Evolutionary Computing for Multi-Objective Sustainable Urban Spatial Planning

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Abstract

The processes of urbanisation and climate change are necessitating the transformation of cities towards sustainable cities that are robustly adapted to natural hazards, while simultaneously reducing energy and resource usage to mitigate further climatic change. Frequently such objectives conflict with each other, negatively affecting sustainability as a whole. For example, urban intensification with the intention of lowering transport energy costs has been found to exacerbate urban heat islands, increase flood risk and lead to poor health outcomes. This paper presents the use of an evolutionary computing spatial optimisation framework as one method by which multiple positively and negatively correlated sustainability objectives can be evaluated in time and space to assist urban planning. A coupled genetic algorithm and pareto optimisation approach is used to evaluate spatial configurations of future development against sustainability objectives (e.g., reduced heat risk, minimal flood risk, brown field development, optimal mobility). The developed approach is evaluated in a Greater London Authority (GLA) case study that simulates future urban development patterns that satisfy projected population growth whilst being sensitive to climate induced hazards and current planning policies. The spatial optimization framework developed significantly improves upon the existing urban development plan with the Pareto-front found to be 35% better than the proposed spatial plan for London. However, trade-offs between objectives were found to exist, most notably it was not possible to achieve a pairwise optimization between heat and flood risk and urban sprawl and heat risk.

1. Introduction

The increased frequency of climate change extreme events is driving a move to designing resilient cities globally (Dawson, 2007; Hunt and Watkiss, 2011). Many major cities are located within high-risk areas such as coastal zones (McGranahan et al, 2007) and experiencing increasing urbanisation which is exacerbating future risk and vulnerability of cities to climate driven extreme weather events (IPCC, 2013). As a result, many national and local governments are considering the adaptation options for their cities with regards to future urban development (Biesbroek et al, 2010; Carter, 2011; Reckien et al, 2014).

A number of previous studies have investigated the impact of current and future extreme events on cities. For example, methodologies have been developed to assess the economic impact of future flooding (Aerts et al, 2013), human mortality from increased heat wave frequency (Hajat et al, 2014) and the resilience of urban infrastructure to natural disasters (Chang et al, 2014). Such approaches are useful to demonstrate the impacts of potential hazards. However, they are often limited to a single hazard or sustainability objective (i.e., climate risk, emissions, employment) (Gasparatos et al, 2008) when it is recognised that multiple hazards and sustainability elements need to be considered simultaneously due to their often-complex relationships and interactions in order to better inform the urban planning process (Dawson, 2011; Zhou and Liu, 2012).

A growing body of work has demonstrated that optimization techniques can be successfully employed to provide optimal infrastructure plans in the presence of multiple objectives. These include planning of water distribution networks (Prasad et al, 2004), design of bus transport networks (Shimamoto et al, 2010) and planning of land use (Khalili-Damghani et al, 2014). In the case of land use, where studies have considered sustainability in a spatial context they have focused almost exclusively on the compactness and compatibility of land use premised on the hypothesis that compact cities are more sustainable (Cao et al, 2010). To date the consideration of adaption to climate risks alongside such sustainability objectives has been limited. This is unfortunate as the literature indicates that major metropolitan areas face the greatest future climate extremes and adaption challenges, and therefore must be a focus of long-term sustainable planning efforts (Reckien et al, 2014).

Increasingly, Genetic Algorithms (GA) are becoming the de facto means by which to tackle spatial optimisation problems (Balling et al, 1999; Cao et al, 2012; Khalili-Damghani et al, 2014), due to their improved ability to find globally optimal solutions in relatively efficient search times (Reeves, 1995. A major advantage of GA is its ability to handle multi-objective optimisation through Pareto-optimisation, whereby a number of mathematically determined optimal solutions which are best trade-offs to a problem are returned (Xiao et al, 2007). This makes them an ‘ideal’ method by which to present the results of optimisation of urban planning (Jiang-Ping and Qun, 2009) and sustainability applications (Kapelan et al, 2005). However, the majority of GA approaches used to identify spatial development configurations optimise a single objective (Stewart and Janssen, 2014) or utilise a weighting system to identify a limited number of optimal spatial development configurations based on prior preferences (Ligmann-Zielinska et al, 2005; Cao et al, 2012) .

To address this weakness, this paper develops a spatial optimization framework powered by a GA and Pareto-optimisation to develop optimal spatial planning strategies of cities in the presence of multiple, conflicting risk and sustainability objectives (Caparros-Midwood et al, 2017). The framework is applied to a case study of planning future development for London to demonstrate its applicability to real world planning (Caparros-Midwood et al, 2017).

2. Methods

2.1 Selection of Risk and Sustainability Objectives

An extensive review was undertaken of the current UK government adaptation policies (Defra, 2010; Defra, 2012) as well as spatial planning literature. Additionally local UK sustainability appraisals and current planning policy were analysed (GLA, 2011a; AMEC, 2014). From this review the set of objectives selected for analysis within the framework were:

(i) Minimizing exposure to future heat wave events: This appeared in 40% of sustainability appraisals reviewed and is a priority of the UK government.
(ii) Minimizing risk from future flood events: Highly prioritised by 70% of sustainability appraisals reviewed and a priority policy for the UK government.
(iii) Minimize travel costs to minimize transport emissions: All sustainability appraisals reviewed stated this as a high priority objective.
(iv) Maximising brownfield development: A national government planning policy objective is to maximise the development to brownfield sites in order to limit unnecessary greenspace development.
(v) Minimizing the expansion of urban sprawl: A national priority through policies encouraging development on previously developed sites within existing urban areas.
(vi) Preventing development of green space: Appears as a sustainability objective in 80% of sustainability appraisals reviewed.

2.2 Problem Formulation

The urban system is spatially represented as a raster grid dataset. A proposed spatial development plan is defined as an array D indexed by l which corresponds to a location in the study area with a coordinate i, j. Assigned residential development sites within the study are defined as d and a collection of these form a development plan D noting that a number of l can remain undeveloped, for example $D = [0, d_1, d_2, 0, 0 \ldots]$. Assigned residential development, d_l, are allotted a density den thus the number of dwellings associated with each development is $d^{dw} = area * d^{den}$. To form a feasible development plan, the following constraint ensures that a required number of dwellings are assigned:

$$Dw_{MIN} \leq D^{dw} \leq Dw_{MAX} \tag{1}$$

where Dw_{MIN} and Dw_{MAX} represent minimum and maximum possible number of dwellings in a development plan and D^{dw} represents the total number of dwellings associated with a particular development plan (i.e., the sum of d^{dw}). This allows the genetic algorithm to fully investigate the objective space. As the total number of new dwellings and their density can vary between these bounds, the objective functions (Equations 2-6) are all proportional to the value of D^{dw}.

Objective (i) was minimized on the basis of the objective function f_{heat} defined as:

$$\mathrm{Min}\left(\sum h_l d_l^{dw} \propto D^{dw}\right) \tag{2}$$

where h refers to a heat hazard value, here defined in terms of the number of heatwave days where temperatures exceed 32ºC (DoH, 2010) at location l. This objective aims to prevent development in areas with high heat wave hazard incidence. Heat wave incidence was identified using the UrbClim heat wave model (De Ridder et al, 2012) which includes existing development density in its derivation (McCarthy et al, 2012).

Objective (ii) is optimised on the basis of the objective function f_{flood} which is characterized by a flood risk assessment of development that occurs within the 1 in 100 and 1 in 1,000-year floodplain zones. These two zones are the thresholds used by the UK government in its Planning and Policy Statement on Development and Flood Risk. Flood risk is a combination of likelihood and impact, so is calculated here in terms of the amount of development in each zone weighted according to the relative likelihood of flooding:

$$\mathrm{Min}\left(\left(10^0 \sum z^{100} d_l^{dw} + 10^{-1} \sum z^{1000} d_l^{dw}\right) \propto D^{dw}\right) \tag{3}$$

where z^{100} and z^{1000} are spatial grids representing the 1 in 100 and 1 in 1,000 flood zone extents respectively.

Objective (iii) is optimised on the basis of an accessibility measure of new development to areas of employment and services, characterised by the distance of proposed development to a town centre. The optimization attempts to minimize the objective function f_{dist} which is expressed as:

$$\mathrm{Min}\left(\left(P(d_l, c_l, R)\ \forall c_l\ \wedge\ d_l \in D\right) \propto D^{dw}\right) \tag{4}$$

where $P(\,)$, is the shortest path between a d_l and it's closest point designated as a town centre centroid, c_{ij}, over a road network, R.

Objective (iv) is optimised on the basis of the objective function $f_{brownfield}$ which attempts to minimize the number of proposed development sites which do not fall on cells designated as brownfield sites, b_l:

$$\mathrm{Min}\left(\sum d_l \neq b_l\ \forall\ d_l \in D \propto D^{dw}\right) \tag{5}$$

Objective (v) is parameterised as a minimization of the number of proposed development sites falling outside the current developed urban land u_l to prevent urban sprawl. This is represented by the objective function f_{sprawl}:

$$\mathrm{Min}\left(\sum d_l \neq u_l\ \forall\ d_l \in D \propto D^{dw}\right) \tag{6}$$

Objective (vi) is enforced through a spatial constraint which prevents development of cells designated as greenspace, g_l:

$$d_l\ \neq g_l \forall\ d_l \in D \tag{7}$$

A final constraint ensures development is only possible on cells that have available space for development:

$$d_l = 1\ if\ d_l \cap\ a_l \tag{8}$$

where a_l represents cells designated as being available for development (also known as active cells).

The final objective performances of spatial strategies are normalised to enable comparison. Normalised objective values were calculated for each development strategy using:

$$f_s^{norm} = (f_s - f_s^{min})/(f_s^{max} - f_s^{min}) \tag{9}$$

where f_s^{min} and f_s^{max} represent the minimum and maximum performance for each objective function, f.

2.3 Spatial Optimisation using a Genetic Algorithm

2.3.1 Implementation of Spatial Genetic Algorithm

Figure 1 shows the structural components of the genetic algorithm approach. Figure 1.a demonstrates the initialization phase consisting of producing an initial set of randomly generated development plans. The initialisation provides an initial set of $parent$ spatial plans for the evolutionary operators to modify.

At each generation, g, for a defined number of generations, G, the GA operators of crossover, mutation and selection are applied to $parent_g$ solutions to produce a next generation, $parents_{g+1}$. The crossover operator exchanges the attributes in D pairs of solutions, based on a probability $p_{crossover}$, around two randomly selected crossover points producing two newly produced spatial plans which are potentially superior. Next the solutions are subject to a mutation operator based on a probability $p_{mutation}$ and their elements mutated based on the probability, p_m. In this work the framework utilises a shuffle index mutation where selected elements are swapped within D. This retains the original D^{dwells} whilst spatially varying the allocation of d. The purpose of the mutation operator is to maintain diversity in the offspring and prevent premature convergence on a set of d_l.

At this point in the operation constraints are applied to the newly produced set to ensure they are feasible spatial plans which meet Equations (1), (7) and (8). Equations (7) and (8) are handled by restricting the variable space to consider only solutions that are in a_{ij} (i.e., areas available for development) but not in g_{ij} (i.e., not areas designated as greenspace). Equation (1) is enforced through discarding infeasible spatial plans which don't meet the prescribed number of dwellings, whilst solutions which do are retained to form a set of $offspring$ solutions. These are combined with the $parent$ solutions before a selection operator extracts superior solutions to form $parents_{g+1}$. This work utilises a selection operator based on the NSGA-II selection procedure to extract the most optimal solutions at each iteration. NSGA-II has been found to be an appropriate selection operator in other spatial optimisation applications (Cao et al, 2011; Mohammadi et al, 2015) and is more efficient than many other algorithms (Deb, 2002).

2.3.2 Pareto-Optimisation

Throughout the operation, the algorithm strives towards identifying the Pareto-optimal set of solutions to the planning problem (Figure 1.b). A Pareto-optimal solution in optimization is defined as a solution that outperforms all other solutions in at least one objective and is based on the concept of domination (Deb, 2001). For F objective functions a solution $s^{(1)}$ is said to dominate solution $s^{(2)}$ if:

1. The solution $s^{(1)}$ is no worse than $s^{(2)}$ in all objectives; $f(s^{(1)}) \leq f(s^{(2)}) \forall f \in F$;

2. The solution $s^{(1)}$ is strictly better than $s^{(2)}$ in at least one objective; $f(s^{(1)}) < f(s^{(2)})$ for at least one $f \in F$.

This process of Pareto-optimisation is shown in Figure 1.b where at the end of each $g \in G$ newly found solutions are assessed against the existing Pareto-optimal set, N, through a process called Non-dominated Sorting. If a solution, s^n, is found to dominate a solution in N, it is added to N, and the solution (s) in N dominated by s^n is removed. This ensures that N comprises the best set of Pareto-optimal set of solutions found throughout the search. During the GA application. Domination is based on the entire set of objectives and as such the resulting set is referred to as Multi-Objective Pareto-optimal solutions (MOPOs). This set is returned upon completion of the algorithm.

2.3.3 Pareto-Optimal Solution Sets

Figure 1.c shows the processing of outputs from the GA once it has completed G generations. The MOPO solution set represents the Pareto-optimal spatial configurations where no other spatial configuration performs better for the combination $F = f_{heat}, f_{flood}, f_{dist}, f_{brownfield}, f_{sprawl}$. However, in order to further understand the conflicts and interactions between pairs of objectives, Pareto-optimal sets are extracted from the MOPO set for different combinations of F. These provide Pareto-optimal sets between objectives and, when plotted against the objectives, present the best trade-off curve referred to as the Pareto front between the objectives of interest. The non-dominated sorting procedure outlined by Mishra & Harit (2010) was used to perform this operation by initially ranking the MOPO set F.

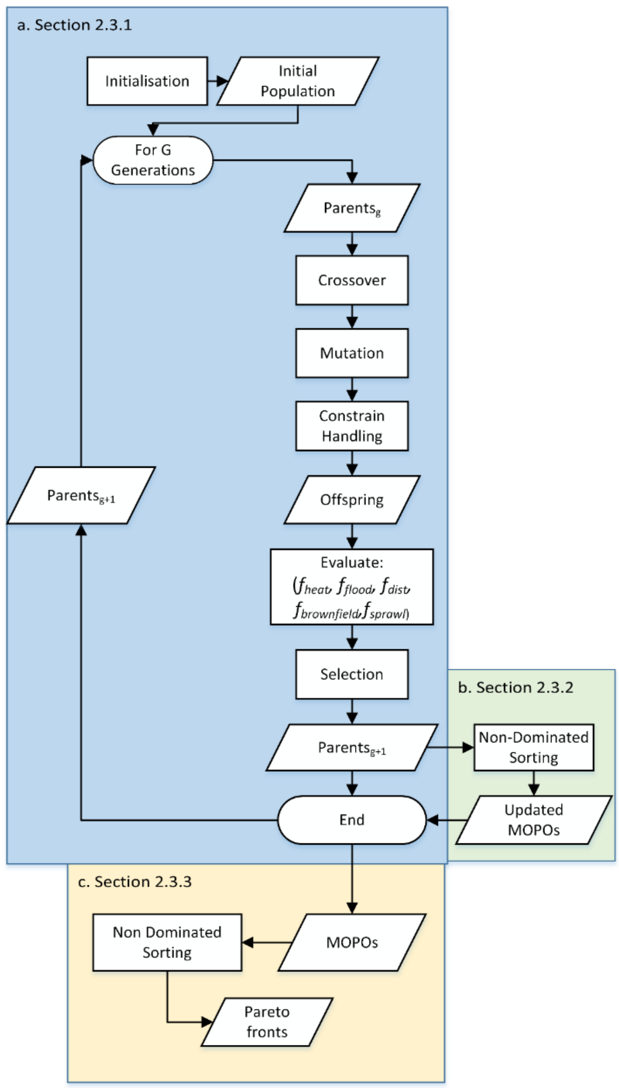

Figure 1. Flow diagram of the Genetic Algorithm Spatial Optimization Framework, separated into key steps (a-c) described in sections 2.3.1 - 2.3.3.

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3. London Case Study

3.1 Case Study Description

To demonstrate the utility of the developed spatial optimization framework it was applied to the problem of determining future residential development in Greater London, an area of 1,572km^2. London is experiencing pressures from high population growth whilst simultaneously facing increased future heatwaves and higher risk of flooding from the Thames and its tributaries due to climate change (Dawson, 2011; GLA, 2011b). London has set itself ambitious CO2 emission reductions of 60 per cent (below 1990 levels) by 2025 (GLA, 2014). The case study considers the residential development priorities set out in the Greater London Authority's (GLA) Spatial Development Strategy. In particular the strategy sets out a focus on development in east London with 25% of all proposed new dwellings planned for just 3 east London boroughs (of 33 boroughs in total). The strategy also identifies key development locations that are centred around a series of suburban hubs within London itself, referred to as 'London's town centre network' (GLA, 2011c). This development strategy is compared with results from the spatial optimisation framework.

3.1.1 Problem Definition

Figures for Dw_{MIN} and Dw_{MAX} were derived from the Greater London's Spatial Strategy's sustainability target of 322,100 net additional dwellings over a 10-year period and the 340,000 estimated to be required to accommodate population growth for the same period (34,000 per annum) (GLA, 2011a). To constrain the search space, a set of development densities were derived from London's Spatial Strategy that capture lower and upper bounds of feasible development, and sensible interim values, $den = \{35,60,100,150,250,400\}$ dwellings per-hectare (uha). A spatial resolution of 200 meters (cell size of 40,000 square metres or 4 hectares) was chosen to provide a suitable balance between computational expense and spatial resolution. The number of dwellings that can be assigned to each cell is therefore four times the density, $dw = \{140,240,400,600,1000,1600\}$.

In order to comply with current planning policy in London a further constraint was added to the spatial optimization to ensure proposed development densities met the Public Transport Accessibility Layer (PTAL) standards for accessibility. This ensures that high densities of development occur in high accessibility PTAL areas derived on the basis of the density of the public transport network at any location. Spatial plans that are generated by the GA, but do not meet this constraint, were automatically discarded.

3.1.2 Model Parameterisation

Figure 2 presents the input datasets for the London application of the spatial optimization framework. Figure 2a shows the spatial representation of heat hazard, h_{ij} represented at 1-kilometre spatial resolution by the UrbClim model (De Ridder et al, 2012). The model disaggregates an ensemble of IPCC climate change models then spatially models the effect of urban heat islands by using land cover data. Floodplain zones (Figure 2b) were provided by the UK Environment Agency (EA). The Ordnance Survey (OS, UK national mapping agency) Mastermap Strategi Settlement Seeds are used to represent London's town centre network (c_{ij}) (Figure 2c), whilst the road network, R, was extracted from the OS Meridian 2 roads dataset. Figure 2d shows the urban extents for the study area, u_{ij}, which were extracted and rasterized from OS Meridian 2 Developed Land Use Areas (DLUA). Figure 2e shows greenspace, g_{ij}, land potentially available for development, a_{ij} and brownfield sites, b_{ij} which are a subset of a_{ij}. Greenspace was defined as land in the OS Mastermap Topographic data defined as 'Natural'. Areas available for development were all those in the OS Mastermap Topographic data which are not developed or water bodies. Vector data for brownfield locations were provided by the London Development Agency's (LDA) London Brownfield Sites Database, before being rasterised to a 200-metre spatial resolution. Of the 1,885 sites identified, the LDA's report found that 20% of the sites require remediation (8% full and 12% partial or potential) (Powney and Hyams, 2009). Lastly, Figure 2f shows the PTAL dataset, which was also provided in vector format and rasterised to a 200m grid.

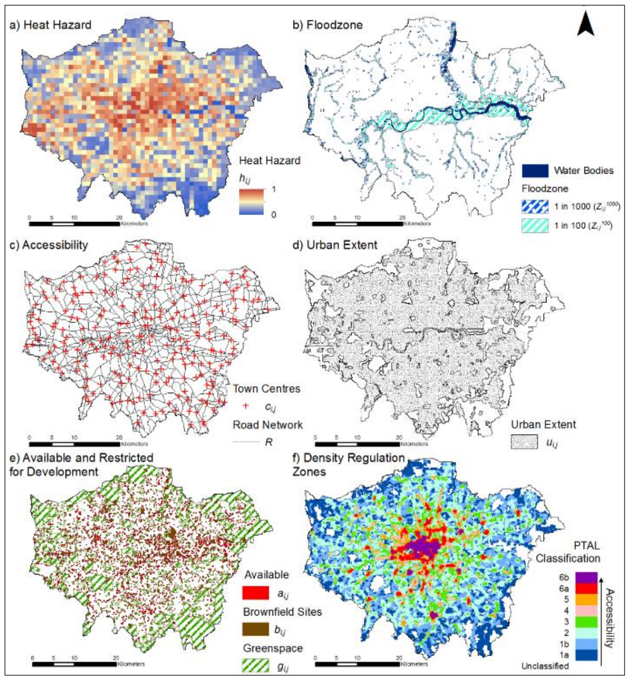

Figure 2. Spatial datasets for the case study.

The genetic algorithm parameters were selected on the basis of sensitivity testing carried out for an application of the spatial genetic algorithm on a much smaller area (55km^2 as opposed to 1,572 km^2 for London). The smaller case study enabled exploration of the efficiency of the genetic algorithm for different parameterisations and showed that a parameterisation comprising a higher ratio of $No_{parents}$ (2,500) compared to G (400) was considered to be most appropriate. As recommended by Konak et al. (2006) the total of $p_{crossover}$ and $p_{mutation}$ was set to 0.9 to ensure a small number of solutions (10%) remained unchanged. Values of 0.7 and 0.2 were set for $p_{crossover}$ and $p_{mutation}$ respectively. The probability for mutation p_m was set at 0.05.

3.2 Results and Discussion

Figure 3 demonstrates the convergence of the Pareto front between f_{heat} and $f_{brownfield}$. Within the first 50 generations there is an 86.2% improvement in $f_{brownfield}$ for min (f_{heat}) and a 22.78% improvement in f_{heat} for min ($f_{brownfield}$). Thereafter, convergence slows with a 11.3% improvement between the 50th and final (400th) generation in f_{heat} for min ($f_{brownfield}$) performance whilst $f_{brownfield}$ for min (f_{heat}) improves 35% over the same time period to achieve the best found spatial strategy for f_{heat}. Overall, the framework is able to improve the uptake of brownfield development by 78.7% from the first generation.

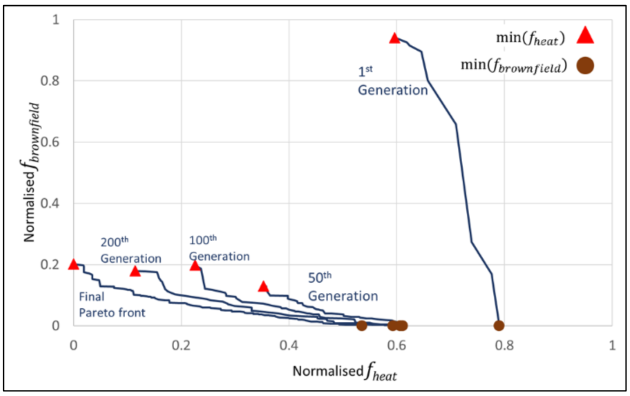

Figure 3. Convergence of the Pareto front (Pareto-optimal set) between f_{heat} and $f_{brownfield}$ throughout the GA operation.

Figure 4 presents the normalized performances of Pareto-optimal fronts between pairs of objectives and Table 1 quantifies the best trade-offs between the objectives. The results show clear conflicts between optimising f_{heat} with the other objectives (Figure 4.a-d). The result $\min(f_{flood}) \Rightarrow f_{heat} \geq 0.65$ shows that areas next to the river Thames with a low heat hazard are avoided to minimize flooding. The spatial plans for $\min(f_{dist}) \Rightarrow f_{heat} \geq 0.65$ and $\min(f_{sprawl}) \Rightarrow f_{heat} \geq 0.72$ reflect the increase in heat hazard close to high-density built-up areas. The best f_{heat} performance can be achieved with 85% of development on brownfield sites however in order to completely restrict development to brownfield the performance in $\min(f_{brownfield}) \Rightarrow f_{heat} \geq 0.54$. Interestingly the results indicate a lack of brownfield sites in close proximity to town centres as $\min(f_{brownfield}) \Rightarrow f_{dist} \geq 0.3$.

		Corresponding value from the Pareto-front				
		f_{heat}	f_{flood}	f_{dist}	$f_{brownfield}$	f_{sprawl}
Optimised	f_{heat}	NA	0.16	0.39	0.2	0.64
	f_{flood}	0.65	NA	0.09	0	0.03
	f_{dist}	0.65	0.08	NA	0.3	0.11
	$f_{brownfield}$	0.54	0	0.18	NA	0.18
	f_{sprawl}	0.72	0.12	0.29	0.1	NA

Table 1. Pareto-front trade-off matrix.

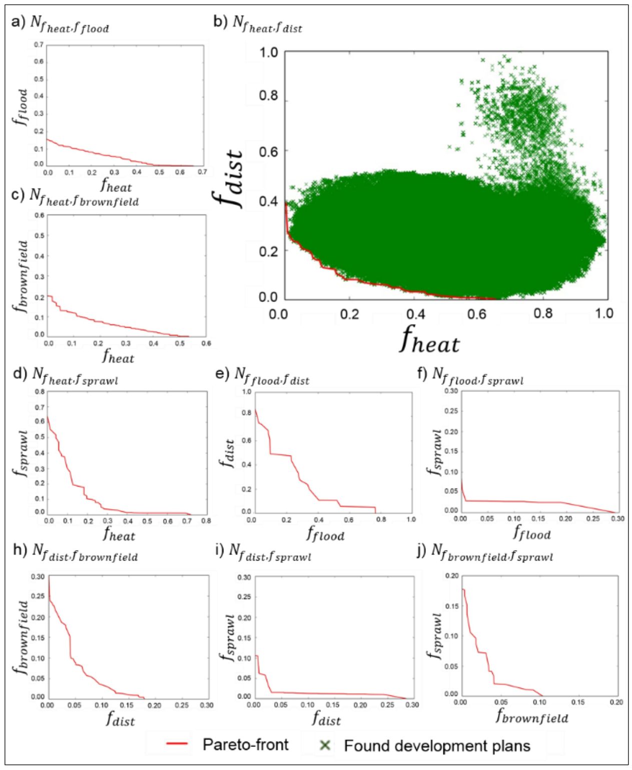

Figure 4. Normalised Pareto fronts between objectives optimised by the framework.

One advantage of the developed framework is the ability to map and compare solutions spatially for different combinations of objectives. Figure 5 presents the best spatial development strategy for $\min(f_{heat})$ as well as a comparison with the spatial configuration for $\min(f_{flood}, f_{brownfield})$ at highlighted areas. Figure 5a demonstrates how the spatial configuration strategically develops brownfield sites which correspond with lower heat hazard in order to achieve a best trade-off with $f_{brownfield}$. However, in order to meet the dwelling target (Equation (1)) the strategy is forced to locate development centrally (Figure 5b) which is where the greatest spatial variance occurs between strategies that are optimal for other criteria.

Figure 5b and 5c demonstrate how the strategies for $\min(f_{heat})$ and $\min(f_{flood}, f_{brownfield})$ vary spatially in these central areas. The spatial plan $\min(f_{heat})$ develops predominantly on the banks of the river Thames to take advantage of corresponding lower heat hazard. However, these correspond with flood zones causing a normalised performance of 0.6 in f_{flood}, equating to development of 67,680 dwellings within the 1 in 100 flood zone and a further 17,200 within the 1 in 1000 flood zone. Whilst the spatial plan $\min(f_{flood}, f_{brownfield})$ avoids central London and concentrates on brownfield sites in the north and west of London, these correspond with higher heat hazard (reflected by the normalised performance of 0.75 in f_{heat}).

Figure 6 presents a borough (local authority) scale comparison of spatial development between the Greater London Authority's (GLA) spatial plan against the Pareto-optimal spatial strategies. The results show east London boroughs identified by the Greater London Spatial strategy for development are unsuitable to meet the risk and sustainability objectives. For example, Hackney, with a GLA target of 11,600 dwellings, has close to no assigned development for the Pareto-optimal spatial plans.

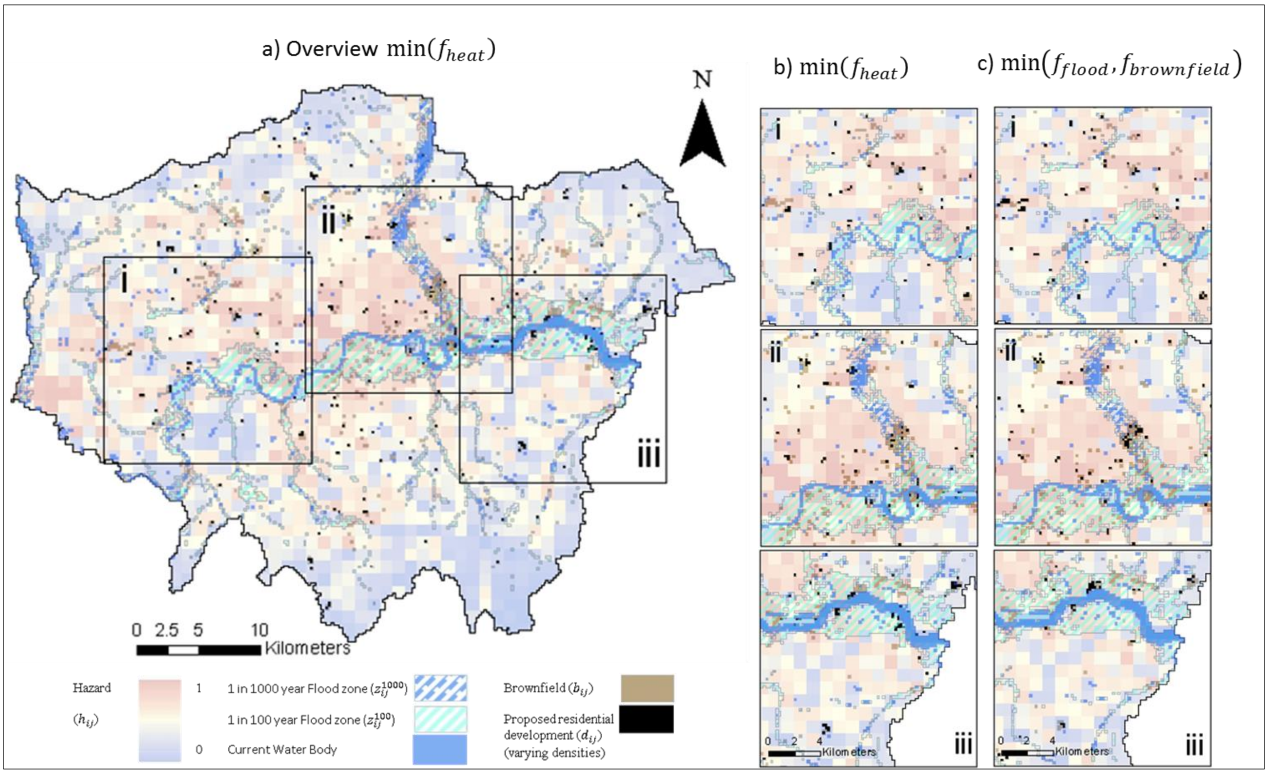

Figure 5. a) Overview of spatial configuration for $\min(f_{heat})$, b) viewing windows i, ii and iii, and c) comparison with spatial plan for $\min(f_{flood}, f_{brownfield})$. For clarity of visualisation varied densities of development are not shown.

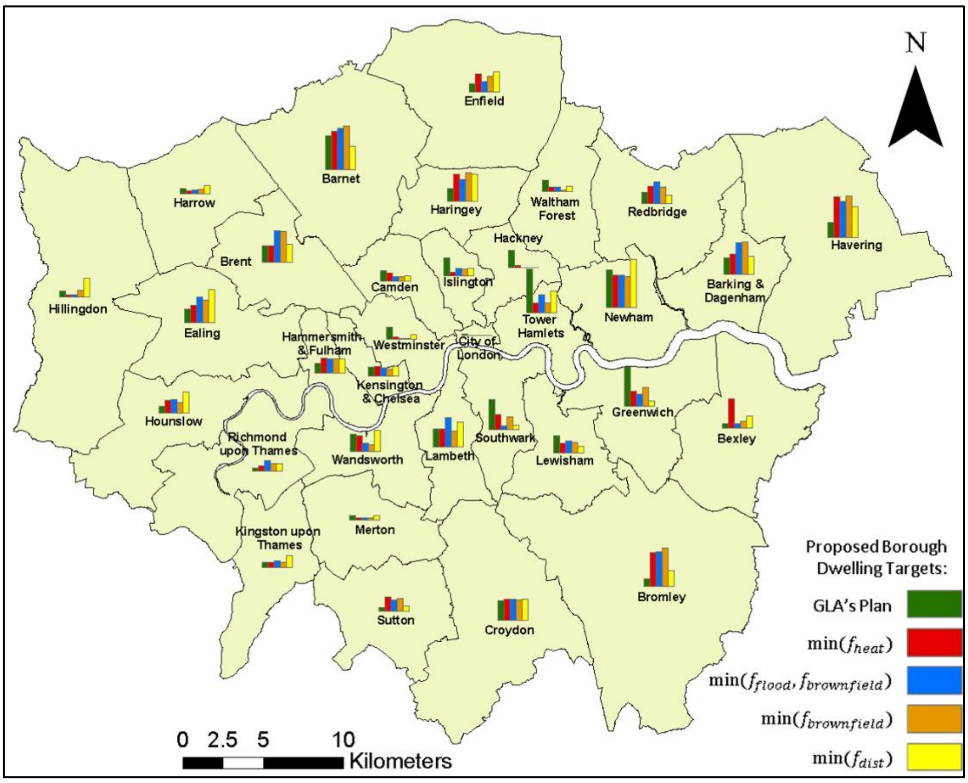

Figure 6. Comparison of London borough proposed dwelling totals based on Greater London Authorities and Pareto-optimal solutions plans.

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4. Conclusions

In the presence of conflicting risk and sustainability pressures planners require decision support tools to better aid the balancing of priorities and allow for optimal planning decisions. In this paper a spatial optimization framework has been developed to provide planners with a means of producing the evidence base for constructing spatial planning strategies that are optimal against multiple criteria and objectives.

The results of the framework demonstrate its ability to produce optimal spatial development strategies which best balance the six risk and sustainability objectives investigated whilst also adhering to planning policies and land use constraints. Plans are found which are optimal against one or more of these objectives whilst diagnostic information from analysis of the results and Pareto sets in particular, provides planners with detailed information on the magnitude and sensitivity of different trade-offs between planning objectives. The case study also highlights the importance of spatial structure in modulating risks and other sustainability objectives: the different spatial structure of the flood and heat hazards limits the number of areas with low heat and flood risk, whilst the location of brownfield sites, makes it impossible to exclusively develop these and optimise other objectives.

Overall, the analysis finds that spatial strategies can be geared to optimally meet specific risk and sustainability objectives with regards to future development within London. However, it is not possible to simultaneously optimise all climate related hazards and sustainability objectives. Therefore London, in terms of the spatial configuration of its potential future development, cannot maximise its full sustainability and resilience potential; instead, planners will need to prioritise a sub-set of objectives. Indeed, the analysis finds that different development strategies are needed to optimise development patterns that meet the two risk objectives, weakening the case that a city structure can provide resilience in its own right. Despite this, an approach such as the one presented in this paper can identify development patterns that better deliver development priorities, whilst recognising that some may only be achievable with social capacity building or demand management.

Further investigation is needed into the effect of assessing the cost of development strategies alongside their sustainability performances. This would reflect heterogeneities in land value across the city, but also explore the tension between the remediation of brownfield land at high cost and minimising urban sprawl. Whilst the work presented uses relatively simple metrics to evaluate risks and sustainability objectives, the framework is developed in such a way that more advanced risk calculations can easily be fitted into the evaluation phase of the framework. For example, the flood risk calculation might be extended to include analysis of a wider range of flood return periods, or consideration of flood defence breach scenarios as described in Dawson & Hall (2006).

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