linear	Variable: 1 lorry per warehouse	Only Top 10

Note: In the scenario names, 'L' stands for linear, while 'NL' stands for non-linear cost function; 'Fix10' or 'Var#' indicates either a fixed (10) or a variable number of lorries (# per warehouse); 'All' or 'Top' indicates if all the infrastructure assets are considered or only the top#.

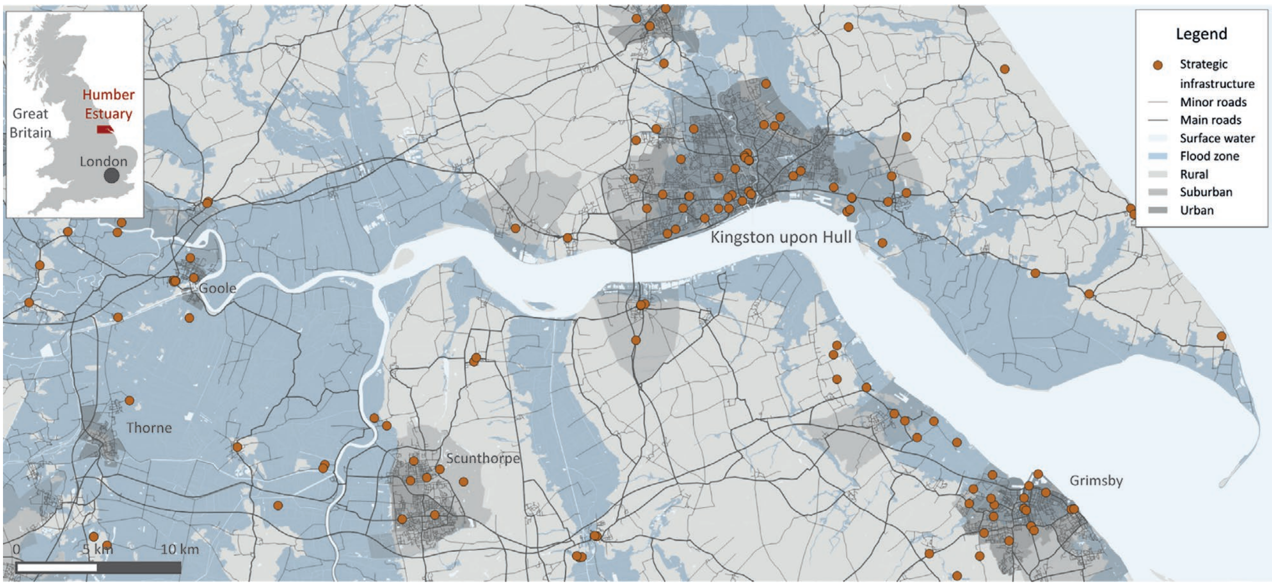

FIGURE 5 | The Humber Estuary case study showing the strategic infrastructure sites identified for protection.

are protected, and more than halved if only the Top 3 assets are protected. However, this comes at the penalty of 20% and 37% of people being left vulnerable to flood disruption of infrastructure services respectively. This information provides decision-makers with a better understanding of the implications of insufficient budget to protect all assets.

4 | Discussion

There is no published TDFP strategy for the Humber Estuary, so the SRAO results cannot be directly compared with an existing strategy. However, the range of Pareto-optimal solutions identified by the SRAO demonstrates the magnitude of trade-offs facing decision-makers. Across the scenarios presented in Figure 9, solutions at the cost-optimised end of the Pareto front typically achieve costs approximately 40%–50% lower than time-optimised solutions, while time-optimised solutions achieve deployment times 60%–70% faster than cost-optimised alternatives. The location of the Pareto front shifts in the solution space according to the scenario's assumptions. For instance, more available lorries reduce deployment times, shifting the Pareto front to the left—and vice versa.

To evaluate the effectiveness of the framework, the improvements to the objectives are considered as well as the spatial structure of the solutions. We examined the progression of the search process by comparing the quality of the Pareto fronts obtained at different stages of the evolutionary run. To quantify the improvement in performance of the multi-objective evolutionary algorithm over the course of 50 generations, the change in the hypervolume indicator (Zitzler et al. 2003) for the Pareto fronts between generation 1 and 50 is calculated (Table 3). The hypervolume measures the area in the normalised objective space dominated by the Pareto front with respect to a fixed reference point. Here, this is defined as 10% larger than the largest values of f_{cost} and f_{dist} across all scenarios; the hypervolume thereby increases as solutions move closer to the origin.

Table 3 shows that, while the percentage gains in hypervolume over 50 generations range from under 1% to around 12%, these seemingly modest improvements conceal more substantial

TABLE 3 | Improvements in global performance (measured in terms of the hypervolume) and individual objectives (defined in Section 3.2.5) between generation 1 and 50 of the SRAO for Scenarios 1–8 (defined in Section 3.2.5).

Scenario		Hypervolume			Maximum objective improvement	
ID	Name	$g=1$	$g=50$	Hypervolume improvement (%)	f_{dist} (min)	f_{cost} (£/year)
1	L-Fix10-All	0.527	0.532	0.96	35	0
2	NL-Var0.5-All	0.778	0.864	11.02	97	30,545
3	NL-Var1-All	0.846	0.930	10.03	39	23,512
4	NL-Var2-All	0.880	0.963	9.44	25	20,094
5	NL-Var3-All	0.867	0.974	12.30	20	20,089
6	NL-Var1-Top3	1.185	1.206	1.78	57	3459
7	NL-Var1-Top5	1.070	1.119	4.63	57	10,007
8	NL-Var1-Top10	0.909	0.991	9.03	16	22,560

benefits to each objective. The greatest improvement in deployment time exceeds 1.5 h; with some flood warning issued at only 2-h notice (Clark 2017) this reduction can make a real difference to the resilience of infrastructure services. Similarly, the maximum improvement to the cost objective could reduce annual storage expenditure by tens of thousands GBP/year; across multiple regions and years these savings add up to tangible benefits for tax and utility bill payers. Thus, even small global improvements in the Pareto front provide material improvements in response time, budget or both.

The computational time of the SRAO is primarily determined by the complexity of the model being analysed, which includes factors such as scale, resolution and the number of variables involved. The scenarios presented in this paper were executed on a laptop equipped with 32.0 GB of RAM and an 11th Generation Intel Core i7 processor; the running time for 50 generations ranged from 6 to 18 min according to the scenario.

Despite some visual similarity among the Pareto solutions mapped in Figures 6–8, the comparison of Pareto fronts plotted in Figure 9 shows the trade-off between costs and accessibility for each solution can vary significantly. An important factor is the influence of land value; locating a warehouse just outside an urban area might slightly increase f_{dist}, but considerably decrease the warehouse costs. Thus, it is crucial for decision-makers to always adopt a holistic view and consider costs, protection and spatial structures when interpreting these results and proposing strategies for TDFP.

Interestingly, all the solutions in Figures 6–8 have a large warehouse in, or at the periphery of, the main town of the region, Kingston upon Hull. This location is advantageous as a cluster of SI assets is present in this densely populated area. Less intuitive is the allocation of a warehouse in the most eastern part of the estuary where fewer assets are located. Solutions that do not allocate a warehouse here would require large travel times to transport and deploy TDFP, making them less desirable. These are penalised even more for scenarios that have a limited number of trucks available that would require multiple trips to deploy TDFP to protect all the assets.

This spatial complexity is captured in Figure 10 which plots a heatmap of the spatial allocation of warehouses across all the Pareto optimal solutions for Scenarios 1–8. This identifies eight significant hotspots where the spatial optimisation consistently identifies warehouses should be sited in most of the scenarios. In Hedon, Withernsea, Scunthorpe and Goole/Drax, warehouses are located in more than 70% of all the Pareto solutions, while Kingston upon Hull, Grimsby, Brigg and Hatfield are identified in over 60% of Pareto solutions. This provides important insights for decision-makers as siting warehouses in these locations should be robust choices. Even if assumptions, such as the availability of lorries, turn out to be incorrect, the locations still provide a good balance between costs and coverage. Furthermore, the SRAO is shown to be able to provide a number of other insights, such as demonstrating how when there is a fixed budget—protection can be prioritised for the most important assets in terms of service provision (i.e., Scenarios 6–8). For Scenario 6 this would allow savings of up to £75k/year, although 37% of people would have unprotected infrastructure services.

The SRAO framework and findings from this case study have immediate practical relevance to the implementation of the emerging Humber 2100+ strategy (Environment Agency 2023). £150 million has already been invested in permanent defences since 2008, but more is required to ensure long-term resilience across the estuary. As the partnership develops their long-term approach to managing tidal flood risk across the estuary, the SRAO offers an effective tool to support the development of a TDFP strategy to support flood risk management in the region.

The SRAO's ability to analyse a wide range of scenarios (Section 3.4) supports the adaptive management approach embedded in the Humber 2100+ framework, which emphasises flexibility and review points to respond to changing circumstances. Decision-makers can use the SRAO to test how optimal TDFP deployment strategies would evolve under different future scenarios; for example, if certain areas receive additional permanent defences, if flood warning systems were able to provide longer lead times, if new infrastructure developments emerge, or if budget allocations shift, thereby ensuring that

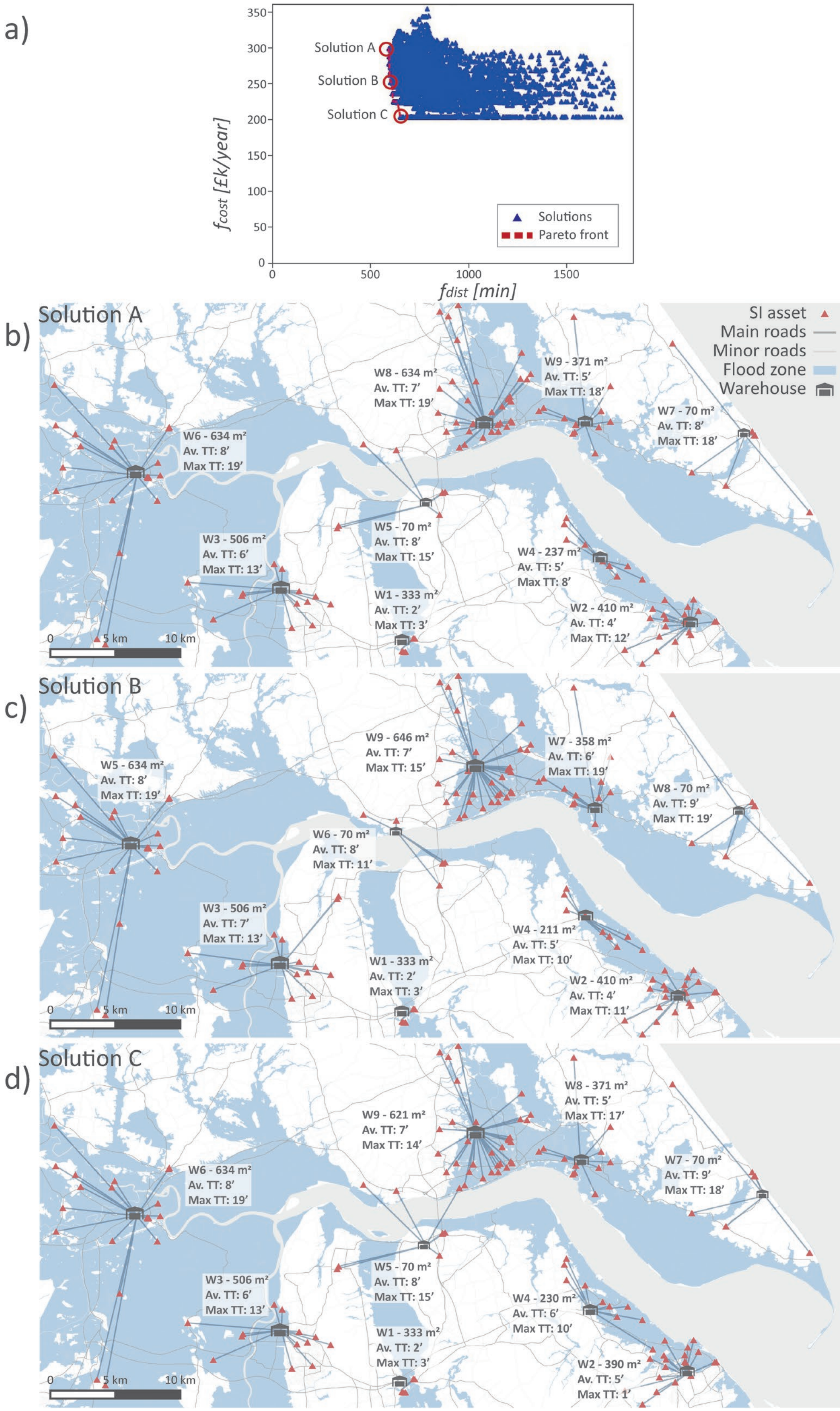

FIGURE 6 | Humber Estuary Scenario 1 (L-Fix10-All). (a) Pareto front and solutions tested by the SRAO. (b–d) Maps showing the three highlighted solutions, where the blue straight lines are for visualisation purposes to show which warehouse has responsibility for storing the TDFP for each infrastructure asset. They do not represent distance, which is calculated over the road network.

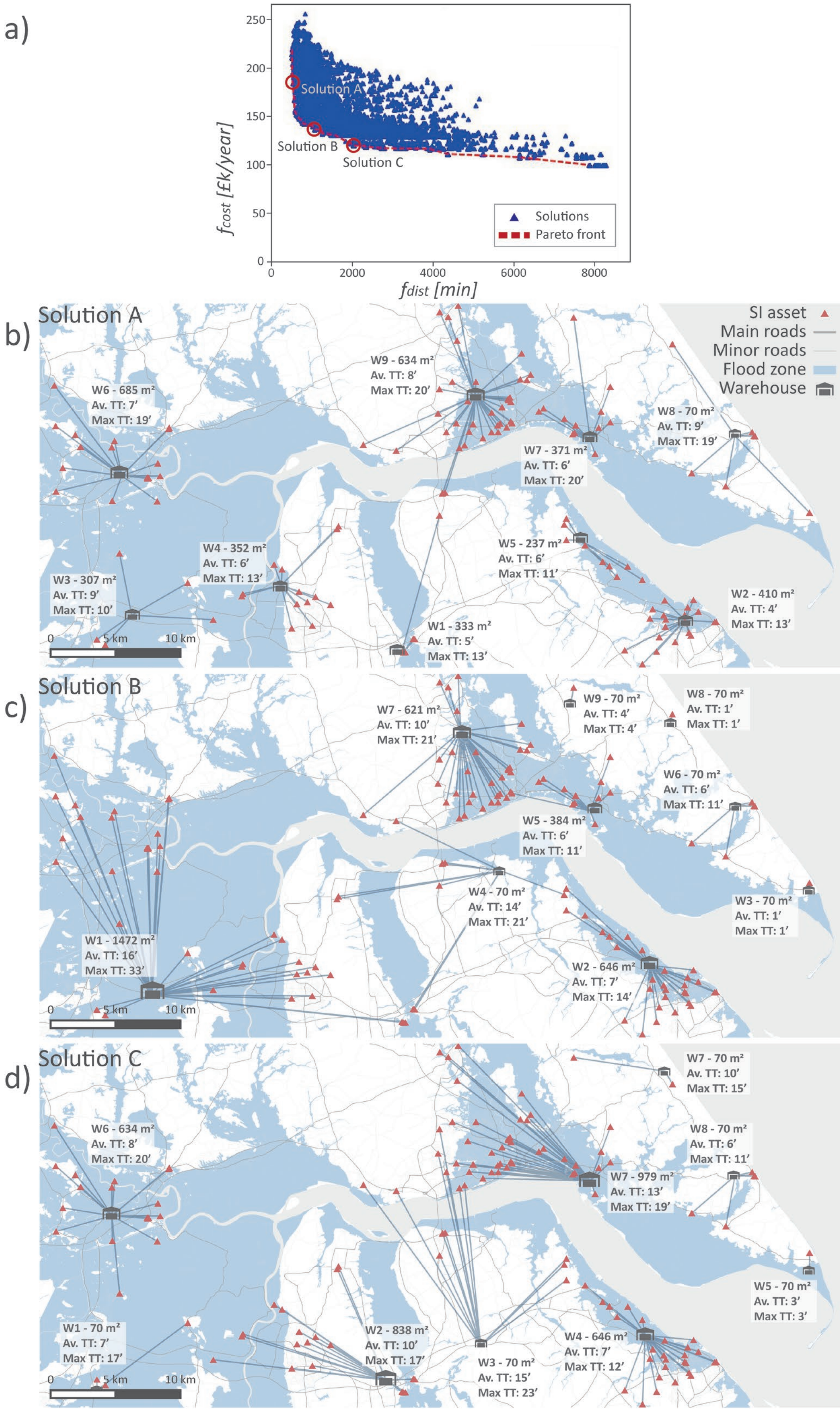

FIGURE 7 | Humber Estuary Scenario 3 (NL-Var1-All). (a) Pareto front and solutions tested by the SRAO. (b–d) Maps showing the three highlighted solutions, where the blue lines are for visualisation purposes to show which warehouse has responsibility for storing the TDFP for each infrastructure asset. They do not represent distance, which is calculated over the road network.

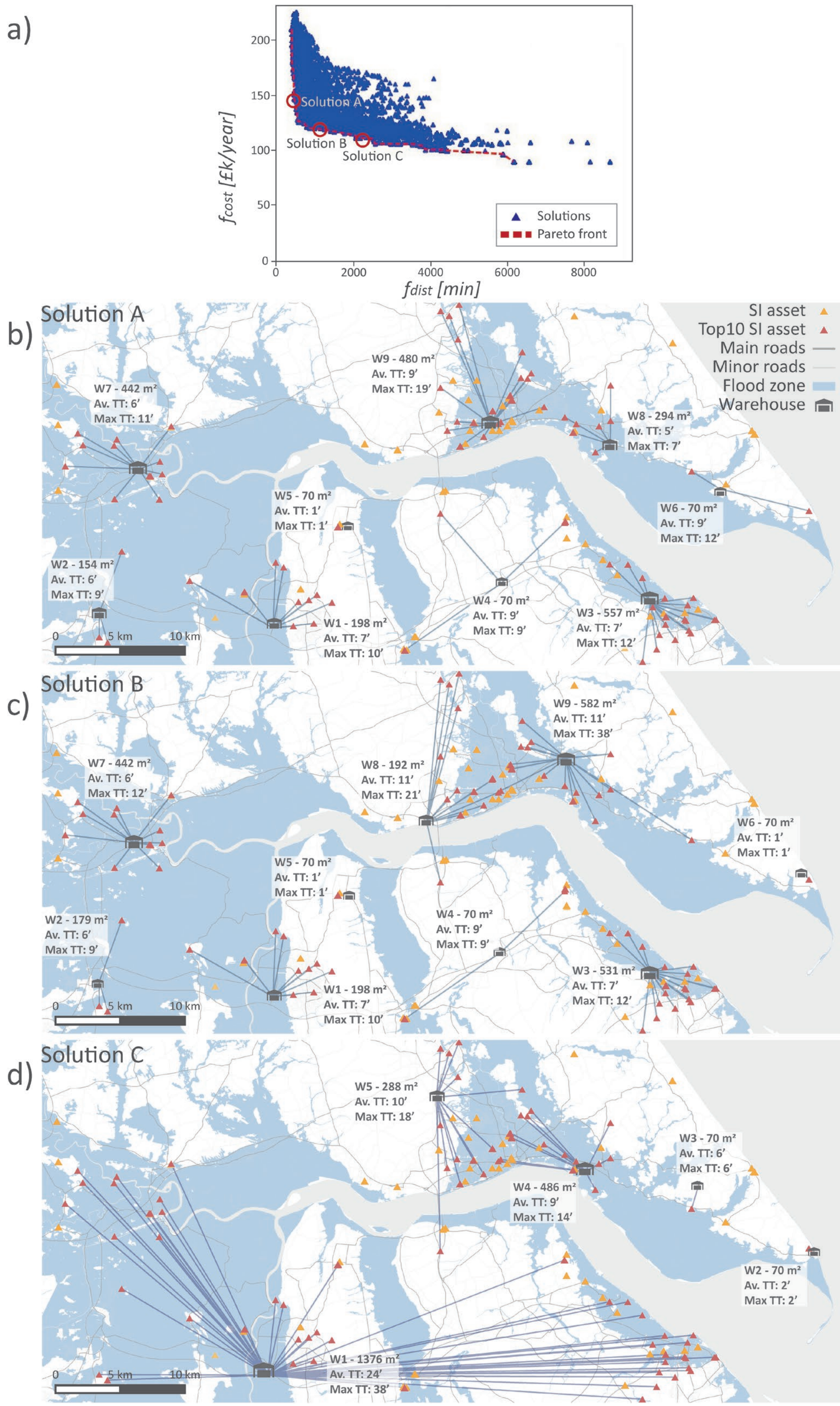

FIGURE 8 | Humber Estuary Scenario 8 (NL-Var1-Top10). (a) Pareto front and solutions tested by the SRAO. (b-d) Maps showing the three highlighted solutions, where the blue straight lines are for visualisation purposes to show which warehouse has responsibility for storing the TDFP for each infrastructure asset. They do not represent distance, which is calculated over the road network.

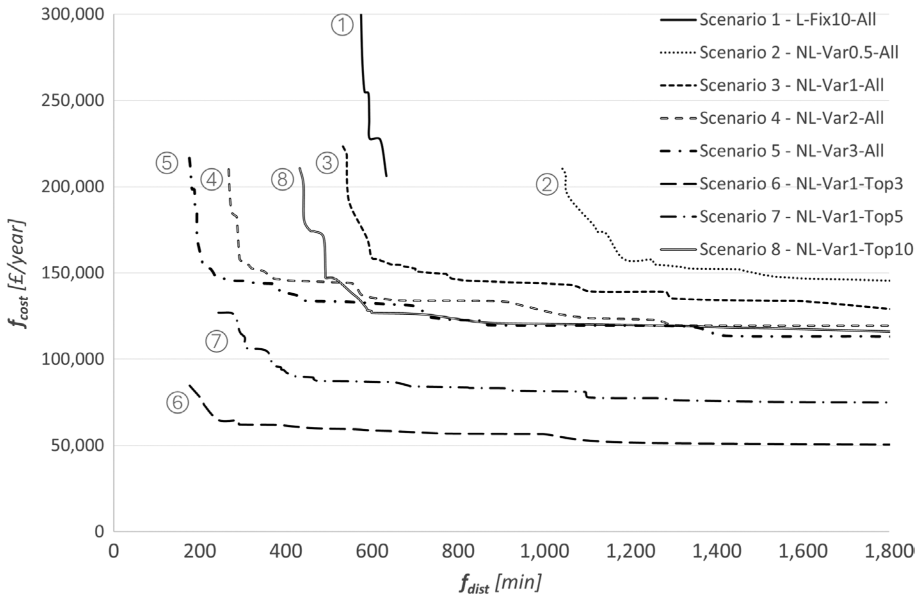

FIGURE 9 | Comparison of Pareto fronts of different scenarios.

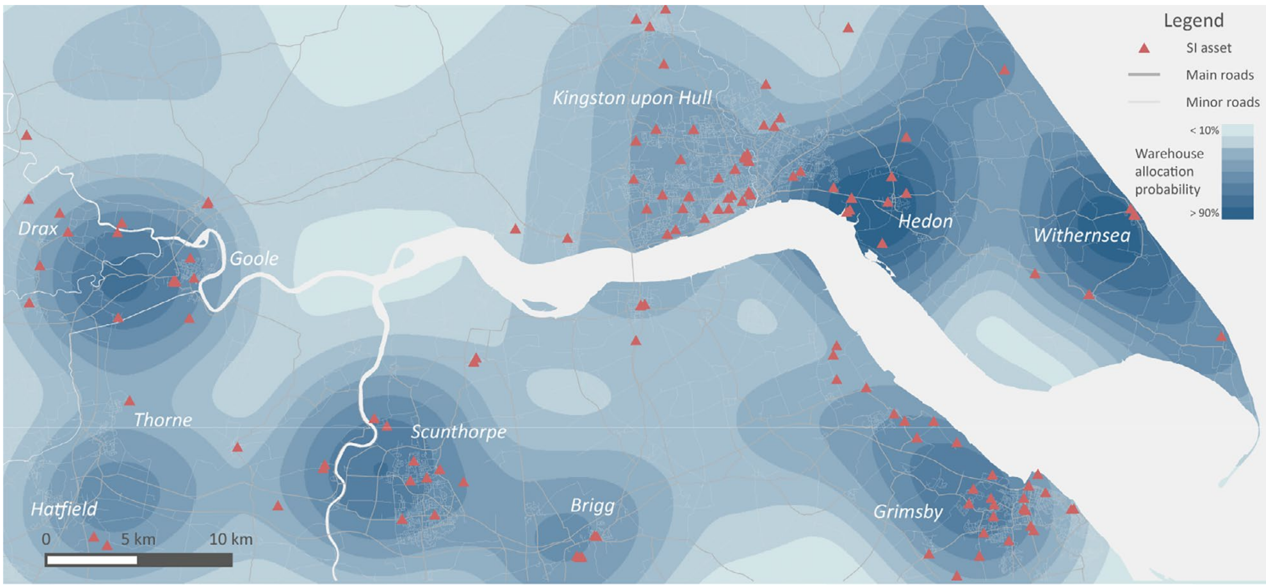

FIGURE 10 | A heatmap of the probability of allocation of a warehouse by the SRAO framework across all scenarios, also showing the location of SI sites.

TDFP investments remain aligned with the broader strategic direction of flood risk management in the region.

Regardless of the number of objectives that are considered, or the sophistication of the processes represented, uncertainty cannot be completely removed. The SRAO provides insights for specific scenarios as well as more generalised findings such as the eight locations that consistently perform well for all objectives. However, as with any such application, the findings should be used to inform discussion and be interpreted in the context of issues such as environmental impacts, social justice and other issues especially those that can only be measured qualitatively. Therefore, we recommend that decision-makers draw upon the solutions identified by the SRAO, but consider them in the context of other issues, rather than use the SRAO to fully automate decisions. Methods such as a fuzzy Analytical Hierarchy Process have shown promise for ranking a range of options against multiple objectives (Spiliotis and Skoulikaris 2019). Such an approach should ensure that the broader implications of TDFP deployment are taken into account, with the SRAO enabling effort to focus on those solutions that provide the best value for managing flood risk, leading to more informed and balanced decision-making. This should ensure that the broader implications of TDFP deployment are taken into account, with the SRAO enabling effort to focus on those solutions that provide the best value for managing flood risk, leading to more informed and balanced decision-making.

The solutions identified above are consistent with the motivations of the National Flood Resilience Review (Cabinet Office, Department for Environment, Food, and Rural Affairs 2016) that sought to optimise the coverage of TDFP at the lowest cost. The SRAO has been designed to be flexible to allow exploration of other scenarios and priorities. For example, while some of the solutions above enable some redundancy of coverage, that is, multiple warehouses protect each infrastructure site, the case study seeks to minimise the overall cost. If redundancy were an objective, the scenarios could be set up to enable the SRAO to identify optimal strategies whereby each infrastructure site was protected by two, three or any number of warehouses. In this case study we made several assumptions (e.g., initial equipment cost is not altered by warehouse location), but the cost model has been defined flexibly to enable future work to analyse sensitivity to a wider range of fixed or variable cost components. Similarly, the case study uses physical constraints such as only allowing warehouses to be built on dry land ensures only physically plausible solutions can be provided by the SRAO. However, other constraints such as not allowing construction on protected green areas could be relaxed under certain scenarios or to prioritise other objectives. Although constraint violation can be implemented, it would introduce additional uncertainty into the SRAO as it requires the calibration of additional penalty functions (Chehouri et al. 2016). Such flexibility ensures that decision-makers can adapt the framework to meet specific needs and constraints, balancing cost and different protection strategies as needed. Finally, post-event recovery logistics could be incorporated in future research to address scenarios with multiple sequential flood events, where equipment turnaround time and warehouse capacity directly affect the ability to respond to subsequent emergencies.

5 | Conclusions

TDFP are increasingly used to protect infrastructure assets. Constrained budgets and limited physical space around infrastructure assets mean many infrastructure assets are unable to have fixed protection or have on-site storage for TDFP. However, the flexibility of TDFP allows multiple infrastructure assets to be covered from shared storage site(s), reducing the need for more costly permanent flood protection structures. Constructing and operating fewer warehouses is cheaper, but to provide storage and logistics to protect more infrastructure assets they will inevitably be located further from some infrastructure assets, requiring more deployment time. For any realistic region, balancing the costs of operating TDFP storage sites with the coverage of protection they provide is an intractable computational problem. In this case study the solution space has an order of magnitude of 10^{46}.

A SRAO method, using a GA, has been developed and demonstrated on a case study in the Humber Estuary, UK, involving 133 SI assets, providing services to over 400,000 people in the floodplain. The findings show that there are tangible trade-offs between costs and protection based on the location of TDFP storage warehouses and other factors such as the number of lorries available to support deployment of protection. Analysis of optimal solutions across eight scenarios shows that decision-makers face trade-offs where prioritising rapid deployment can increase annual costs from approximately £130,000/year to over £225,000/year (40%–50% higher costs in those scenarios that include all infrastructure assets), while prioritising cost minimisation can increase deployment times from under 600 min to over 1800 min (a 200% increase in deployment time). These quantified trade-offs enable informed decision-making about the appropriate balance between cost efficiency and operational responsiveness.

Moreover, if budget limits the number of assets that can be protected, the SRAO is able to identify optimal strategies for the most critical assets. In the case study, protecting only the Top 10 most critical assets per infrastructure sector (rather than all 133 assets) can reduce the costs by approximately 40%, though this leaves 20%–37% of people vulnerable to flood disruption of their infrastructure services depending on the scenario. Analysis of a range of different scenarios showed that eight warehouse locations in the estuary (Hedon, Withernsea, Scunthorpe, Goole/Drax, Kingston upon Hull, Grimsby, Brigg and Hatfield) consistently perform well and appear in over 60% of all optimal solutions. This indicates they are robust to a wide range of uncertainties, providing decision-makers with a shortlist of candidate warehouse locations. The SRAO has been designed to be flexible. Further improvements to the SRAO will consider the implications of differential flood hazard and the impact of roads flooding on access and congestion delays by integrating it with a transport model (Pregnolato et al. 2016). The SRAO could be further expanded to include protection of property and other non-infrastructure assets, and to incorporate other quantifiable impacts, costs and test a wider range of different scenarios include the impact of future socio-economic and climate change. Decisions on the use of TDFP are increasingly being considered at regional and national scales and so further work will also increase the spatial scale of the study.

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Data Availability Statement

Python code for this work is available on GitHub at github.com/fdlopane/SRAO_HumberEstuary_P3.

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Appendix A

Extended Costs Formulation

The generalised cost equation is decomposed into capital and operational costs:

$$f_{\text{cost}} = W_h + R_s = \left(W_{\text{capex}} + W_{\text{opex}}\right) + \left(R_{\text{capex}} + R_{\text{opex}}\right) \tag{A1}$$

where

$$W_{\text{capex}} = \begin{cases} \sum_{i=1}^{W} f_i \cdot p_i, & \text{linear formulation} \\ \sum_{i=1}^{W} \left(\alpha \cdot \ln(f_i) + \beta\right) \cdot p_i, & \text{non-linear formulation} \end{cases} \tag{A2}$$

$$W_{\text{opex}} = m_w \tag{A3}$$

$$R_{\text{capex}} = p_b \cdot l_{ab} \tag{A4}$$

$$R_{\text{opex}} = hp \cdot n_p \cdot n_h + p_l \cdot n_l + m_r \tag{A5}$$

where f_{cost} represents the total cost of warehouses and emergency resources; W_{capex} is the warehouses' capital cost, W_{opex} is warehouses' operational cost, R_{capex} is the emergency resources capital cost, R_{opex} is the emergency resources' operational cost, W is the total number of warehouses; f_i is the floor space of the ith warehouse (m^2); p_i is the annual rental price per square metre of ith warehouse; α and β are the parameters of the logarithmic equation (regression from Yorkshire rent prices); h_p is the hourly pay for personnel; n_p is the number of workers for strategic resources' deployment; n_h is the number of working hours for deployment and removal of temporary defences; p_l is the rent price of a single lorry and n_l the number of additional lorries to existing fleet; m_w represents the warehouses' maintenance costs; m_r represents the emergency resources' maintenance costs; p_b is the unitary price of demountable barriers (£/m) and l_{ab} is the total length of additional demountable barriers needed (in addition to current local stock).

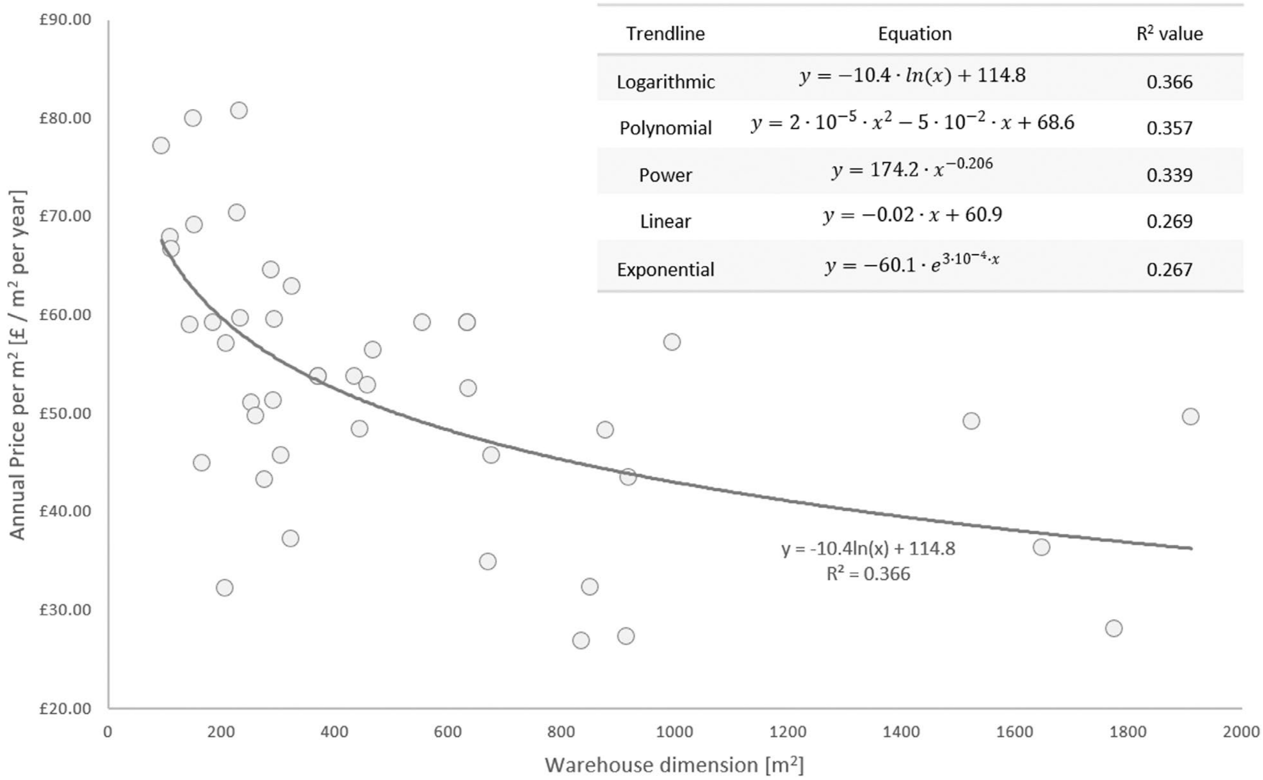

FIGURE A1 | Market analysis of Yorkshire warehouses' rent prices and warehouses categorisation according to size.

Appendix B

Input Data

TABLE B1 | List of input data with indication of data sources.

Input data set	Format	Source	Link
Road network edges	Line shapefile	OS OpenData	OS Open Roads https://osdatahub.os.uk/downloads/open/OpenRoads
Road network nodes	Point shapefile	OS OpenData	OS Open Roads https://osdatahub.os.uk/downloads/open/OpenRoads
Surface water	Polygon shapefile	OS OpenData	OS NGD Water Features https://docs.os.uk/more-than-maps/demonstrators/os-ngd-national-geographic-database/os-ngd-water-features
Power grid substations	Point shapefile	ITRC MISTRAL	(Data set not in the public domain) https://www.arcc-network.org.uk/itrc/
Fire stations	Point shapefile	OS Digimap	Points of interest https://digimap.edina.ac.uk/roam/map/os
Gas distribution/storage	Point shapefile	OS Digimap	Points of interest https://digimap.edina.ac.uk/roam/map/os
Hospitals	Point shapefile	OS Digimap	Points of interest https://digimap.edina.ac.uk/roam/map/os
Police stations	Point shapefile	OS Digimap	Points of interest https://digimap.edina.ac.uk/roam/map/os
Flood zones	Polygon shapefile	Environment Agency	Flood Risk Areas https://environment.data.gov.uk/dataset/f3d63ec5-a21a-49fb-803a-0fa0fb7238b6