

Spatially Optimised Sustainable Urban
Development



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Abstract

Tackling urbanisation and climate change requires more sustainable and resilient cities, which in turn will require planners to develop a portfolio of measures to manage climate risks such as flooding, meet energy and greenhouse gas reduction targets, and prioritise development on brownfield sites to preserve greenspace. However, the policies, strategies and measures put in place to meet such objectives can frequently conflict with each other or deliver unintended consequences, hampering long-term sustainability. For example, the densification of cities in order to reduce transport energy use can increase urban heat island effects and surface water flooding from extreme rainfall events. In order to make coherent decisions in the presence of such complex multi-dimensional spatial conflicts, urban planners require sophisticated planning tools to identify and manage potential trade-offs between the spatial strategies necessary to deliver sustainability.

To achieve this aim, this research has developed a multi-objective spatial optimisation framework for the spatial planning of new residential development within cities. The implemented framework develops spatial strategies of required new residential development that minimize conflicts between multiple sustainability objectives as a result of planning policy and climate change related hazards. Five key sustainability objectives have been investigated, namely; (i) minimizing risk from heat waves, (ii) minimizing the risk from flood events, (iii) minimizing travel costs in order to reduce transport emissions, (iv) minimizing urban sprawl and (v) preventing development on existing greenspace.

A review identified two optimisation algorithms as suitable for this task. Simulated Annealing (SA) is a traditional optimisation algorithm that uses a probabilistic approach to seek out a global optima by iteratively assessing a wide range of spatial configurations against the objectives under consideration. Gradual ‘cooling’, or reducing the probability of jumping to a different region of the objective space, helps the SA to converge on globally optimal spatial patterns. Genetic Algorithms (GA) evolve successive generations of solutions, by both recombining attributes and randomly mutating previous generations of solutions, to search for and converge towards superior spatial strategies. The framework works towards, and outputs, a series of Pareto-optimal spatial plans that outperform all other plans in at least one objective. This approach allows for a range of best trade-off plans for planners to choose from.

Both SA and GA were evaluated for an initial case study in Middlesbrough, in the North East of England, and were able to identify strategies which significantly improve upon the local authority's development plan. For example, the GA approach is able to identify a spatial strategy that reduces the travel to work distance between new development and the central business district by 77.5% whilst nullifying the flood risk to the new development. A comparison of the two optimisation approaches for the Middlesbrough case study revealed that the GA is the more effective approach. The GA is more able to escape local optima and on average outperforms the SA by 56% in the Pareto fronts discovered whilst discovering double the number of multi-objective Pareto-optimal spatial plans.

On the basis of the initial Middlesbrough case study the GA approach was applied to the significantly larger, and more computationally complex, problem of optimising spatial development plans for London in the UK – a total area of 1,572km². The framework identified optimal strategies in less than 400 generations. The analysis showed, for example, strategies that provide the lowest heat risk (compared to the feasible spatial plans found) can be achieved whilst also using 85% brownfield land to locate new development. The framework was further extended to investigate the impact of different development and density regulations. This enabled the identification of optimised strategies, albeit at lower building density, that completely prevent any increase in urban sprawl whilst also improving the heat risk objective by 60% against a business as usual development strategy. Conversely by restricting development to brownfield the ability of the spatial plan to optimise future heat risk is reduced by 55.6% against the business as usual development strategy.

The results of both case studies demonstrate the potential of spatial optimisation to provide planners with optimal spatial plans in the presence of conflicting sustainability objectives. The resulting diagnostic information provides an analytical appreciation of the sensitivity between conflicts and therefore the overall robustness of a plan to uncertainty. With the inclusion of further objectives, and qualitative information unsuitable for this type of analysis, spatial optimization can constitute a powerful decision support tool to help planners to identify spatial development strategies that satisfy multiple sustainability objectives and provide an evidence base for better decision making.

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Publications based on this Research

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Table of Contents

Abstract	i
Acknowledgments	iii
Publications based on this Research	v
Table of Contents	vi
List of Figures	xii
List of Tables	xvii
List of Abbreviations and Notation	xix
Glossary of Notation	xx
Chapter 1 Introduction	1
1.1 Urbanism and Climate Risks	1
1.2 Conflicting Sustainability Initiatives	3
1.3 Aims, Objectives and Thesis Outline	4
Chapter 2 Sustainable Cities and Development	7
2.1 Introduction	7
2.2 Definition of Sustainable Development	9
2.3 Models of Sustainable Urban Spatial Form	14
2.3.1 Introduction	14
2.3.2 Urban Intensification: The Compact City model	15
2.3.3 Dispersed Cities	19
2.3.4 Decentralised Centralisation: Transit Orientated Development	21
2.3.5 Garden Cities	24
2.3.6 Smart and Resilient Cities	26
2.3.7 Multiple Pathways	26
2.4 Barriers to Sustainable Urban Form	27
2.5 Spatial Planning to Achieve Sustainable Cities	31
2.5.1 Introduction	31

2.5.2 Environmental Sustainability Assessments	33
2.5.3 Integrated Sustainability Assessments	34
2.5.4 UK Sustainability Appraisals	36
2.5.5 Consideration of Conflicts between Sustainability Objectives	42
2.6 Decision Support	43
2.7 Conclusion	44
Chapter 3 Multi-objective Spatial Optimisation for Urban Planning	47
3.1 Introduction	47
3.2 Definition of an Optimisation Problem	48
3.2.1 Decision Variables	48
3.2.2 Objective Functions	49
3.2.3 Constraints	51
3.3 Multi-objective Optimisation	52
3.4 Spatial Optimisation Approaches	56
3.4.1 Introduction	56
3.4.2 Linear Programming	56
3.4.3 Meta-Heuristics	58
3.4.4 Simulated Annealing	58
3.4.5 Tabu Search	60
3.4.6 Population Based Searches	61
3.4.7 Genetic Algorithms	62
3.4.8 Particle Swarm	67
3.5 Evaluation Simulation Tools	68
3.5.1 Introduction	68
3.5.2 Water Distribution Networks	69
3.5.3 Transit/ Transport Networks	70
3.5.4 Resource and Land Use Allocation	70
3.5.5 Urban Simulation	71

3.5.6 Sustainable Spatial Optimisation	77
3.5.7 Evolutionary Urban Planning	79
3.6 Discussion	80
3.7 Conclusions	83
Chapter 4 Methodological Framework	85
4.1 Introduction	85
4.2 Problem Formulation	85
4.2.1 Design Considerations	85
4.2.2 Planning Problem Representation	87
4.2.3 Selection of Objectives	88
4.2.4 Data Characterisation of Objectives	91
4.2.5 Objective Formulation	92
4.2.6 Pareto-optimality	94
4.3 Spatial Optimisation Software	96
4.3.1 Choice of Development Environment	96
4.3.2 Overall Spatial Optimisation Framework Design	97
4.4 Simulated Annealing Approach	99
4.4.1 Simulated Annealing Operators	99
4.4.2 Simulated Annealing Implementation	103
4.5 Genetic Algorithm Approach	104
4.5.1 Genetic Algorithm Operators	104
4.5.2 Software Implementation	110
4.6 Summary	111
Chapter 5 Medium Sized Urban Case Study- Middlesbrough	113
5.1 Introduction	113
5.2 Middlesbrough Case Study	113
5.2.1 Problem Formulation	114
5.3 Middlesbrough Datasets	116

5.3.1 Available Land for Development	116
5.3.2 Data for Objective Formulation	118
5.4 Optimisation Parameters	121
5.4.1 Simulated Annealing Parameters	121
5.4.2 Genetic Algorithm Parameters	124
5.5 Middlesbrough Optimisation Results	127
5.5.1 Pareto-optimal Fronts between Pairwise Sustainability Objectives	127
5.5.2 Comparison of Pareto front Convergence	131
5.5.3 Pareto-optimal Spatial Configurations	134
5.5.4 Multi-objective Pareto-optimal Solutions	137
5.5.5 Findings for Middlesbrough	138
5.5.6 Comparison to Middleborough's Current Development Plan	141
5.5.7 Post Pareto Analysis	143
5.6 Discussion and Recommendations	146
5.6.1 Performance of the Optimisation Approaches	146
5.6.2 Effectiveness of the Pareto Optimisation Approach	148
5.6.3 Spatial Planning Problem Representation	148
5.7 Summary	149
Chapter 6 Large Urban Case Study- London	151
6.1 Introduction	151
6.2 Modifications to the Multi-Objective Spatial Optimisation Framework	151
6.2.1 Planning Problem	151
6.2.2 Modifications to Constraint Handling	154
6.2.3 Changes in Objective Function Parameterisation	155
6.3 London Case Study Configuration	158
6.3.1 The Greater London Authority	158
6.3.2 Problem Formulation	159
6.3.3 Input Datasets	161

6.3.4 Identifying Developable Areas	162
6.3.5 Planning Constraints	164
6.4 Further Analysis	166
6.4.1 Scaled Pairwise Preference Vectors	166
6.4.2 Regulatory Scenarios	170
6.5 Application Parameters	170
6.6 Results	172
6.6.1 Resulting Pareto Fronts	175
6.6.2 Pareto-optimal Spatial Configurations	177
6.6.3 Comparison with London's Current Development Plan	183
6.6.4 Multi-Objective Pareto-Optimal Development Sites	187
6.6.5 Prioritised Spatial Plans	189
6.6.6 Regulatory Scenarios	193
6.7 Summary	195
Chapter 7 Discussion	196
7.1 Introduction	196
7.2 Case Studies Findings	197
7.2.1 Sustainable Planning Conflicts	197
7.2.2 Optimal Spatial Development Strategies for Sustainable Development	201
7.2.3 Comparison to Current Development Strategies	203
7.2.4 Limitations of the Case Studies	203
7.3 Discussion of the Multi-objective Spatial Optimisation Framework	205
7.3.1 Utility of the Approach	206
7.3.2 Appropriateness of the Optimisation Approach	207
7.3.3 Assessment of the Pareto-Optimisation Approach	210
7.3.4 Choice of Software Platform	212
7.4 Conclusion	213
Chapter 8 Summary, Conclusions and Future Work Recommendations	215

8.1 Introduction	215
8.2 Summary	215
8.3 Implications and Key Findings	218
8.4 Further Research	220
8.4.1 Inclusion of Further Infrastructure	220
8.4.2 Further Qualitative and Quantitative Assessment	221
8.4.3 Temporal Optimisation and Handling Uncertainty	223
8.4.4 Further Decision Support	224
References	227
Appendix A Review of Sustainability Appraisals	267
Appendix B Evaluation Modules	269
B.1 Middlesbrough Framework Evaluation Module	269
B.2 London Framework Evaluation Module	271
B.3 Calculate Accessibility Module	273
Appendix C Non-dominated Sorting Module	277
Appendix D Pre-processing Models	279

List of Figures

Figure 2.1 Sustainable Development mapped as interlinking rings (adapted from ICLEI, 1996).	11
Figure 2.2 Sustainable development as a combination of economic growth, environmental protection and social justice (reproduced from Connelly 2007).	12
Figure 2.3 Area and Gasoline expenditure per person in world cities (data collected 1995) (Kenworthy et al. 1999).	16
Figure 2.4 Comparison of the urban extents of Atlanta and Barcelona with similar population sizes (Bertaud & Richardson 2004).	16
Figure 2.5 TOD development over the State of Denver centred around transport nodes (Ratner & Goetz 2013).	23
Figure 2.6 Garden Cities as polycentric centres on transport nodes connected to the main urban area (Howard 1902).	24
Figure 2.7 Idealised Garden City of Uxcester extending out from an existing city along transport roots and centred round poly-centric centres (reproduced from Rudlin & Falk (2014)).	25
Figure 2.8 Traditional conflicts arising from sustainable development (adapted from Campbell (1996)).	28
Figure 2.9 Sites identified in Birmingham to be considered for future development (AMEC Environment & Infrastructure 2014).	38
Figure 2.10 Assessment of Birmingham’s Development Plan Policies against the Sustainability Objectives.	39
Figure 2.11 Assessment of Manchester Planning Policies against sustainability objectives (sample adapted from Atkins 2009).	40
Figure 2.12 Handling of the conflicts arising from a particular development scheme for Birmingham’s development plan (reproduced from AMEC Environment & Infrastructure (2014).	41
Figure 2.13 Compatibility matrix from the sustainability appraisal for a) London (Mouchel 2010) and b) Basildon Council (Basildon Council 2011).	42
Figure 3.1 How the selection of variable set, X , in the variable space (left) leads to the performance of $F(x)$ in the objective space (right) (adapted from Deb, 2001).	50
Figure 3.2 The Pareto-optimal solution set (red curve) from the found solutions, $s \in S$, in the variable space (blue) assuming minimisation of f_1 and f_2	55
Figure 3.3 Workflow of a Genetic Algorithm.	63
Figure 3.4 Two point crossover operator on binary list representation.	63

Figure 3.5 Mutation operator on a binary list representation.	64
Figure 3.6 NSGA-II selection procedure consisting off a) Pareto ranking and b) Crowding distance.	66
Figure 3.7 SPEA2 selection procedure of dominance ranking.....	66
Figure 3.8 Urban lanscape representations for land use allocation applications consisting of a) grids of cells (Cao et al. 2011) and b) vector parcels (Masoomi et al. 2012).....	72
Figure 3.9 Input raster data sets from a) Cao et al 2012, b) Ligmann-Zielinska & Jankowski (2010), Ligmann-zielinska et al. (2005), and d) Aerts & Heuvelink (2002).	73
Figure 3.10 Moore a) 3x3 and b) 5x5 neighbourhood predominantly used in Cellular Automata modelling.	74
Figure 3.11 Evolution of land-use from initial state (top left) over: 10 (a), 20 (b), 30 (c) and 40 (d) iterations (White & Engelen, 1994).	74
Figure 3.12 Accessibility based on proximity to the road network (from Cao et al. (2012)....	78
Figure 4.1 Developed Spatial Optimisation Framework.	98
Figure 4.2 Flow diagram of the Simulated Annealing approach to spatial optimization.	100
Figure 4.3 The changes to selected $di, j \in D$ at an iteration of the SA algorithm search.	103
Figure 4.4 Current fitness and best fitness scores throughout the SA algorithm.	103
Figure 4.5 Flow diagram of the Genetic Algorithm Spatial Optimisation Framework.....	105
Figure 4.6 Application of the two-point crossover operator to two selected D	108
Figure 4.7 Application of the fixed integer mutation operator to a selected D	108
Figure 4.8 NSGA-II selection operator applied to the <i>parentg</i> and <i>offspringg</i> to form <i>offspringg</i> + 1 (adapted from Deb et al., 2002).	108
Figure 4.9 Demonstration of generating a lookup table converting cells from <i>ij</i> locations to a <i>l</i> value to excluded infeasible development sites.....	110
Figure 5.1 Case study area of Middlesbrough within the Tees Valley.....	114
Figure 5.2 Digitisation of Middlesbrough Council’s spatial plan; a) Interactive Local Development Framework (Middlesbrough Council 2010), b) digitised proposed residential, employment and mixed use sites and c) rasterised at a 100 metre spatial resolution.....	116
Figure 5.3 Currently Water and Developed Constraints shapefiles extracted from OS MasterMap topographic area layer.	117
Figure 5.4 Rasterised water and developed constraints at 100 metre spatial resolution.	118
Figure 5.5 Spatial datasets for the Middlesbrough case study.	119
Figure 5.6 a) Middlesbrough’s town centre boundary and CBD centroid (ci, j), road network (R) and b) & c) digitisation of Middlesbrough town centres boundary from Middlesbrough’s interactive LDF (Middlesbrough Council 2010).	120

Figure 5.7 Middlesbrough greenspace in a) vector format and b) rasterised at a 100 metre spatial resolution.....	120
Figure 5.8 Convergence during the Simulated Annealing runs (a-c) using the input parameters set out in Table 5.3.....	123
Figure 5.9 Proposed development sites represented in the <i>parent</i> set at stages of the GA operation.....	125
Figure 5.10 Convergence of Pareto front of <i>offspringg</i> during the Genetic Algorithm search with a) every 50 th generation and b) between generations 160-200.	126
Figure 5.11 Pareto-optimal solutions between sustainability objectives found by the SA approach.	129
Figure 5.12 Pareto-optimal fronts found between sustainability objectives utilising the GA approach.	130
Figure 5.13 Comparison of the Pareto fronts from the GA and SA approaches (normalised through all solutions found).	133
Figure 5.14 Best performing spatial configurations resulting from the SA investigation for a) $\min(f_{heat})$, b) $\min(f_{flood}, f_{sprawl})$, c) $\min(f_{dist})$ and d) $\min(f_{sprawl}, \in N_{fheat}, f_{sprawl})$	136
Figure 5.15 Best performing spatial configurations resulting from the GA investigation for a) $\min(f_{heat})$, b) $\min(f_{flood}, f_{sprawl})$, c) $\min(f_{dist})$ and d) $\min(f_{sprawl}, \in N_{fheat}, f_{sprawl})$	136
Figure 5.16 Parallel line plots of best performing Pareto-optimal spatial plans from the SA (hatched) and GA investigation (Figure 5.14 and 5.15) normalised throughout the solutions found.	137
Figure 5.17 Spatial frequency of site assignment based on the resulting MOPO solution from a) the SA investigation and b) the GA investigation.	137
Figure 5.18 Parallel Line plots of the normalized objective score of the MOPO solutions ($F = \{f_{heat}, f_{flood}, f_{dist}, f_{sprawl}\}$) against the best performing un-weighted Pareto-optimal solution.....	138
Figure 5.19 Pareto optimal spatial configurations within N_{fheat}, f_{dist}	139
Figure 5.20 Parallel line plots of Pareto-optimal spatial configurations in N_{fheat}, f_{dist} . .	140
Figure 5.21 Density matrix for spatial configurations within N_{fheat}, f_{dist}	140
Figure 5.22 Comparison of a) Middlesbrough's current spatial plan and Pareto-optimal spatial configurations selected on the basis of equal priorities for b) the GA run and c) the SA run.	142
Figure 5.23 Parallel line plot of the prioritised Pareto-optimal spatial configurations.....	144

Figure 5.24 Prioritised Pareto-optimal spatial configurations.....	145
Figure 6.1 Mapping how development sites within a development plan, D relate to cells designated as available throughout the study area.....	154
Figure 6.2 Case study area of Greater London.....	158
Figure 6.3 Input spatial datasets for London case study.....	162
Figure 6.4 Planning constraints for London case study.....	163
Figure 6.5 Available areas for development at a 200m spatial resolution including designated brownfield sites.	164
Figure 6.6 a) PTAL Classifications (sourced from the London Datastore) and b) simplified PTAL for planning constraints in Table 6.2.	165
Figure 6.7 Pairwise comparison matrix nine point rating scale	168
Figure 6.8 Development sites represented in the initial ($g = 0$) <i>parents</i> set.	172
Figure 6.9 Convergence of the Pareto front $Nfheat, fbrownfield$ during the GA application.	174
Figure 6.10 Convergence of the Pareto front $Nfheat, fdist$ during the GA application.	174
Figure 6.11 Pareto fronts between sustainability objectives for the London case study.....	176
Figure 6.12 a) Overview of spatial configuration for $minfheat$, b) viewing windows i, ii and iii, and c) comparison with the spatial plan for $minfflood, fbrownfield$. For clarity of visualisation varied densities of development are not shown.	179
Figure 6.13 The spatial plan for $minfdist$ shown against brownfield sites.	180
Figure 6.14 The spatial plan for the solution which is $minfdist$ against heat hazard.....	181
Figure 6.15 The spatial plan for the solution which is $minfbrownfield$ in the Pareto-set $Nfheat, fbrownfield$	182
Figure 6.16 Parallel line plot showing the performance of the best Pareto-optimal spatial plans across the range of objectives.....	183
Figure 6.17 Borough level comparison between GLA plan and Pareto-optimal spatial plans.	185
Figure 6.18 Sub-Borough level (community forum areas) comparison between GLA plan and optimal spatial plans.	186
Figure 6.19 Ranked Pareto-optimal Development sites	188
Figure 6.20 Parallel line plot of sample of MOPO solutions.	189
Figure 6.21 Parallel line plot of the prioritized Pareto-optimal spatial plans.....	190
Figure 6.22 Prioritized Pareto-optimal spatial plans.	191
Figure 6.23 Borough comparison of prioritized Pareto-optimal spatial plans.	192

Figure 6.24 Convergence of the Pareto fronts a) Nf_{heat}, f_{dist} and b) Nf_{heat}, f_{sprawl} under differing regulatory frameworks.	193
Figure 6.25 The effect on development densities of the spatial plan $\min(f_{heat})$ under differing regulatory frameworks.	194
Figure 6.26 Borough development densities of the spatial plan $\min(f_{heat})$ under density deregulation compared to business as usual.	194
Figure 8.1 Visualisation tools to convey the performance of solutions over multiple objectives from a) Kumar et al. (2013) and b) Fu et al., (2013).	225
Figure 8.2 Idealised visual support system for multi-objective spatial optimisation from Xiao et al. (2007).	225

List of Tables

Table 1.1 Thesis objectives and outline.....	4
Table 2.1 Timeline of significant uptake of sustainable development as a concept by international and national governments, as well as international organisations in legislation and/or the setting up of public bodies.....	8
Table 2.2 Characteristics of Compact and Dispersed Cities (adapted from Neuman 2005)....	21
Table 2.3 Potential conflicts of sustainability issues (adapted and expanded from Dawson, 2011).....	30
Table 2.4 Development allocations for sites outlined in Figure 2.9 (AMEC Environment & Infrastructure 2014).....	37
Table 5.1 Housing targets based on population scenarios in Middlesbrough’s Local Development Framework (Middlesbrough Council 2013a).....	115
Table 5.2 Amendments to policy CS1 on dwelling totals (Middlesbrough Council 2013a).	115
Table 5.3 Parameters for the testing the Simulated Annealing approach.....	122
Table 5.4 Performance of the Simulated Annealing search at different stages during testing.	122
Table 5.5 Genetic Algorithm Search Parameters for Case Study Application.....	126
Table 5.6 Normalised Pareto front trade-off matrix from SA results (see Figure 5.11).	131
Table 5.7 Normalised Pareto front trade-off matrix from GA results (see Figure 5.12).....	131
Table 5.8 Comparison of Pareto front statistics between the Genetic Algorithm and Simulated Annealing approach.....	132
Table 5.9 Performance of the best un-weighted Pareto-optimal result (Figure 5.22) against Middlesbrough Council’s development plan.....	142
Table 5.10 Preference vectors for prioritised spatial plans.	144
Table 6.1 Indicators for monitoring the sustainability effects of the London Plan (table 1 (Greater London Authority 2011d). Objectives address directly and indirectly by the framework are highlighted.	160
Table 6.2 PTAL accessibility standard for new development in London (adapted from Table 3A.2 in London’s Spatial Strategy (Greater London Authority 2011e).....	165
Table 6.3 Outline of differing planning priorities	168
Table 6.4. Pairwise comparison matrix for the differing planning priorities. Note these are unscaled values and are modified before the weights are applied.....	169
Table 6.5 Run Parameters for case study application of the Spatial Optimization Framework	172
Table 6.6 Run statistics.....	173

Table 6.7 Convergence statistics for <i>Nfheat, fbrownfield</i> during the case study application.	173
Table 6.8 Convergence statistics for <i>Nfheat, fdist</i> during the case study application.	174
Table 6.9 Pareto front trade-off matrix.	176
Table 6.10 Derived preference vectors for prioritized spatial plans.	190

List of Abbreviations and Notation

AHP	Analytical Hierarchy Process
BAU	Business as Usual
CBD	Central Business District
DECC	Department for Energy and Climate Change
Defra	Department for Environment, Farming and Rural Affairs
DCLG	Department for Communities and Local Government
DoH	Department of Health (UK)
EA	Environment Agency (UK)
EIA	Environmental Impact Assessment
GA	Genetic Algorithm
GIS	Geographic Information System
GLA	Greater London Authority
IIA	Integrated Impact Assessment
IP	Integer Programming
IPCC	Intergovernmental Panel on Climate Change
LP	Linear Programming
LIP	Linear Integer Programming
MOPO	Multi-Objective Pareto-optimal
MOO	Multi-objective Optimisation
MOSPOF	Multi-Objective Spatial Optimisation Framework
NSGA-II	Non-dominated Sorting Genetic Algorithm II
ODPM	Office of the Deputy Prime Minister (UK)
SA	Simulated Annealing
SEA	Strategic Environmental Assessment
SOO	Single Objective Optimisation
SSSI	Special Sites of Scientific Interest
TOD	Transit Oriented Development
u/ha	Units per Hectare
UN	United Nations

Glossary of Notation

Notation	Description
<i>Optimisation Problem</i>	
$X = (x_1, x_2, \dots, x_m)$	Variable set consisting of m variables.
$F(X) = (f_1(X), f_2(X) \dots f_n(X))$	Objective function set consisting of n objective functions to optimise.
s	A feasible solution found by the optimisation application.
i, j	Location on grid.
<i>Pareto-optimisation</i>	
p	Non-dominated solution within the non-dominated list.
N	Non-dominated (Pareto-optimal) list.
f	An objective function within F .
F	Set of objective functions.
N_{f_1, f_2}	Non-dominated/ Pareto-optimal list between the objectives f_1 and f_2 .
<i>Urban Planning Problem</i>	
d	Proposed development site.
D	A collection of development sites where $d \in D$.
$dens$	Collection of possible development densities.
dw	Number of dwellings assigned to a development site based on proposed <i>density</i> and area of cell.
D^{dw}	Total number of dwells associated with a proposed development plan, D .
DW_{MAX}	Maximum number of dwellings a feasible D can contain.
DW_{MIN}	Minimum number of dwellings a development plan, D , must contain.
l	1,2,...,n; where n is the total number of elements in D . Each l links to a i, j location within the study area via use of a lookup table.
<i>Sustainable Planning Objectives</i>	
f_{heat}	Objective function representing heat risk (Equation 4.2 and 6.2).
f_{flood}	Objective function representing flood risk (Equation 4.5 and 6.3).
f_{dist}	Objective function representing the average distance of development to CBD (Equation 4.6 and 6.4).
f_{sprawl}	Objective function representing urban sprawl (Equation 4.7 and 6.5).
$f_{brownfield}$	Objective function representing brownfield development (Equation 6.6).
<i>Objective Parameterisation</i>	
$h_{i,j}$	Heatwave hazard annual frequency raster.
$v_{i,j}$	Population vulnerability raster; population density.

$v_{i,j}^+$	Increase in population density as a result of a development site $d_{i,j}$.
$H_{i,j}^{Future}$	Future heat risk raster; product of h_{ij} and updated $v_{i,j}^+$.
$z_{i,j}^{1000}$	Cells within 1 in 1000 flood zone.
$z_{i,j}^{100}$	Cells within 1 in 100 flood zone.
$c_{i,j}$	CBD centroid/ town centre point.
C	Collection of town centres centroids.
R	Road network.
P	Shortest path along the road network.
$u_{i,j}$	Cells designated as within the current urban extent.
$b_{i,j}$	Cells designated as brownfield sites.
$g_{i,j}$	Cells designated as greenspace.

Simulated Annealing (SA) Search Parameters

S	List of D found by the SA algorithm
n	Iterations within entire SA algorithm procedure
m	Iterations of the application of the SA algorithm
f_n	Objective functions of a solution at the n th iteration
f_b	Best objective function found throughout the SA operation.
D_n	Spatial configuration of the solution at the n th iteration.
D_b	Best performing spatial configuration found throughout the SA operation.
Δ	Magnitude of difference between f_n and f_{n+1} .
T	Temperature variable used by the SA procedure.
C	Cooling factor applied to temperature variable T .
T_{end}	Ending parameter for T which terminates the algorithm.
\mathbb{R}	Real number between 0 and 1.

Genetic Algorithm (GA) Search Parameters

G	Number of generations in the GA application.
$No_{parents}$	Number of individuals to select for the next generation.
$p_{crossover}$	Probability of applying a crossover to two solutions.
$p_{mutation}$	Probability of mutating an solution.
p_m	Probability of mutating an element within an solution.

Chapter 1 Introduction

1.1 Urbanism and Climate Risks

‘Urbanisation is one of the most powerful and visible anthropogenic forces on Earth,’ (Dawson 2007). Currently 50% of the world’s population reside in cities with this set to rise to 60% by 2030 equating to around 5 billion people (United Nations Population Fund 2011). As cities take up a maximum of 3% of the Earth’s land surface area (Balk et al. 2005) and are frequently associated with naturally high risk locations (Mitchell 1999) this process is spatially concentrating exposure to natural hazards and aggregating disaster potential (Carter 2011). For example 64% of the world’s urban population currently reside in coastal zones (Balk et al. 2005), whilst 13% reside in coastal lowlands at risk from flooding (McGranahan et al. 2007). These are subject to further exposure as the historical development of urban areas has led to a spatial form which is poorly adapted to hazards with the paving of roads increasing surface run off contributing to flooding (Nirupama & Simonovic 2007) and the proximity of buildings exacerbating the urban heat island effect (Hunt & Watkiss 2011). Moreover the increasing urban population tends to consist of most vulnerable in society with the least resources and, therefore, have limited adaptive capability (e.g. aging populations are particularly vulnerable to heat stroke during heat waves (Porfiriev 2014; Krebs et al. 2010)).

As urbanisation is leading to higher exposure and vulnerability to natural disasters this is compounded by climate change induced temperature, precipitation and wind changes, leading to more frequent and severe extreme natural hazard events (IPCC 2007b). The predicted severity of these events are dependent on the emission scenarios employed. However the key expected impacts of climate change on cities include but are not limited to:

1. Sea level rise increasing the risk of storm surges on coastal cities.
2. More frequent intense precipitation events leading to higher risk of flooding.
3. Extreme weather events damaging built infrastructure (e.g. from wind and flooding events).
4. Health effects arising from higher average temperatures and/or extreme events (including heat and cold related mortality and morbidity). (Hunt & Watkiss 2011)

Additionally urbanism and climate change is putting pressure on vital resources, such as water and energy. The International Panel on Climate Change (IPCC) (2014) projects higher incidences of droughts due to climatic change as water stored in glaciers and snow decline,

reducing the availability of water to settlements reliant on melt water. The effect will be especially felt in developing countries when there is already a lack of available water resources for newly urbanised areas (Janakarajan et al. 2006; Jiang 2009). Whilst higher magnitude weather events such as cold snaps and heat waves can put pressure on energy capacity due to demand from air conditioning and central heat potentially leading to blackouts (Hunt & Watkiss 2011). As the consequences of climate change loom large it is ironic that cities are the major contributors to climate change drivers producing 71% of energy-related CO₂ emissions according to some sources (International Energy Agency 2008).

These factors combined are making cities a foci for risk prevention measures, energy reduction and resource efficiency necessitating a move towards more resilient and sustainable cities (Reckien et al. 2014). Cities must become more resilient to higher magnitude and frequency climate induced hazards through risk adaptation measures whilst continuing to contribute to international efforts to avert further climate change by reducing emissions (Rosenzweig et al. 2010). Moreover there is a need for better management of scarce resources in cities through waste reduction and improved efficiency. With continued rapid population growth expected in the first half of the 21st century and hence continued urban growth, the need for sustainable urban development is increasingly becoming recognised (Harriet Bulkeley & Betsill 2005).

The spatial layouts of cities are crucial to meeting these pressures. It is estimated that up to 70% of consumed energy is dependent on land use arrangements (Barton 1990) and the continued extension of the urban area (sprawl) can lead to higher emissions from increased travel distances and congestion (Burge et al. 2013). Moreover the layout of the urban form is crucial to not only prevent the exacerbation of climate change, with dense development increasing the urban heat island effect and concreting exacerbating the risk of pluvial (rain-fall) flooding (Stone 2005; Nirupama & Simonovic 2007), but also careful consideration must be made to the location of the residing population within urban areas so as to not expose them to these risks (Depietri et al. 2013; Porfiriev 2014). Therefore the increased risks associated with climate change needs to be accounted for within the planned development of cities to alleviate the potential effects of extreme events on their populations and infrastructure (Carter 2011).

This is becoming all the more urgent with the impending internationally agreed aim of limiting climate change to a 2°C increase in global temperatures to prevent devastating future climate change (IPCC 2013; Committee on Climate Change 2015). Meanwhile climate change has

failed to be averted in the short term (IPCC 2007a) and the IPCC's warning of the effects of climate change will be felt shortly (IPCC 2014).

1.2 Conflicting Sustainability Initiatives

These pressures are necessitating a transition towards cities which are more robust to potential natural (and other) hazards while at the same time mitigate energy use, reducing the effect of further climatic change. Unfortunately the simultaneous pursuit of these desirable aims has the potential for pitfalls between the sustainability policies and strategies necessary to facilitate this move, as well intended interventions in one sector can interact and have undesirable impacts on other sectors (Mcevoy et al. 2006; Barnett & O'Neill 2010; Dawson 2011). Indeed IPCC identifies that the pursuit of preventing and adapting to climate change will have negative impacts on other elements of sustainability (IPCC 2007b).

For example in the previous decade European governments have focused almost exclusively on mitigation of GHG emissions through urban intensification (Biesbroek et al. 2010) to reduce private car emissions through better accessibility and public transport provision. However with impending climate change it's becoming increasingly clear that this high density development exacerbates natural hazard events such as flooding and urban heat islands due to increased surface run-off and the proximity of buildings (Melia et al. 2011) whilst leading to numerous negative consequences such as poor air quality and increased crime (Newton et al. 1997; Elizabeth Burton 2000). This is reciprocated with numerous adaptation responses negatively affecting mitigation attempts (Barnett & O'Neill 2010). Dispersed development to alleviate heat and flood risk can lead to higher transport emissions from increased travel distances whilst the use of air conditioning to alleviate heat stress leadings to higher energy use. Moreover economic, social factors and governance policies have been found to disrupt adaptation efforts (Jones & Clark 2014).

As a consequence urban planners are presented with a multi-objective spatial optimisation problem to balance these sustainability pressures and require robust spatial planning decision tools to analytically assess the conflicts and best trade-offs between objectives to make coherent planning decisions. Spatial planners need to avoid making assumptions about the relative merits of sustainability interventions and instead make evidence based decisions which consider the performance of short term adaptation objectives and longer term mitigation objectives. Indeed

traditionally spatial planning decisions have been taken on the basis of ‘satisficing’ (Simon, 1996) i.e. selecting plans which exceed an acceptability threshold for planning objectives.

However in response there is growing body of work that has demonstrated that analytical methods, including optimization techniques, can be successfully employed in the decision making tools providing optimal infrastructure plans in the presence of multiple objectives (Kapelan et al. 2005a). These include the preparation of flood responses (Woodward et al. 2013; Sayers et al. 2014), the planning of water distribution networks (Vamvakeridou-Lyroudia et al. 2005; Prasad et al. 2004; Kapelan et al. 2005) and bus transport networks (Delmelle et al. 2012; Shimamoto et al. 2010; Yu et al. 2005; Bielli et al. 2002). Optimisation has been applied to several land use applications (Cromley & Hanink 1999; Aerts et al. 2005; Stewart & Janssen 2014; Liu et al. 2015).

The potential of optimisation to act as a decision support tool for sustainable development is acknowledged in the literature (Kapelan et al. 2005a). However where these have concerned cities they focus on maximising land use compatibility (Cao et al. 2011; Masoomi et al. 2012; Khalili-Damghani et al. 2014) whilst studies concerning sustainable development focus on compact cities and omit consideration of climate risk management (Ligmann-Zielinska et al. 2005; Ligmann-zielinska et al. 2006; Cao et al. 2012).

1.3 Aims, Objectives and Thesis Outline

The aim of this research is to generate an optimisation based methodology for decision support to assist urban planners enable the transition of cities to be more climatically sensitive and sustainable by accounting for a range of different, and often competing, policy objectives. In order to meet this aim the Thesis has 5 distinct objectives addressed in the following 7 chapters. Table 1.1 outlines these objectives and the chapter in which they are addressed.

Table 1.1 Thesis objectives and outline.

Objective	Chapter
<p>1. Review the field of sustainable urban planning in order to recognise the conflicts and barriers that can occur during the transition to more sustainable cities and the best methods to overcome these;</p>	<p>Addressed in Chapter 2 through a study of sustainability literature and spatial planning documents (such as sustainability appraisals) allowing for an appreciation of the major sustainability challenges faced by urban planners.</p>

Objective	Chapter
<p>2. Recognise the major spatial planning objectives and aims of sustainable urban planning to be addressed by this work;</p>	<p>Addressed partly by Chapter 2 but also a review of sustainability appraisals in Section 4.2.3.</p>
<p>3. Review the field of algorithmic optimisation, in particular their application to urban spatial planning and infrastructure assessment, to identify a series of suitable optimisation approaches for addressing the sustainable spatial planning of cities;</p>	<p>Chapter 3 provides a theoretical background into optimisation algorithms including the different approaches available and a critical analysis of previous applications. This is then used to identify a number of best practices and approaches from which to constitute a decision support methodology.</p>
<p>4. Develop a spatial optimisation framework, consisting of the approaches identified by objective 3, to enable and act as a decision support tool for planners to meet the objectives identified in objective 2;</p>	<p>Chapter 4 outlines the methodology and software to develop a spatial optimisation framework which optimises urban residential development against key sustainability objectives.</p>
<p>5. Apply the optimisation suite developed to several real sustainable urban planning problems to demonstrate the utility of the spatial optimisation approach developed.</p>	<p>Chapters 5 and 6 outline case studies of the application of the developed framework for Middlesbrough and London, medium and large urban areas respectively. Chapter 7 discusses the major findings of the applications to Middlesbrough and London and critically assesses the developed framework.</p>

Chapter 2 Sustainable Cities and Development

2.1 Introduction

As introduced in Section 1.1 there is a need to move towards cities which are sustainable, not only in the short-term to preserve infrastructure (Biesbroek et al. 2010), but also in the long-term to mitigate against and adapt to greenhouse gas emissions that may lead to more frequent climate change induced hazards (IPCC 2007a; Rosenzweig et al. 2010; IPCC 2014). This move towards sustainable cities is also being driven by the realisation that there is a need to more effectively manage scarce resources (e.g. water (Taikan & Kanae 2006; House of Commons Environmental Audit Committee 2015) and combustibles (Krebs et al. 2010; Newman et al. 2009), whilst also continuing to provide a good quality of life for a growing urban population (Meara et al. 1999; Gordon 2008; Chourabi et al. 2011). This chapter analyses the issues surrounding this move towards sustainable cities and urban form. Current thinking on the best methods and practices to facilitate a move towards sustainable cities and urban development are reviewed, whilst the potential barriers are also considered, in order that the analytical developments presented in this thesis are sensitive to and take into account the broader sustainable cities agenda.

Sustainable development is synonymous with the move to urban sustainability (Lele 1991; Beatley & Manning 1997; Gasparatos et al. 2008) representing the method by which to deliver sustainable urban form (Banister et al. 1997). Sustainable development has been an significant concept since the publication of the 1987 report by United Nation's World Commission on Environment and Development (Brundtland 1987) (often referred to as the Brundtland Report) which set out the considerable challenges urban areas faced in the future. Since then, numerous governments and non-governmental institutions and bodies have been created which are dedicated to the concept. Table 2.1 details a timeline of the concept entering into legislation and the creation of associated bodies. For example, the UN Commission on Sustainable Development was created explicitly to promote and monitor sustainable development (United Nations 1992a), whilst the 1997 Treaty of Amsterdam (European Communities 1997) explicitly commits the European Union (EU) to promoting sustainable development. Despite this, the means by which the sustainable development cause has been progressed has been questioned (Lele 1991; Stirling 1999; Berke & Conroy 2000; Redclift 2005). For example, Dernbach (2002) argues that despite the United States government setting up the President's Council on Sustainable Development in 1993, very few of its recommendations have been implemented.

This is a common criticism of many governmental bodies associated with sustainable development with critics accused their creation is merely to pay lip service to the concept (Lele 1991; Redclift 2005).

Table 2.1 Timeline of significant uptake of sustainable development as a concept by international and national governments, as well as international organisations in legislation and/ or the setting up of public bodies.

Organisation	Date of Establishment/ Publication	Body or Publication
United Nation's World Commission	1987	Brundtland Report (Brundtland 1987)
United Nations	1992	Agenda 21 (Voluntary commitment to National Sustainable Development Strategies) (United Nations 1992b)
United Nations	1992	Commission on Sustainable Development (United Nations 1992a)
Australia	1992	National Strategy for Ecologically Sustainable Development
United States Government	1993	President's Council on Sustainable Development
European Union	1997	Treaty of Amsterdam (European Communities 1997)
China	1997	The People's Republic of China National Report on Sustainable Development
United Kingdom Government	2000	Sustainable Development Commission
African Union	2001	New Africa Initiative
European Union	2001	EU Sustainable Development Strategy
New Zealand	2003	Sustainable Development Programme of Action

One of the reasons for this failure to implement sustainable development is the lack of consensus on its specific aims (Connelly 2007), with few clear definitions of many key concepts such as social justice (Redclift 2005) and environmentalism (O'Riordan 1999a). Section 2.2 in this chapter critically examines the different definitions and thinking of sustainable development in order to come to provide a definition and agreed set of objectives that underpin the approaches developed in this thesis. In the pursuit of sustainable development, several idealised conceptual models of what a sustainable urban form constitutes have been put forward along with specific policies to achieve this (Haughton 1997). Section 2.3 critically assess these models, such as the compact city (Dantzig & Saaty 1973), dispersed city (Buxton 2000) and transport-oriented development (Belzer & Autler 2002), to assess what contributions they can make individually and also collectively towards achieving sustainable development (Williams et al. 2000). There are a number of barriers to sustainable development, ranging from conflicting sustainability objectives (Mcevoy et al. 2006; Barnett & O'Neill 2010; Dawson 2011) through to uncertainty (Willows & Connell 2003; Ben-Haim 2012). Section 2.4 identifies

theses and critically analyses the literature to discern methods by which these difficulties can be at best avoided or at worse mitigated.

Spatial planning is the favoured method by which governments control and manipulate urban form to reach agreed concepts of sustainability. Section 2.5 reviews how spatial planning has been used to facilitate the move to sustainable urban forms by ensuring new development meets sustainability commitments, setting criterion in the form of Environmental Impact Assessments (Gasparatos et al. 2008), undertaking Strategic Environmental Assessments (Tetlow & Hanusch 2012) and Sustainability Appraisals (Singh et al. 2012). These methods are critically examined to identify potential weaknesses and therefore areas for improvement before the utility of decision support to aid this process is explored.

2.2 Definition of Sustainable Development

In order to achieve sustainable development it is essential to define what it constitutes. Despite numerous attempts by intergovernmental bodies to define sustainable development several sources have lamented the vagueness and ambiguity over what the term actually refers to (Hopwood et al. 2005; Connelly 2007). One of the earliest and most widely quoted definition (Eppel 1999; Quaddus & Siddique 2001; Woodward 2004; Redclift 2005; Gibson 2006; Jepson et al. 2014) comes from the Brundtland Report, which defines sustainable development as:

“...meeting the needs of the present without compromising the ability of future generations to meet their own needs.” (UN, 1987)

Hopwood et al. (2005) point out that the vagueness of the term potentially allows politicians and leaders to justify policies of extremes such a ‘communal agrarian utopianism’ through to ‘extreme market systems’. Policy makers can justify any policy, no matter how regressive, on the basis that it meets this loose definition. For this reason Richardson (1997) describes how the term was originally viewed by some as a “rhetorical cloak” for undesirable policies, while the term sustainable development was latched on to by social equity campaigners and the environmentalist movement to advance their own ideas. Because of this, several governments deliberately avoided using the term. For example, New Zealand’s original attempt at legislating sustainable development purposefully excluded the term in its Resource and Management Act to avoid conflict (Ericksen et al. 2004).

However, it has been argued that governmental definitions were purposefully ill defined so as to not to alienate potential allies and to allow for a ‘broad church’ approach in the early stages of pushing for sustainable development (e.g. such as in the environmentalist and social justice movements) (Wackernagel & Rees 1996; O’Riordan 1999a). Moreover, the earliest definitions came at a time when there was a lack of proven routes to towards sustainable development and as such a loose definition allows for a wider exploration of different methods in order to deliver sustainability (Redclift 2005). Thus, to some extent, its greatest weakness is also its greatest strength, as the ambiguity allows for more encompassing view of sustainability.

Connelly (2007) is highly critical of the early ambiguous definitions, suggesting they hamper sustainable development by focusing on rhetoric and principles, and ignore any complexity from which best practice can be discerned.

“As long as sustainable development is viewed as ‘everything and nothing’ it is weakened as a policy goal, and those wishing to promote environmental sustainability and social justice are hampered if they attempt to do so without a clear understanding of the tensions and potential conflicts between these desirable goals.” (Connelly, 2007)

The work of Pearce et al. (1989) was one of the first to frame sustainable development in terms of a combination of economic growth, social justice and environmental protection. Often referred to as the ‘three pillars of sustainability’ (Pope et al. 2004; Gibson 2006; Mahida 2011), Houghton & Counsell (2003) argues that this definition was instrumental to the acceptance of sustainable development as a concept, as it allowed the debate around sustainable development to move away from pure environmentalism or social justice to also include economic considerations. This broad concept defines sustainability as having:

- i. An economic role – building a sustainable economy through ensuring sufficient land and office space to keep up with demand whilst providing the necessary infrastructure to enable economic growth;
- ii. A social role – meeting people’s needs for housing in a high quality environment whilst providing the relevant local services and amenities to support health, social and cultural wellbeing; and,
- iii. An environmental role – protecting and enhancing the environment and biodiversity whilst prudently managing natural resources.

Indeed the simplicity in reconciling the complexities of sustainable development into 3 objectives allowed initial research and moves towards sustainable development to avoid being dogged down into the technicalities of further definitions (Connelly 2007; Giddings et al. 2002). The definition has been widely interpreted by many non-governmental organisations and governments as a Venn diagram consisting of a series of rings representing social justice, economic development and environmental protection where the intersection denotes sustainable development (Figure 2.1) (State of New Jersey Planning and Sustainable Communities 1996; ICLEI (International Council for Local Environmental Initiatives) 1996). This method found popularity with many governments as it conveys sustainable development as a ‘win-win’ situation (Myerson & Rydin 1996), where the different elements of sustainability are reconcilable whilst ignoring any potential downsides to groups of society.

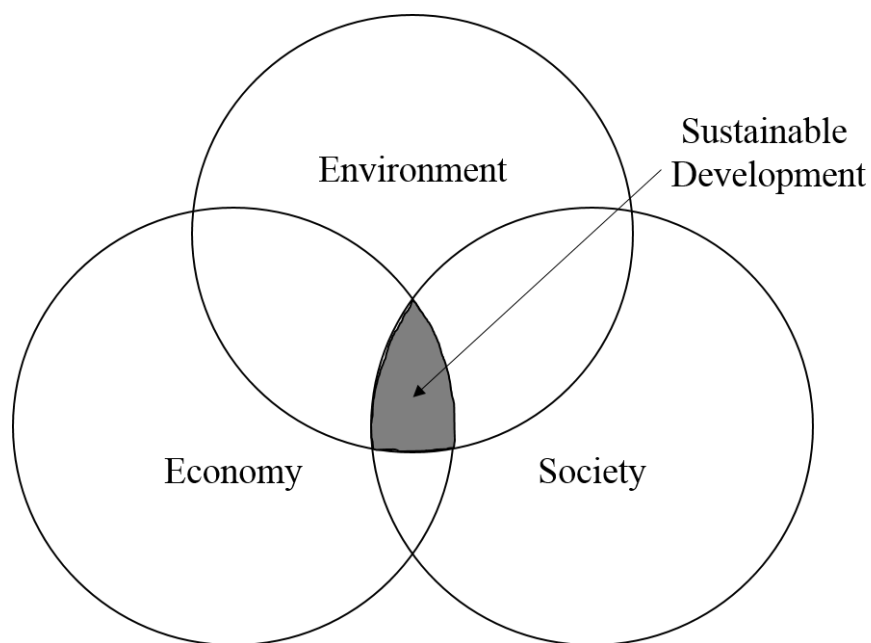


Figure 2.1 Sustainable Development mapped as interlinking rings (adapted from ICLEI, 1996).

Alternatively, Campbell (1996) interpreted this definition as a triangle specifically to convey contradictions that could occur from the pursuit of sustainable development. As Figure 2.2 demonstrates, each point of the triangle prioritises environmental protection, economic growth or social justice at the expense of the other two. The centre represents pure sustainable development, which while desirable is ultimately impossible to realise (Jones 2014). This method of mapping the concept conveys that as policies lean towards a certain philosophy, other constituents of sustainability are lost, such as in the case of eco-socialism which focuses towards environmental protection and social justice, but at the expense of economic growth. Connelly (2007) goes further with this definition using the triangle to map out the sustainability

of approaches proposed by different stakeholders. This allows for an easy visualisation of the priorities of the stakeholders and conveying priorities to certain elements.

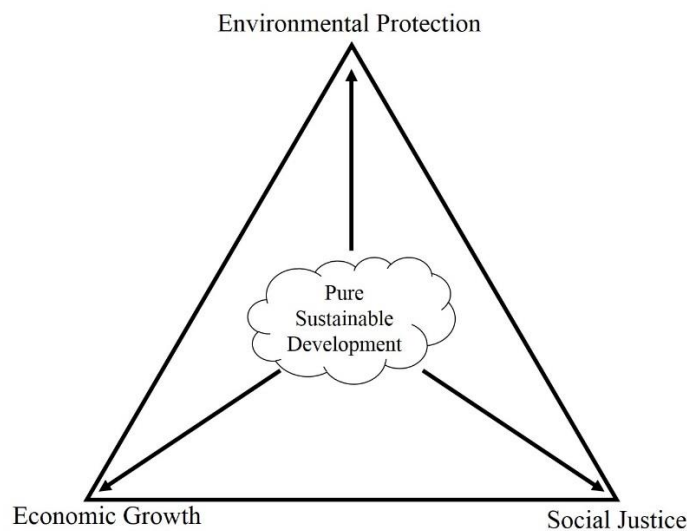


Figure 2.2 Sustainable development as a combination of economic growth, environmental protection and social justice (reproduced from Connelly 2007).

The three pronged definition of sustainable development has been widely employed (Berke & Godschalk 2006), with its principles being adapted by the 2000 United Nations Millennium Declaration (United Nations General Assesmbly 2000). Indeed, the UK governments 2005 ‘Sustainable Development Strategy’ (Defra 2005) framed their definition along these ‘3 pillars’ and the UK’s most recent National Planning Policy Framework (NPPF) continues to categorises sustainable planning in terms of these elements (Department for Communities and Local Government (DCLG) 2011a). Despite this definition of sustainable development as a combination of environment, social justice and economic growth being a popular and often used definition, the concept has gradually grown to encompass further (and well defined) elements such as such as good governance (Williams 2004; Kenworthy 2006; Kourtit et al. 2014), quality of life (Swanson et al. 2004; London Sustainable Development Comission 2005; Mahida 2011) (which is a more objective measure than social justice) and the elimination of poverty (Quaddus & Siddique 2001; United Nations Population Fund 2011).

Sustainability efforts are centred on urban areas as they contain high density populations which as Chapter 1 detailed, is further increasing with urbanism. With regards to urban sustainability, this has in recent times been increasingly viewed through the prism of climate change (Adger et al. 2005; H Bulkeley & Betsill 2005; Carter 2011). This has coincided with major publications by the International Panel on Climate Change (IPCC) (an scientific

intergovernmental body set up by the UN) outlining the threat and scale of climate change (IPCC 2007a; IPCC 2013; IPCC 2014) following from initial international efforts to avoid significant climatic change such as the signing of the Kyoto agreement which established a requirement of at least a 5% cut in emissions from a 1990 baseline by 2012 (UNFCCC 1998). Responses to climate change in cities mainly relate to two concepts, mitigation and adaptation. Mitigation is defined by the IPCC as:

“An anthropogenic intervention to reduce the anthropogenic forcing of the climate system; it includes strategies to reduce greenhouse gas sources and emissions and enhancing greenhouse gas sinks.” (IPCC 2007a)

Whilst adaptation is defined as:

“Adjustments in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderate harm or exploit beneficial opportunities”. (IPCC 2012)

In terms of urban development, adaptation is viewed as how well urban areas adapted to the effects of climate change (Carter 2011) such as higher incidence heat waves, floods, as well as droughts and cold snaps (Hajat et al. 2014; Staden 2014). Whilst mitigation is thought of how well urban areas can curb their energy use and reduce emissions of greenhouse gases from transport and domestic use. Significant efforts at climate change mitigation for urban areas have been made since the signing of the Kyoto agreement, with for example the EU agreeing to on average 8% decrease in emissions by 2012. However, adaptation was not adopted as early as mitigation with policies in relation to modifying cities to account for climate change occurring much later (Biesbroek et al. 2010; Carter 2011; Berrang-ford et al. 2014; Reckien et al. 2014). Indeed the emphasis on adaptation began with the growing evidence that even with substantial reductions in GHG emissions, climate change was inevitable (IPCC 2007d). Thus it became clear that organisations needed to prepare suitable responses to climate change impacts. Krebs et al. (2010) considers that these adaptation and mitigation efforts will compliment other elements of sustainability, and are in fact central to ensuring environmental (through more efficient resource use), societal and economically (protecting population and businesses from the effects of climate change) sustainable cities.

This wider concept of sustainability has weakened the definition of sustainability around the three pillars and practitioners have commented that the three pillars concept is hard to follow in practice as a lot of the elements of sustainability now considered don't fit neatly into this definition (Gibson 2006; Bond et al. 2012). However, the wide use and the easy dissemination of sustainability around the 'three pillars' ensures that it will continue to be incorporated into definitions (Connelly 2007). Based on this, the research presented in this thesis acknowledges and employs a broad definition to sustainable development. The traditional definitions revolving around the economy, environmental and societal sustainability are included along with factors such as adaptation and mitigation. By considering such concepts to be part of sustainable development (of cities) the work developed agrees with the principles now widely held views of what constitutes sustainable urban development (Adger et al. 2005; IPCC 2007c; Carter 2011; Hunt et al. 2013): namely:

1. A small ecological footprint, where resources are efficiently used and emissions are minimised;
2. Environmentally friendly where the current biodiversity and ecology is protected and enhanced;
3. Sustainable economic activity is met but not at the expense of the environment;
4. Policies where the health and quality of life of the cities occupants are promoted;
5. Inclusive governance where inhabitants have a stake in decision making; and
6. Resilient with sufficient capacity to cope with future climatic events such as heat waves and flooding.

2.3 Models of Sustainable Urban Spatial Form

2.3.1 Introduction

Urban areas are the highest emitters of greenhouse gases and consumers of resources whilst containing the largest concentration of humans, and therefore have the most to lose from climate change (Hunt & Watkiss 2011). Due to this, they are at the forefront of ensuring sustainable development and are seen as the centre of sustainability efforts (Rosenzweig et al. 2010). Despite some initial scepticism at the ability of cities to meet these pressures (UN-Habitat 2004; Redclift 2005), a number of sources are optimistic that urbanisation provides an opportunity to spear-head sustainable development (Robinson 2004; Nijkamp & Kourtit 2012), as urban areas are ideally suited to deliver sustainable solutions through their ability innovate, modify their form and provide effective governance structures (Burgess & Jenks 2000).

There are currently a number of city level climate change and sustainability cooperative initiatives including the C40 Large Cities Leadership Group (Román 2010), the Rockefeller 100 resilient cities challenge (Rodin 2014), the ICLEI–Local Governments for Sustainability’s Cities for Climate Protection Programme, the Mexico City Pact and Europe’s Covenant of Mayors, the Asian Cities Climate Change Response Network (ACCCRN) and the Durban Adaptation Charter (Walsh et al. 2013). However, cities are extremely complex and the search for sustainable solutions is intimidating (Jenks, M., Burton, E. & Williams 1996). Therefore several ideas of what constitutes sustainable urban form have been proposed to meet the agreed principles of sustainable development outlined in the previous section.

The question of sustainable urban form is hugely contested (Breheny 1996; Newton et al. 1997; Banister et al. 1997; Guy & Marvin 2000; Chen et al. 2008), with some proponents arguing that cities must be at an appropriate scale to allow for walking, cycling and efficient public transport (McLaren et al. 1991), whereas others have argued that dispersed urban development best meets environmental pressures and quality of life considerations (Buxton 2000). More recent proposed sustainable urban forms include concepts such as Transit/ Transport Oriented Development (Belzer & Autler 2002), Garden Cities (Garden Cities and Suburbs Expert Group 2012) and Resilient Cities (Newman et al. 2009). All of these ultimately aim to provide a sustainable urban form but are based on different ideas of what constitutes sustainable urban form. However, each of these models attempts to address one or all the elements of sustainability (resource efficiency, perceived quality of life etc.) and propose patterns of development and policies to reconcile their ideals. These concepts are important to consider in order to determine the best practices for planners to meet their sustainability goals and are reviewed in detail in this section.

2.3.2 Urban Intensification: The Compact City model

Originally envisaged by Dantzig and Saaty (1973) as a means of protecting surrounding countryside from urban sprawl, and heavily advocated by a group known as New Urbanists (Leccese & McCormick 2000), the Compact City model came to prominence as a sustainable urban form with Newman & Kenworthy (1989) which found that dense (compact) cities led to much lower automobile reliance. This is demonstrated in Figure 2.3, where European cities with higher population densities are found to have lower gasoline expenditure per-capita than

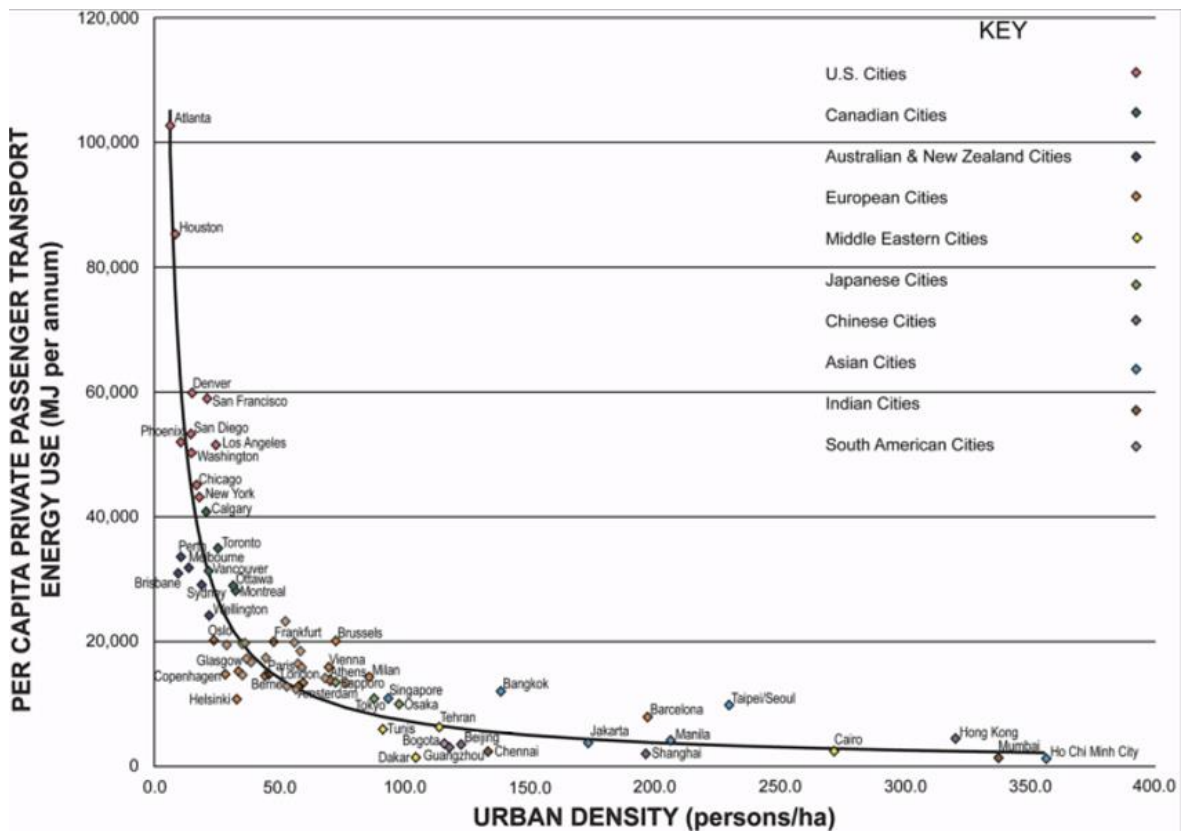


Figure 2.3 Area and Gasoline expenditure per person in world cities (data collected 1995) (Kenworthy et al. 1999).

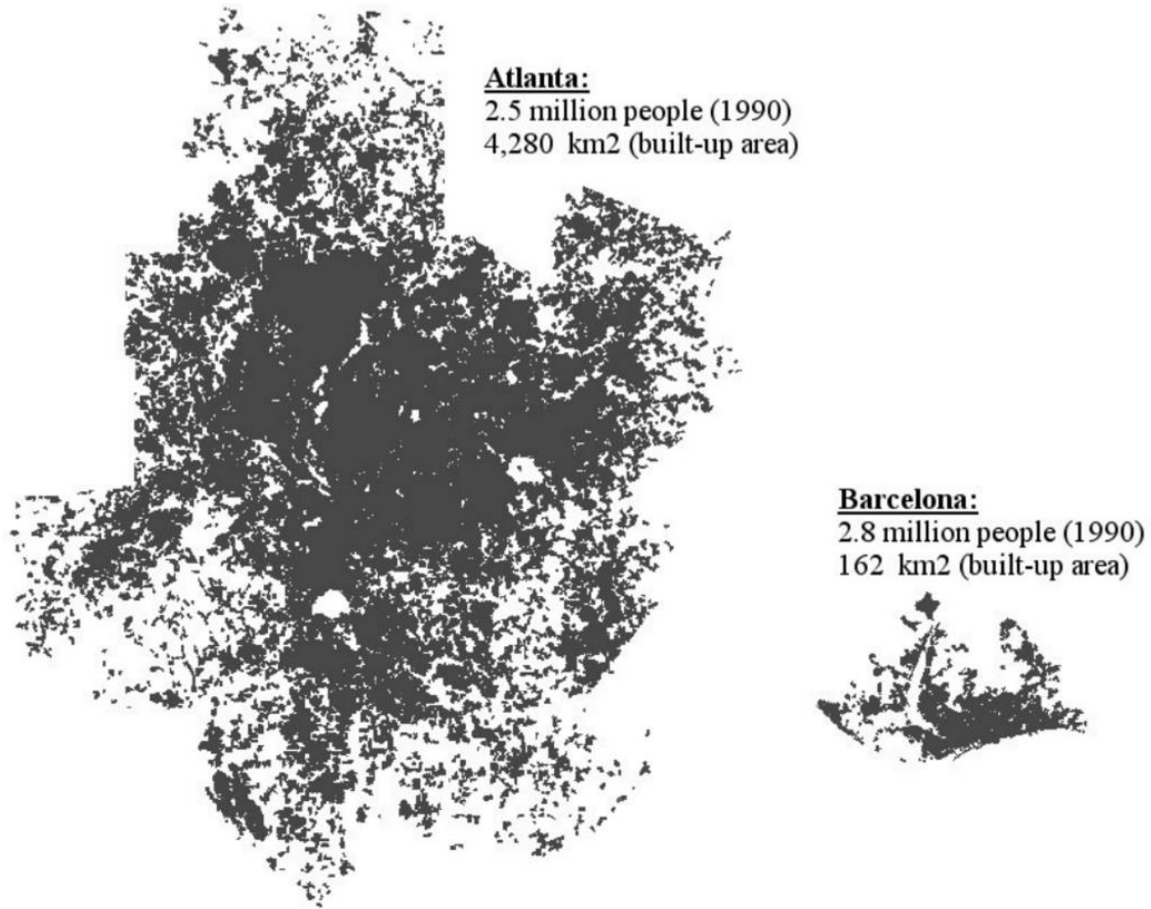


Figure 2.4 Comparison of the urban extents of Atlanta and Barcelona with similar population sizes (Bertaud & Richardson 2004).

less dense Australian and American cities. Moreover, Asian cities with the highest population densities have the lowest emissions. The role of urban form can be appreciated by comparing Atlanta and Barcelona (Figure 2.4) which have approximately the same population. However, Atlanta covers an area 12 times larger than Barcelona leading to 6 times the amount of emissions primarily as result of transport.

The Compact City model has been proposed primarily as a means to reduce carbon emissions and prevent urban sprawl through urban densification (European Commission 1997). In particular the model advocates high density housing in order to facilitate better public transport provision (Kenworthy 2006), and emphasises diverse/heterogeneous land use patterns in order to reduce the need for travel by private cars to services, employment and facilities, as they are located closer to residential areas (Leccese & McCormick 2000). Despite the emphasis on reductions in transport emissions, proponents also describe how the model addresses other elements of sustainability through environmental protection and social justice (E Burton 2000). To ensure compactness the model constrains development within the current urban extent protecting surrounding countryside and green belt land. In Europe this is achieved by policies relating to development on previously used land (brownfield) to protect urban greenspace (Williams 2004).

Improved resource usage and building energy efficiency is facilitated by high density development to allow for district heating and combined heat and power systems (CHP). The latter uses the heat by-product from electricity production from local power stations to heat buildings and is becoming increasingly effective and, as a result, prevalent worldwide (Wu & Wang 2006). Indeed Rode et al. (2014) found higher density residential areas to be the most energy efficient with as low as quarter the energy expenditure compared to lower densities. Furthermore, social justice is addressed via better access to facilities and reduced social segregation (van Kempen 1994) by mixing different socio-economic classes in a small spatial extent. Amenities located within the locale, such as shops and hospitals, and the increase in walkability advantages those with the least resources, whilst shorter distances to employment potentially improve work prospects for the low skilled (Castells & Hall 1994).

However the claim of Compact City proponents that higher population density leads to lower automobile use is coming under consistent criticism in the literature. Critics have contested that the relationship presented in Newman and Kenworthy (1989)'s study as casual and proposed

lower automobile usage is more related to income (Gordon 2008). However, Newman (2014) refutes this for developed countries, which is contrary to the findings of Melia et al. (2011) whose study that found that although densification was likely to reduce car use, the reductions were insignificant and conclusion supported by Echenique et al. (2012) who modelled several future development scenarios and found that urban intensification had little effect on vehicle metres travelled. Notably they found that compaction resulted in higher congestion potentially negating any reductions in GHGs emissions. Kim & Brownstone, (2010) found that although residential density had a modest influence on household travel behaviour the biggest relationship with household annual mileage was rural/urban locations.

A further negative of the Compact City cited by Newton (1997) is that current and future inhabitants are subjected to poorer air quality than edge and corridor cities. Burton (2000) in his study on 'the Potential of the Compact City for Promoting Social Equity' also found unintended consequences of higher death rates from respiratory disease and increases in crime due to the compact city form. In policy terms, compact cities are hard to deliver as they invoke negative perceptions by residents over issues such as the feeling of overcrowding and loss of urban quality (Jenks et al., 1996). However, Newman as an original advocate of the compact city model responds to these criticisms in Newman (2014) by arguing that income is more an indicator of poor health (Marmot & Wilkinson 2006) and crime rates (Kelly 2000) rather than the urban form.

Perhaps most worryingly are the negative impacts the compact urban form has on adaptation (Mcevoy et al. 2006). The compact cities design exacerbates risk to heat islands due to the close proximity of buildings and restrictions on air flow (Graves & Phillipson 2000; Hunt & Watkiss 2011). In addition the compact development increases vulnerability to climate hazards as multi-storey residential buildings (crucial to reach sufficiently high density development) leads to higher mortality rates during heat waves (Semenza et al. 1996; Naughton et al. 2002), decreased permeability of developed areas increases the likelihood of flooding (Sanders & Phillipson 2003; Nirupama & Simonovic 2007) whilst the close proximity of capital increases potential damage during flooding (Hunt & Watkiss 2011).

Despite these wide criticisms, the Compact City has had a profound impact on urban planning at the national scale in several countries including the UK (Williams 2004), Germany (Wentz 2000) and the US (American Planning Association 2000). In addition, international institutions such as the Organisation of Economic Cooperation and Development (OECD) recommend

aspects of the model to governments (Matsumoto 2012) while growing countries such as China see the compact city model as an answer to their rapid urbanisation (Burgess & Jenks 2000; Chen et al. 2008). Indeed one of the biggest advocates has been the European Community whose green paper on the Urban Environment (Commission of the European Communities 1990) explicitly advocated high density development and urban containment. In cities worldwide there have been efforts to contain the extent of the urban area. Strategically northern European cities of the UK, France, Germany and Belgium have realised this through targeting and promoting brownfield development (Syms et al. 2003). For example, the UK government has set targets of 60% of all new development to be located on re-used (brownfield) land in urban areas (DETR, 1998). Meanwhile local governments in the US have used development impact fees to discourage urban fringe development (Burge et al. 2013). However in light of these there is increasing scepticism of the pursuit of compact city principles by planners (Neuman 2005) which is necessary if some of the negative consequences are to be alleviated.

2.3.3 Dispersed Cities

The antitheses of the compact city concept is the dispersed cities structure typical in Australia and the US (Kenworthy et al. 1999; Buxton 2000), and increasingly in southern European cities (Salvati et al. 2013). This is predominantly a product of urban sprawl which describes the low density development taking place on the outskirts of a city (Johnson 2001). Although the literature tends to treat dispersed cities as an alternative model of sustainable development (Neuman 2005; Hirt 2007; Mitchell et al. 2011; Echenique et al. 2012) there are very few details of any organisation, institutions or authors which advocate them as a sustainable urban form. Instead, it is used as a comparative worst case scenario alternative urban form by proponents of compact city principles. However it is worth reviewing as it has its own (to a large extent historically unintended) contributions to sustainability.

Rather than the intended policy of governments, dispersed cities are more a result of market forces such as consumer preference for detached housing in the suburbs, lower house prices away from the centre of cities and increased preference for automobiles over public transport (Buxton 2000). The result of these pressures are scattered development patterns with no poly centric pattern. Significantly dispersed cities are regarded as more liveable (Neuman 2005), especially compared to higher density urban areas, as demonstrated by people preference to live in low density sub-urban development. This urban form is better adapted to environmental

issues, for example the increased space between developments relieves heat stress and the spread of capital reduces the potential cost of flooding (Buxton 2000).

Despite this, sources have been extremely critical of dispersed urban areas with the majority of relevant literature viewing it negatively. Most of this criticism is aimed at urban sprawl which is the main cause of dispersed development. As development extends out from the centre there is an inevitable separation of land uses that increases resulting in increased travel distances between housing, employment and services increase (Ewing 1997; Burchell et al. 1998) which is almost predominantly undertaken by private car increasing emissions substantially (Banister & Banister 1995). As a result, countries with more dispersed urban areas have much higher per-capita energy consumption and high levels of road use (Newman & Kenworthy 1999). For example the US and Australia have over 3 and 2.2 times higher transport related CO₂ emissions of transport per capita respectively, with 5.2 and 3.8 tCO₂/cap (tonnes of CO₂ per capita), compared to the EU average of 1.7 tCO₂/cap (World Energy Council, 2013).

As such, this urban form is extremely contentious in an era when there is a global movement to limit GHG emissions (IPCC 2007a). Indeed sustainable interventions such as increasing public transport provision are hampered as the scattered pattern of housing prevents effective utilisation. Furthermore, sprawl causes infrastructure and public service costs to rise, as there is more need for roads and services to facilitate a wider area (Speir & Stephenson 2002; Haughton & Hunter 2003). Despite the perceived environmental advantages the often cited work of Johnson (2001) identifies a number of negative environmental impacts of sprawling development such as loss of environmentally fragile land and farmland and ecosystem fragmentation.

The dispersed city model provide an (extreme) comparison to the compact city model. Table 2.2 adapted from Neuman (2005) highlights the main differences between these two urban models. In particular it demonstrates how dispersed cities have formed around to the use of automobiles with wide spread of commercial activities (only made viable by people driving) and the availability of car parking and roads within the cities. Meanwhile the centralised and effective governance of compact cities has resisted this through initiatives such as pedestrianisation and legal limits urban expansion.

Table 2.2 Characteristics of Compact and Dispersed Cities (adapted from Neuman 2005)

Compact City Characteristics	Dispersed City Characteristics
1. High residential and employment densities	Low residential densities
2. High rise flats and apartments	Detached and semi-detached housing
3. Multimodal transportation	Transportation dominated by privately owned automobiles
4. Mixture of land uses	Spatial segregation of different types of land uses through zoning
5. Pedestrianisation and use of bicycle lanes	Car parking
6. Centralised commercial activities	Widespread commercial development along roads as well as out of town shopping malls
7. Contained urban development, demarcated by legible limits	Unlimited outward extension and leap frogging of new development
8. Low open-space ratio	High open-space ratio
9. Urban infrastructure; especially sewerage and water mains	Decentralised infrastructure, for example septic tanks
10. Good governance with strong planning regulation	Poor governance, development is market led
11. Unitary Control of planning	Fragmented control
12. Nucleated development pattern out from the centre of the urban area	Linear settlement alongside transport routes.
13. High degree of impervious land use	High degree of pervious land use
14. Older cities (formed before the invention of automobiles)	Newer Cities (developed in conjunction with rising use of automobiles)
15. Increased social and economic interaction	Socio economic groups isolated by house prices
16. No gardens	High proportion of housing with gardens.

2.3.4 Decentralised Centralisation: Transit Orientated Development

The concept of Transit Orientated Development (TOD) came about by the acceptance that not all urban areas were suitable for urban densification and a realisation of how people want to live and commute. This can be seen in Melia et al. (2011) review of urban intensification policies where compact city principles applied to Portland resulted in higher congestion and worse local pollution as residents continued to commute by cars. Thus, reflecting the fact that the success of the compact city depends on culture change for example, inhabitants moving to walking and public transport use over private vehicle usage.

TOD model of sustainable development advocates decentralised urban neighbourhoods on the outskirts of urban areas which have self-sufficient services and amenities and surrounding transit stations with good links to the centre of cities (Cervero et al. 2002). This type of development around transport nodes can be visualised of as a series of polycentric development centres as in Figure 2.5 and can be thought of as a compromise between the ‘extreme’ centralisation of the compact city model and the ‘extreme’ decentralisation of dispersed cities (Breheny 1996). The model intends to address sustainability by combining ideas around compaction locally to reduce travel costs to services and amenities, lower density (compared to compact city) and suburban living to appeal to market forces (Neuman 2005). Good quality transport to the centre of the city utilising public transport makes transport efficient and sustainable. For these reasons it is often referred to as smart growth in the literature (Heid 2004). One of the ways governments have attempted to impellent this approach is by introducing policies that relax development densities around transit stations (Cervero et al. 2002).

Proponents of TOD model take their motivation from the argument that lower emissions in compact cities are not a result of high density residential development (as new urbanists insist), but rather the result of sustainable transport (Renne 2009). This is supported in studies such as Echenique et al. (2012), which found accessibility was more related to reductions to vehicle miles travelled than the level of compaction. TOD principles are most commonly employed in the US and Australia’s, where cities are dispersed and automobile dependency is high (Ratner & Goetz 2013). However, TOD as a sustainable urban form is criticised for not sufficiently reducing automobile dependence to meet mitigation targets, especially compared to compact cities (Newman et al. 2009), and areas where it has been implemented, such as Denver, US, still have high automobile dependency (Ratner & Goetz 2013). As Belzer & Autler (2002) acknowledges TOD doesn’t necessarily constitute the most sustainable urban form however as it is impossible to completely redesign cities to become compact it is intended to improve upon the current situation and meet a compromise for the travelling culture of residents within those cities.

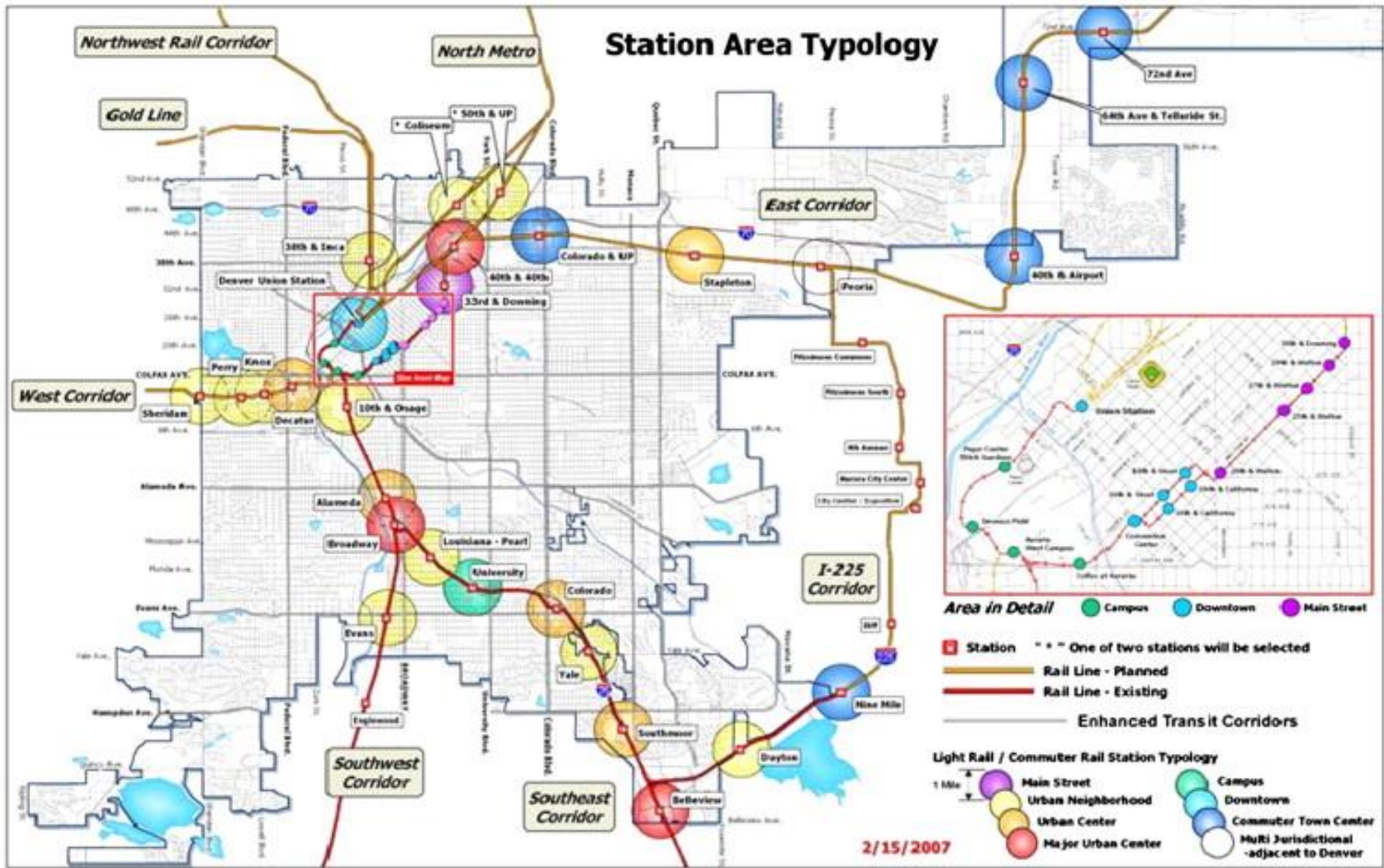


Figure 2.5 TOD development over the State of Denver centred around transport nodes (Ratner & Goetz 2013).

2.3.5 Garden Cities

Recently an historic urban spatial form known as Garden Cities has been receiving attention with respect to its sustainability credentials. It was first conceived by Ebenezer Howard (Howard 1902) as part of his ‘Garden City movement’ and proposed for environmental purposes so urban populations were closer to nature. The concept entails self-contained urban development surrounded by greenbelts. Indeed, to some extent, the TOD concept appears to take inspiration for polycentrism from Howard’s idea (as seen by the similarity between Figure 2.5 and 2.6). Howard himself developed two Garden Cities in the UK - Letchworth and Welwyn. The green cities concept was ultimately marginalised by the emphasis on Compact Cities with bodies such as the European Commission coming out heavily against peripheral development (Commission of the European Communities 1990). However they are currently becoming an increasingly prominent urban form in the lexicon of sustainable development (Randolph 2013).

Several sources have identified Garden Cities as a way to ease development pressures which are a direct result of the Compact City model (e.g., the restriction of greenbelt development and preventing the extension of urban development), by allowing peripheral development. Likewise with TOD, modern concepts of the Garden City propose to mitigate the potential increase in automobile usage by developing along established transport corridors which either provide good public transport or along highways so travel distance is reduced. An example of this is the planned Garden City of Ebbsfleet which is to be built on the periphery of London alongside sufficient transport routes to allow access to the centre of London (Mann 2008). However, there is in this case, and more generally, significant resistance to the development in green belt that is required by this model (Heid 2004; Rudlin & Falk 2014; Blundell 2014). As with TOD the resulting extension in distance between the urban centre needs to be carefully considered to ensure it doesn’t result in higher emissions (Garden Cities and Suburbs Expert Group 2012).

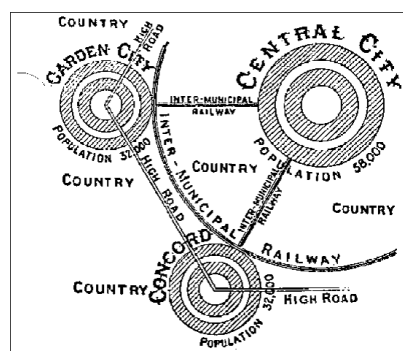


Figure 2.6 Garden Cities as polycentric centres on transport nodes connected to the main urban area (Howard 1902).

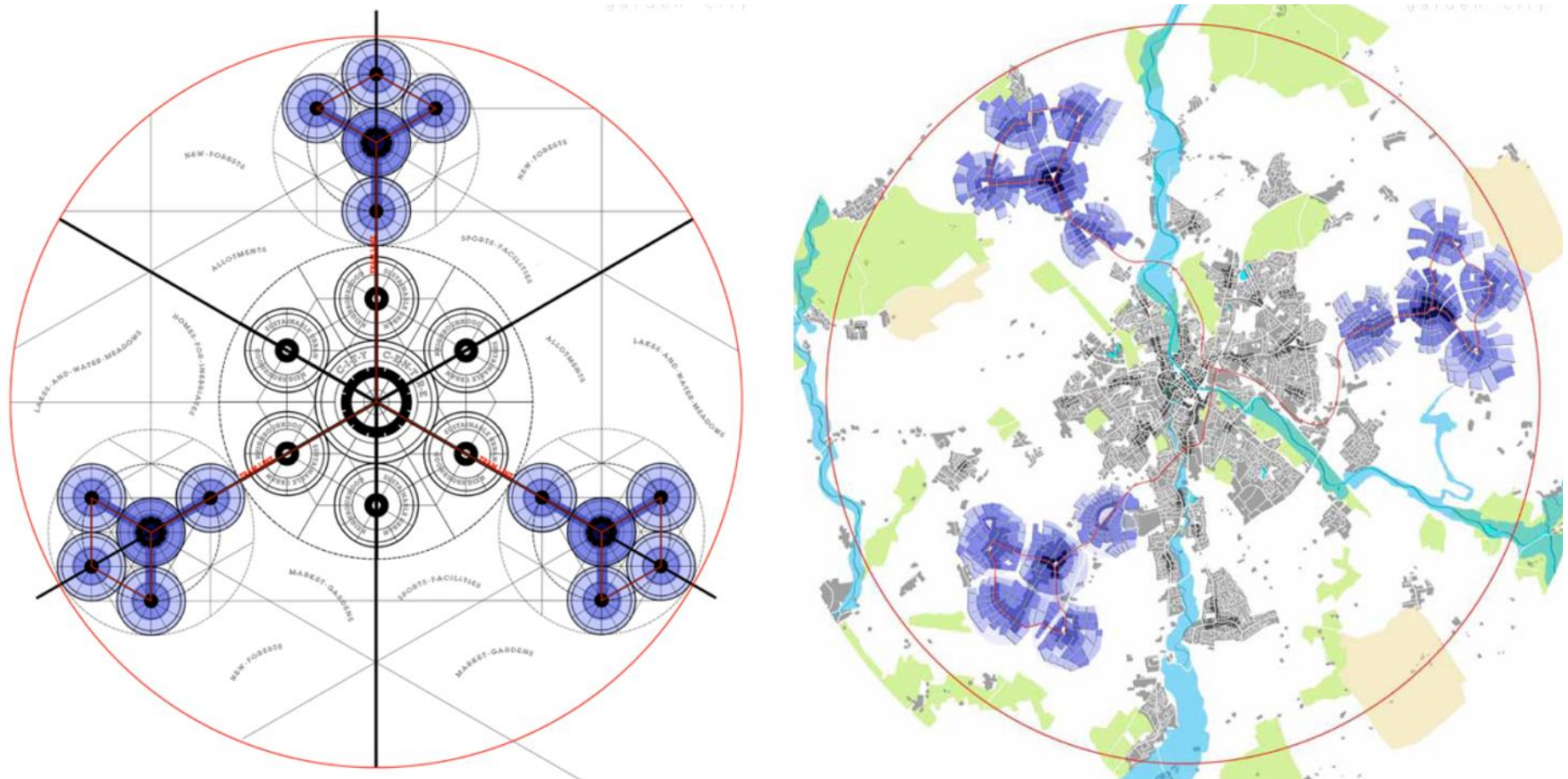


Figure 2.7 Idealised Garden City of Uxcester extending out from an existing city along transport roots and centred round poly-centric centres (reproduced from Rudlin & Falk (2014)).

2.3.6 Smart and Resilient Cities

Although not exclusively linked to sustainable development goals, Smart Cities are often put forward as a method of applying technologically driven approaches to urban areas to reduce energy consumption and to better manage resources. Smart City concepts include the use of smart grids which adapt the energy supply delivery system based on actual demand, an approach gaining prominence as a planning paradigm, especially in Europe (Caragliu et al. 2011). However, it has been argued that technology is only a partial solution to urban sustainability (Bedsworth & Hanak 2010). For example, in the case of flood risk a smart city approach to adaptation would provide better warning systems. However, hard/soft flood defence infrastructure would also still be required (Dawson 2007). In case of transport more responsive 'intelligent' transport might reduce emissions, however, up to 70% of emissions are related to the spatial pattern of land uses which requires spatial planning intervention (Barton 1990).

Another recent urban sustainability paradigm is that of Resilient Cities which are characterised by a number of hard and soft infrastructure adaptations to urban areas in preparation for expected more frequent and higher magnitude climate change induced hazards (Hunt & Watkiss 2011). The increased focus on the resilience of cities is a response to the failure to avert short term climate change (IPCC 2013) and reaction to a number of recent climate disasters including hurricane Katrina (Krebs et al. 2010) with attentions focused on to how to best manage expected climate change (Rodin 2014). However a number of adaptive responses implemented to increase the resilience of cities have been found to negatively affect mitigation efforts as they are energy intensive processes which increase emissions (Barnett & O'Neill 2010); highlighting that care must be taken to ensure adaptive responses compliment other sustainability efforts (Dawson 2011).

2.3.7 Multiple Pathways

Whilst these idealised sustainable urban forms provide pathways and policies which contribute to addressing a number of urban form sustainability issues, they ultimately fail to achieve sustainable cities (Williams et al. 2000). This has led to practitioners to argue that such one-size fits all models of urban development, especially the compact city model, have in fact hindered urban sustainability as no single model adequately addresses all critical components of sustainability (Haughton 1997; Williams et al. 2000; Guy & Marvin 2000; Finco & Nijkamp

2001). Thus, to develop a sustainable city which addresses a wide range of sustainability concepts, , one must draw from the diverse models discussed (Breheny 1996; O’Riordan 1999b; Finco & Nijkamp 2001); as Williams et al. (2000) summarise:

‘Instead of prescribing one ‘end product’ in terms of urban form (such as urban intensification), move towards formulating decision making process to ensure the right solution in any given location’.

Thus, while elements of the compact city model will likely contribute to a sustainable city, in particular policies to constraining urban sprawl (Matsumoto 2012), elements of the TOD and Green Cities models may allow spatially localised planning to occur that will make cities more sustainable with respect to hazards such as flooding and heat waves. Technology and Smart City concepts will help provide greater resilience and longer term sustainability in relation to resource usage, but this also needs to be coupled with concepts from Resilient Cities where again infrastructure investment can help make cities more sustainable with respect to future climate change. As such, all the models review have useful contributions and concepts to developing sustainable cities; the challenge is to select spatial development strategies on the basis of contextualised evidence which demonstrates that the policies selected will increase sustainability of the city as a whole (Barnett & O’Neill 2010; Dawson 2011).

2.4 Barriers to Sustainable Urban Form

Despite an increased appreciation of the best pathways to meet sustainable urban form, there remain significant barriers to meeting sustainable urban development (Dawson 2011). It is not simply enough to define the aims of sustainable development but there must also be a consideration of the conflicts that obstruct their adaptation. The critique of urban models of sustainable development in Section 2.3 reveals a number of barriers, the scale and importance of which warrants a significant investigation themselves. Early literature such as Campbell (1996) recognised a number of conflicts which could occur between the pursuit of economic growth, environmental and social sustainability goals during the planning of sustainable cities. These are shown in Figure 2.8 and classically revolve around:

1. **Resource conflicts:** Ensuring there are sufficient land and resources to facilitate economic development while avoiding conflicts with the environmental need to protect biodiversity and effectively manage resources.

2. **Property conflicts:** Providing adequate residential for the population conflicting with the need for employment to facilitate economic activity.
3. **Development conflicts:** Ensuring environmental protection and efficient resource use whilst allowing populations to increase their quality of life. (Campbell 1996)

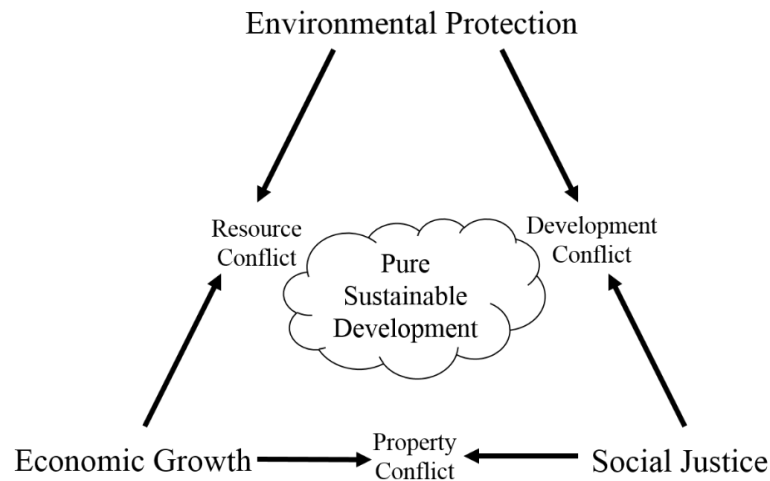


Figure 2.8 Traditional conflicts arising from sustainable development (adapted from Campbell (1996)).

However, as the concept of sustainability becomes more complex, so the challenges of reconciling these conflicts becomes increasingly difficult (Mcevoy et al. 2006; Dawson 2011). Table 2.4 outlines a series of augmented potential conflicts between sustainable interventions adapted from Dawson (2011). Critically, a number of these conflicts occur between adaptation and mitigation responses (Klein et al. 2005) which is important as both of these areas is receiving significant effort currently (IPCC 2007d). The most common conflict identified are contradictions resulting from compact city development. As Section 2.3 outlines, urban intensification is often put forward as a policy to reduce emissions (Williams 2004). However as outlined in Section 2.3.2 the form of development has a direct effect of the ability of cities to adapt to climate induced hazards (Hunt & Watkiss 2011). Highly concentrated development in cities intensifies urban islands (Holderness 2012a) and restricting development within the current urban extent concentrates population within this urban heat island (Kazmierczak 2012). Meanwhile increasingly urbanisation leads to larger areas of impermeable surfaces and therefore higher risks of flooding (Sanders & Phillipson 2003). For example, Nirupama and Simonovic (2007) observed for a case study of London, Ontario, Canada, a 120.95% increase in urbanised land that led to a quadrupling of observed peak flow during flood events.

On the other hand there are a number of instances of adaptation responses have been found, and indeed the IPCC (IPCC 2007a) acknowledges, to affect the achievement of other elements of sustainability. An example of this Hamin & Gurran (2009) identifies a particular problem in Bryon Shire in New South Wales, Australia where strict development restrictions to avoiding climate risks (in this case flooding) has severely restricted the ability to plan development in close proximity to the city centre in order to facilitate walkability and better cycling infrastructure. Barnett & O'Neill (2010) define a series of unintended negative consequences for mitigation efforts that can be caused by other well-intended adaptation interventions which he refers to as Maladaptation:

1. **An increase in emissions of GHGs from energy intensive sustainability interventions:** For example the use of desalinisation plants and air conditioning;
2. **A disproportionate burden on the most vulnerable:** For example interventions which increase costs on people unprogressively (i.e. not based on your ability to pay) such as higher water bills resulting from the use of desalination plants and higher electrical costs from environmental taxes on electricity production;
3. **Reduced incentives to adapt:** For example development in floodplains as a result of hard flood defences and the use of desalination plants disincentives efficient use of water;
4. **Limiting alternate choices available to future generations:** Large infrastructure developments commit a lot of capital and institutional lock-in. (Barnett & O'Neill 2010)

This is compounded as planners are being tasked with developing policies that mitigate GHGs emissions, such as the 2003 Energy White Paper (Defra, 2003), which sets a 60% emissions reduction target in the UK for 2050. At the same time cities are required to become more resilient to climate induced hazards (Adaptation Sub-Committee, 2010). As such, it is crucial that these efforts are achieved simultaneously and in a mutually supportive manner (IPCC 2012).

A significant cause of conflicts in sustainable cities policy can be directly attributed to a lack of communication between sectors (Lindley et al. 2006; Barnett & O'Neill 2010; Dawson 2011). Often sustainability initiatives are unique to a particular sector and as such both negative and positive effects on other sectors are overlooked (Russel & Jordan 2009; Walsh et al. 2011). Therefore, an integrated approach is required with more inclusive modelling over different sectors to assess the impacts of initiatives across social, economic and environmental domains. This must be complimented with the ability to understand the trade-offs and interactions between sustainability efforts in order to balance them (Lindley et al. 2006; Dawson 2011).

Table 2.3 Potential conflicts of sustainability issues (adapted and expanded from Dawson, 2011)

Sustainable Intervention	Intended positive effects	Potential Negative Impacts	Reference
Air Conditioning	Reduce heat stress	Increases energy usage and subsequent emissions Exacerbate heat island effect from heat produced	(Shimoda 2003)
Biofuels for transport and energy	Reduces overall GHG emissions	Encourages deforestation and replaces agriculture	(Cassman 2007)
Desalination	Secure water supply	Increased emissions, costs and reduced incentive to adapt	(Barnett & O'Neill 2010)
Densification of cities	Reduce automobile dependence Increased public transport use Encourage walking	Exacerbation of urban heat islands and risk of flooding Exposure to emissions and greater noise pollution Less housing choice	(Burton 2000; Sanders & Phillipson 2003; Hunt & Watkiss 2011; Echenique et al. 2012; Holderness 2012a)
Dispersed Development	Reduced flood risk Better quality of life	Increased automobile dependence Higher infrastructure costs	(Buxton 2000; Speir & Stephenson 2002)
Carbon Regulations on industry	Decrease national emissions	Offsets industries emissions to other countries Discourages economic activity	(Böhm & Dabhi 2008)
Brownfield Development (Previously developed land)	Protects greenspace Prevents the development of previously undeveloped sites	Concentrates development within urban heat islands and in de-industrialised areas with little employment Often requires decontamination Insufficient land for development	(Heid 2004; Baing 2010; Kazmierczak 2012)
Traffic bypasses or radial routes	Displace noise and air pollution from traffic out of cities	Lead to longer travel times and consequently more emissions	(Wood et al. 2007)
Catalytic Converters for automobiles	Improve Air Quality	Environmental damage from large scale mining	(Amatayakul & Ramna 2001)
Cavity Wall Insulation	Reduce energy need in housing	Increase potential damage from flood events	(CIRIA 2003)
Insurance and disaster relief scheme	Spread risk from high-impact events	Discourages adaptation	(Fankhauser et al. 1999)
Preventing greenfield development	Protect environment Helps alleviate heat stress	Hampers efforts to provide sufficient and cheap housing	(Heid 2004)
Vehicle User charging (i.e. congestion charge)	Discourage automobile use in cities	Greater social inequality	(Gusdorf & Hallegatte 2007; GLA et al. 2011)

A significant hurdle to avoiding conflicts, and to the move towards sustainability as a whole, is dealing with uncertainty (IPCC 2012). One instance of this is climate change uncertainty which will directly influence adaptation options. Modelled scenarios are usually conditional on some sort of trajectory (Dawson, 2007) such as emission projections (Jones et al. 2009). However, there is some contention on whether these climate models underestimate the extent and magnitude of climate change (Guemas et al. 2013). Attempts to address this include the use of probabilistic approaches (such as the UKCP09 climate projections (Jones et al. 2009)) in order to quantify the uncertainties in climate projections (Kilsby et al. 2007; Jenkins et al. 2014). Using such information, adaptation measures can be prepared for the most probable scenarios.

Another response to dealing with this type of uncertainty is ensuring proposed adaptation measures perform well across a number of different scenarios (Ben-Haim 2012; Woodward et al. 2013). Kabat et al. (2005) provide examples of how long term adaptive planning can take into account possible scenarios of climate change, which they refer to as ‘climate proofing’. In relation to this approach, it has been argued that it is better for adaptation plans to perform acceptability over a large number of scenarios rather than be optimally for a single specific instance of future climate change induced impact (Dawson 2007).

2.5 Spatial Planning to Achieve Sustainable Cities

2.5.1 Introduction

A major method by which governments attempt to deliver sustainable urban development goals is through manipulating urban form via spatial planning (Jackson 2006; Alshuwaikhat 2006; Gasparatos et al. 2008). The spatial form of a city is integral to its ability to manage resources and react to climate change (Alberti et al. 2008; Marique & Reiter 2014). Whilst it is accepted that wide scale reconfiguration of cities is improbable, sustainability can be achieved by ensuring that planned new development is sensitive to key sustainability-objectives (Lele 1991; Beatley & Manning 1997; Gasparatos et al. 2008). One of the earliest definitions of spatial planning comes from European Regional/Spatial Planning Charter adopted in 1983 by the European Conference of Ministers responsible for Regional Planning;

“Regional/spatial planning gives geographical expression to the economic, social, cultural and ecological policies of society. It is at the

same time a scientific discipline, an administrative technique and a policy developed as an interdisciplinary and comprehensive approach directed towards a balanced regional development and the physical organisation of space according to an overall strategy." (Council of Europe 1983)

Traditionally sustainable spatial planning concerned resolving competing land uses. However in the last decade planning has been specifically tasked to address sustainability issues such as combating climate change (Alshuwaikhat 2006; Jackson 2006). For example in the UK the ‘Sustainability Appraisal of Regional Spatial Strategies and Local Development Frameworks Consultation Paper’ (ODPM (Office of the Deputy Prime Minister) 2004) extended the spatial planning remit as the main driver for sustainable urban development. This has been continued by the 2012 UK National Planning Policy Framework (NPPF), which states from the outset sustainable development as principle the aim of the planning system (DCLG 2011a).

As a consequence of neoliberalism, Jackson (2006) redefines spatial planning as a “facilitator that manages development” carried out by the private sector. Therefore, Governments implement their sustainability aims through the setting of regulatory frameworks and requirements which the private sector must meet (ODPM (Office of the Deputy Prime Minister) 2004; Jones 2014). There are a number of ways governments can express their sustainability aims in the spatial planning process, for example through identifying of zones for specific land use activity (Jepson et al. 2014), restricting of development on greenfield sites to protect biodiversity (DCLG 2011a) and setting specific objectives to be met by any new development, such as of 60% of development on brownfield sites (Baing 2010) and new housing being zero carbon (Turner et al. 2008).

Despite sustainability being a widely used concept, there remains a lack of agreement on how best to ensure sustainable development within the spatial planning process (Quaddus & Siddique 2001; Connelly 2007). Along with the broader sustainability agenda, sustainable spatial planning was initially hampered by a lack of clear definitions and goals (Beatley & Manning 1997). Therefore, the first attempts at ensure sustainability in the spatial planning system focused on environmental sustainability (Smith & Sheate 2001; Lenzen et al. 2003; Pope et al. 2004). These include methods such Environmental Impact Assessments and Strategic Environmental Assessment and have culminated and contributed to the most recent

form, Sustainability Assessments and Sustainability Appraisals which assess the sustainability of new development across a larger range of sustainability objectives (Thérivel & Minas 2002; Haughton & Counsell 2004; Gibson 2006).

2.5.2 Environmental Sustainability Assessments

One of the first and most widely used methods encapsulating environmentally sustainable development in the spatial planning process is the application of Environmental Impact Assessments (EIA) (Glasson et al. 2005). The environmental consequences of proposed development is assessed using detailed environmental studies to prepare an environmental impact statement (Sadler 1999). This is then used to ensure plans meet a minimum standard of environmental protection and evaluate modifications to mitigate these impacts (Lenzen et al. 2003). EIAs were originally introduced in the U.S. by the National Environment Policy Act (NEPA) in 1969 as a result of increased interest in environmentalism and has subsequently been adopted in over 100 countries worldwide (Wood 2003) including; EU countries (European Council 1997), Hong Kong (Hong Kong Government 1997), Australia (Australian Government 1999), New Zealand (Ministry for the Environment 1991) and China (National People's Congress 2003). Crucially EIAs are applied after the proposal stage, and thus their ability to influence plans towards maximisation of environmental considerations, and other objectives is limited (Steinemann 2001; Lenzen et al. 2003).

Whilst effective at delivering environmental benefits (Holder & McGillivray 2007), the ability of EIA to assess sustainability as a whole for development is restricted due to its focus on the environmental impact of development (Pope et al. 2004). However, it has been argued that environmental sustainability is integral to sustainable development (Sadler 1999) and EIA in particular provides a sound basis for a more complete sustainability assessment (Sheate et al. 2001). Therefore EIA is often incorporated in the planning system of countries alongside other sustainable development measures (Mahida 2011).

Alternatively, Strategic Environmental Assessments (SEA) are applied at the beginning of the planning process (Tetlow & Hanusch 2012), ensuring they have more a proactive influence on ensuring sustainability considerations in the early planning stages (Wood & Djeddour 1992; Sadler & Verheem 1996). As such, SEA have a greater potential for supporting the decision making process than EIA. Whilst they have also been adopted internationally, they aren't as

widely used as EIAs with approximately of 60 countries worldwide employing them (Sadler 2011).

There is some debate on how well SEA promotes sustainability as a whole (Thissen 2001; White & Noble 2013), and as with EIA it is restricted in scope to environmental issues (Partidário 1996). Despite this Caratti et al. (2004) argue that it has been integral to developing a more proactive process of sustainable solutions as an integral part of strategic planning activities. More recently SEA has been developed to incorporate multiple elements of sustainability, usually alongside the 3 pillars of sustainability (White & Noble 2013). However, the utility of the SEA approach to multiple sustainability objectives has been criticised for lacking ambition as it focuses on ‘satisficing’ decisions (a term coined by Simon (1956) to represent decisions made on the basis of meeting a criteria), rather than attempting to optimise the sustainability objectives under consideration (Pope et al. 2004). While non-environmental sustainability objectives can be considered within SEA, Verheem & Dusik (2011) found that the majority of SEA pursued internationally were still limited in scope to environmental issues.

2.5.3 Integrated Sustainability Assessments

A more promising approach to ensuring and assessing the sustainability of new development during spatial planning are sustainability assessments (Pope et al. 2004; Haughton & Counsell 2004; Institute of Environmental Management and Assessment (IEMA) 2006; Gibson 2006; Ness et al. 2007). As with SEA, sustainability assessments are applied at the early stages of spatial planning decisions with the intention of aiding and directing decision makers to more sustainable plans (Land Use Consultants & Royal Institute Town Planning 2008; Bond, Morrison-Saunders & Howitt 2012). Because of this sustainability assessments are commonly considered a decision making tool and their aid to improve strategic decision making is well documented as well as being recognised as an important tool to aid the shift toward sustainability (Land Use Consultants & Royal Institute Town Planning 2008). Crucially sustainability assessments allow for the assessment of urban development against a wide range of sustainability factors (Smith & Sheate 2001) which mirrors the move to integrated interpretations of sustainability, leading to more ‘win-win’ situations as sustainability objectives are considered simultaneously (Gibson 2001).

Where sustainability assessments has a significant strength over SEA and EIA, is that it is an objective-driven approach whereby the decision maker attempts to design plans to meet aspirational objectives as well as to meet specific targets and baselines. Whilst not as commonly utilised as SEA, sustainability assessments are becoming increasingly popular (Mahida 2011; Ness et al. 2007). The earliest forms of sustainability assessments were driven from SEA and EIA approaches (Pope et al. 2004; Gibson 2001) and typically involved assessing development against the three pillar definition. Especially with EIA methods, this was easily facilitated by using experts to assess each of the elements. However the assessment of individual components of sustainability fails to integrate sustainability aims and instead the task of reconciling them is done at the end of the process; potentially missing the opportunity to maximise performance. Integration of sustainability objectives within SEA as per the sustainability assessments approach has been used by a number of countries such as Czech Republic, Denmark, Netherlands, New Zealand, Portugal and South Africa (Chaker et al. 2005). However crucially SEA is seen as a baseline/threshold approach, whereby they attempt to meet sustainability targets (Pope et al. 2004) and as such may fail to deliver optimal plans. Another strength of sustainability appraisal is that its application is at a local scale which along with its objective-oriented approach allows for assessments to be designed to incorporate localised objectives (Bond et al. 2012). This means the sustainability assessment process is dependent on a robust evidence base which is becoming even more attractive with more sophisticated sustainability indicators (Singh et al. 2012).

A number of sources have expressed concern at environmental objectives being considered alongside social and economic issues as they believe it will lead to them being prioritised over environmental protection (Pope et al. 2004; Morrison-Saunders & Therivel 2006; Bond, Morrison-Saunders & Pope 2012). Kumi et al. (2013)'s review of sustainable development collaborates this with evidence of economic development being pursued to the detriment of the environment and argues that environmental protection should be considered much more highly than the other two elements. Meanwhile others have argued for the continued use of EIA and SEA alongside sustainability assessments for added protection and prioritised environmental protection (Morrison-Saunders & Therivel 2006). Overall sustainability assessments represent an integrated approach, which aim to support the decision-making process with respect to all aspects of sustainability.

2.5.4 UK Sustainability Appraisals

Sustainability appraisals are a type of sustainability assessment which is unique to the UK (DCLG 2011a) and which has been lauded as a sustainability assessment (Bond et al. 2012). They were established as a planning tool in the UK before SEAs were made legally binding by the EU (European Council 2001). In particular, the UK's National Planning Policy Framework states that sustainability appraisal process "should seek opportunities to achieve each of the economic, social and environmental dimensions of sustainable development, and net gains across all three" (DCLG 2011a). To achieve this the sustainability appraisal is employed during the preparation of a local plan of development (ODPM 2004). As a number of options are identified for proposed development they are assessed against a number of environmental, economic and social objectives. These are then used to compare a range of alternatives with the intention to divert the planning process to the most sustainable options. This is enforced through granting or refusing planning permission to developers based on how well the development meets these objectives, ensuring local authorities can wield a huge influence on how development changes and grows.

An example of an sustainability appraisal to the planning of a large urban area is shown in Figures 2.9 from the sustainability appraisal of a Development Plan for Birmingham (AMEC Environment & Infrastructure 2014); the second largest city in the UK. A number of potential spatial areas have been identified for residential and economic development and an allocation of dwellings or economic land outlined (see Table 2.4). In accordance with the National Planning Policy Framework (DCLG 2011a), local plans set their own specific sustainability criteria on the basis of local requirements; these in turn form the sustainability objectives used by the subsequent sustainability appraisal to assess a proposed development. This approach meets the requirement for contextualised sustainability (see Section 2.3.7) by allowing local authorities to set out their own localised sustainability objectives for development to be assessed against.

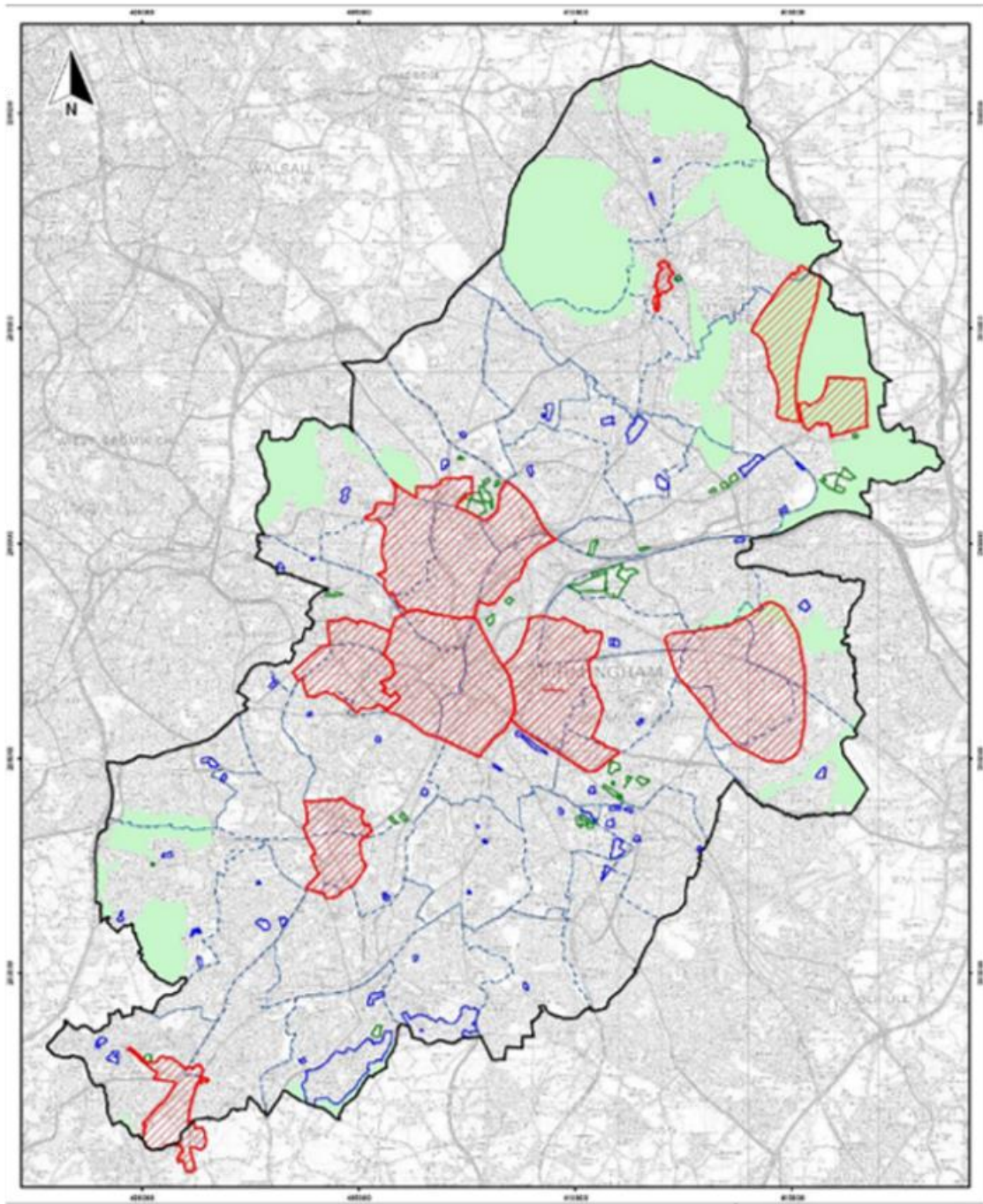
Figure 2.10 demonstrates how a number of the potential development schemes outlined in Figure 2.9 and Table 2.4 are assessed against the particular objectives under consideration along with an assessment of how well addresses them. Whilst a wide range of sustainability issues are addressed, they're handled in a highly subjective manner, with a basic scale of impact (positive, negative or neutral impact). Figure 2.11 demonstrates an improved assessment of the

sustainability appraisal of a potential development site in Manchester; the UK's sixth largest city. The assessment evaluates how well the proposed site caters for the needs of residents (e.g., within 30 minutes of a local supermarket). However there is no quantitative assessment of for example accessibility times. Mitigation of emissions for Birmingham's sustainability appraisal is handled via objectives for sustainable transport and reducing the need for travel. While for Manchester's sustainability appraisal proxies for walking and cycling and renewable energy are employed. Meanwhile both of the sustainability appraisals reviewed have little consideration of climate change impacts and are limited to flood risk.

Even when conflicts are identified their exploration is often limited. This is demonstrated in Figure 2.12 where the conflicts associated with the proposed development at Peddimore are considered. The sustainability appraisal finds that it is likely that the development will increase the need to travel as it extends out from the current urban extent. However, again there is no quantitative measure of this. The development is justified on the basis of it providing employment opportunities but there's no appreciation of cost-benefit from the likely resulting increase in vehicle metres travelled. The highly subjective and qualitative nature of the assessments has been a consistent criticism of sustainability appraisals within the planning process, along with the limited analytical consideration of evidence, trade-offs and potential synergies between objectives (Gibson, 2006).

Table 2.4 Development allocations for sites outlined in Figure 2.9 (AMEC Environment & Infrastructure 2014).

Development Area	Housing (dwellings)	Office space (m ²)	Retail space (m ²)	Employment space (ha)
City Centre	13,740	749,800	254,500	3
Greater Icknield	2,890	0	2,500	0
Aston, Newtown & Lozaells	1,520	10,000	25,000	26
Sutton Coldfield	310	20,000	37,500	0
Sustainable Urban Extension	5,750	0	0	0
Peddimore	0	0	0	80
Bordesley Park	640	0	0	30
Cole Valley Triangle	1,170	tbc	tbc	12
Selly Oak and South Edgbaston	930	tbc	tbc	5
Longbridge AAP	2,020	10,000	13,500	225



Key:

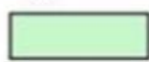




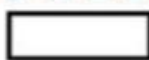
- | | | | |
|---|--------------------------|---|------------------------------|
|  | Green Belt |  | Significant Employment Sites |
|  | Growth Areas |  | Significant Housing Sites |
|  | Birmingham Wards | | |
|  | Birmingham City boundary | | |

Figure 2.9 Sites identified in Birmingham to be considered for future development (AMEC Environment & Infrastructure 2014).

Sustainability Theme	Sustainability Objectives																																																	
	BDP Policy																																																	
1. Natural resources and waste	7. Waste Minimisation	8. Efficient use of land	2. Sust. Design & Construction		4. Energy Efficiency		5. Sustainable Transport		6. Reduce the need to travel		9. Reduce climate change		10. Manage Climate Change		12. Built and Historic Env.		13. Natural Landscape		14. Biodiversity		15. Air Quality		16. Water Quality		17. Soil Quality		18. Noise		20. Economy and Equality		21. Learning and Skills		11. Sense of Place		19. Social and Env. Responsibility		22. Community Involvement		23. Equality		24. Poverty		25. Health		26. Crime		28. Culture/Sport/Recreation		27. Housing	
			3. CO ₂ emissions		3. Renewable Energy		3. Energy Efficiency		3. Sustainable Transport		3. Reduce the need to travel		3. Manage Climate Change		3. Built and Historic Env.		3. Natural Landscape		3. Biodiversity		3. Air Quality		3. Water Quality		3. Soil Quality		3. Noise		3. Economy and Equality		3. Learning and Skills		3. Social and Env. Responsibility		3. Community Involvement		3. Equality		3. Poverty		3. Health		3. Crime		3. Culture/Sport/Recreation		3. Housing			
GA2: Greater Icknield	+	+	++	++	++	++	++	++	++	+	+	+	+	+	++	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	++	++							
GA3: Aston, Newtown and Lozells	+	+	++	++	++	++	++	++	++	+	+	+	+	+	++	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	++	++							
GA4: Sutton Coldfield Town Centre	+	+	++	++	+	+	+	++	+	+	?	+	+	+	+	+	+	+	+	+	?	#	#	0	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	++	++					
GA5: Sustainable Urban Extension	-	0?	-	++?	++	++	++	++	++	0	+	+	+	+	+	+	+	+	+	+	?	#	#	0	+	?	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	++	++					
GA6: Peddimore	-	0?	-	++?	++?	++?	0?	-?	0	0	0?	0?	0?	0?	0?	0?	0?	0?	0?	0?	?	#	#	-?	++	++	0?	#	#	++	++	+	+	+	+	+	+	+	+	+	+	+	+	#	#					
GA7: Bordesley Park	+	+	++	++	++	++	++	++	++	+	+	+	+	+	++	+	+	+	+	+	?	#	#	0	++	++	++	+	+	+	+	+	+	+	+	+	+	+	+	+	+	++	++							
GA8: Cole Valley Triangle	+	+	++	++	++	++	++	++	++	+	+	+	+	+	++	+	+	+	+	+	?	#	#	0	++	++	++	+	+	+	+	+	+	+	+	+	+	+	+	+	+	++	++							
GA9: Selly Oak and South	+	+	++	++	+	+	++	++	+	+	+	+	+	+	+	+	+	+	+	+	+	#	#	0	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	++	++						

++	Major Positive Impact	+	Positive Impact	0	Neutral Impact	-	Negative Impact	--	Major Negative Impact	#	No Relationship	?	Uncertain Relationship
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Figure 2.10 Assessment of Birmingham’s Development Plan Policies against the Sustainability Objectives.

SA Objective	Indicator	Economic Development								Residential Development															
		ES 1 Strangeways	ES2 Central Park	ES 3 Sportcity	ES 4 Victoria Station	ES 5 Easten Gateway	ES 6 Oxford Rd- Piccadilly Basin	ES 7 Roundhorn	ES 8 Manchester Airport	HS 1 Collyhurst	HS 2 East of Rochdale Road	HS 3 Moston Harpurhey	HS 4 Lower Irk Valley	HS 5 Booth Hall Hospital	HS 6 Blackley Village	HS 7 Holt Town	HS 8 Chancellor's Place	HS 9 Lower Medlock Valley	HS 10 Miles Platting	HS 11 Newton Heath	HS 12 West Gorton	HS 13 Brunswick	HS 14 Coverdale		
3 Improve health of the population and reduce health inequalities	Is it within 30 mins of a GP, dentist and hospital by public transport?																								
	Will it lead to a direct loss of public open space or open access land?																								
	Will the site contribute to noise pollution?																								
8 Ensure people's needs for goods, services and amenities are met	Is it within 30 min of the Manchester city Centre or Local Centres by public transport?																								
	Is it within walkable/ cycleable distances (800m and 2-5km) to key services?																								
10 Promote the use of sustainable transport modes and reduce motorised traffic	Good accessibility to local facilities																								
	In close proximity to a public transport route or in a walkable/ cycleable distance?																								
11 Improve Air Quality	Within an Air Quality management Area																								
13 Ensure efficient use of land	Is the site proposed on greenfield land?																								
	Will it lead to the loss of best and most versatile agricultural land (Grade 1, 2 and 3a)																								
	Will it lead to the remediation of contaminated land?	?	?	?	?	?	?	?		?								?						?	
14 Maintain and enhance biodiversity, including habitats and species	Is the site in proximity (2km) to statutory biodiversity site (SSSIs etc)																								
	Is the site in proximity (500m) to a site of Biological Interest or Local Nature Reserve.																								
	Are Biodiversity Action Plan Habitats known to be on the site?																								
15 Maintain and enhance the quality of landscape, townscape and built environment	Is the site in or adjacent (40m) to a Green Corridor																								
18 Reduce contribution to climate change	Will it increase the proportion of energy needs being met by renewable sources?																								
19 Reduce impact of climate change	Within Environmental Agency Floodzone 2, 3a or 3b or is within 9m of a river?																								

Figure 2.11 Assessment of Manchester Planning Policies against sustainability objectives (sample adapted from Atkins 2009).

GA6: Peddimore																												
SA Theme	1. Natural Resources and Waste			2. CO ₂ emissions			3. Climate change adapt.	4. Historic environment, landscape, biodiversity and geodiversity			5. Pollution			6. Economic growth	7. Communities, healthy lifestyles and equality					8. Housing								
SA Objective	1. Resource Use	7. Waste Red'n & Minimisation	8. Efficient use of land	2. Sustainable Design	3. Renewable Energy	4. Energy Efficiency	5. Sustainable Transport	6. Reduce the need to travel	9. Reduce climate change	10. Manage Climate Change	12. Built and Historic Env.	13. Natural Landscape	14. Biodiversity	15. Air Quality	16. Water Quality	17. Soil Quality	18. Noise	20. Economy and Equality	21. Learning and Skills	11. Sense of Place	19. Social and Env. Responsib.	22. Community Involvement	23. Equality	24. Poverty	25. Health	26. Crime	28. Culture/Sport/Recreation	27. Housing
Assessment Score	-	0?	-	++?	+	+	0?	-?	0	0	0?	0?	0?	0?	#	#	-?	++	++	0?	#	#	++	++	+	#	#	#

Commentary: The provision of high quality employment land is critical to the strategy of the BDP and existing constraints indicate the necessity of this allocation. There are a variety of negative sustainability effects such as loss of greenfield land and transport impacts, but also the opportunity to try and integrate the development into the existing urban edge and provide for a range of employment opportunities for existing and new residents in the immediate vicinity and further afield.

Geographical scale: Locality

Temporary or Permanent: Permanent, subject to effective implementation

Timing: Medium to long term

Figure 2.12 Handling of the conflicts arising from a particular development scheme for Birmingham’s development plan (reproduced from AMEC Environment & Infrastructure (2014)).

2.5.5 Consideration of Conflicts between Sustainability Objectives

As Sections 2.3 and 2.4 have shown there are a multitude of instances where sustainability objectives may conflict during the pursuit of sustainable development, with a significant number related to the spatial layout of cities. ODPM (2004b) provides guidance to assess potential conflicts between sustainability objectives outlined in their Local Development Framework to identify potential conflicts which could occur. A number of SAs address this guidance using a compatibility matrix between their sustainability objectives. Figure 2.13 demonstrates compatibility matrices for the SA of the Greater London Spatial Strategy (Figure 2.13a) (Mouchel 2010), and Basildon Councils Local Development Framework (Figure 2.13b) (Basildon Council 2011).

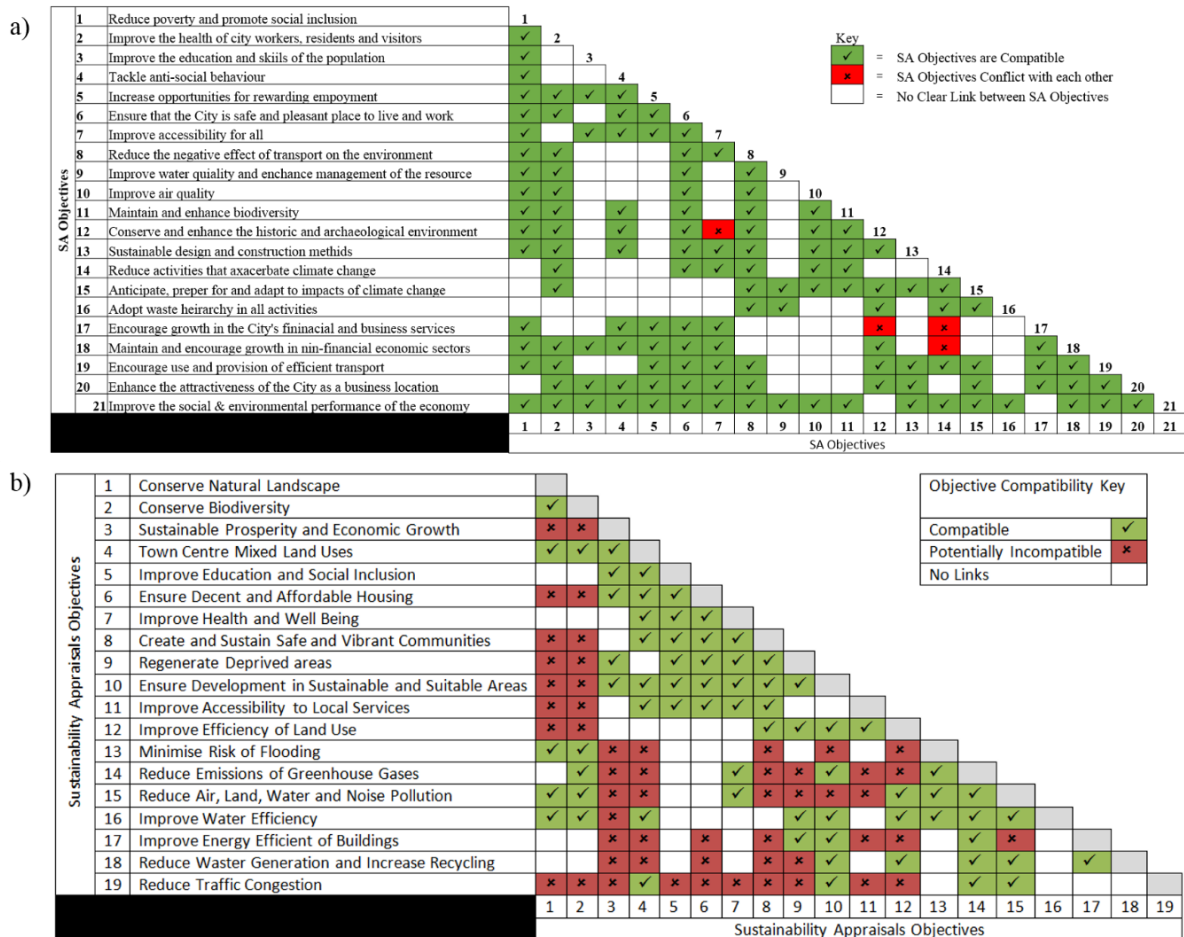


Figure 2.13 Compatibility matrix from the sustainability appraisal for a) London (Mouchel 2010) and b) Basildon Council (Basildon Council 2011).

Basildon Council's (Figure 2.13b) matrix identifies a number of conflicts between the pursuit of economic and social objectives with regards to environmental protection, mirroring the classical planning resource and development conflicts described in Section 2.4. Meanwhile conflicts in London's compatibility matrix centre on new economic activity increasing emissions. Acknowledging these potential conflicts the plans go on to consider strategies to mitigate them. However these are handled in an overly qualitative way with no quantitative appreciation of the best trade-offs that can be made in each of the sustainability aims.

2.6 Decision Support

Despite the potential of SA to contribute towards sustainable development there are a number of weaknesses that could be improved by the use of decision support approaches in the planning process. Decision support tools (DST) are increasingly being used to help spatial planning decision making (Linkov et al. 2006; Komendantova et al. 2014), as they offer a particular advantage in their ability to manage and analyse larger quantities of data and understand the complex interactions between planning objectives (Uran & Janssen 2003). The planning pressures outlined in this chapter come at a time of increasing decentralization of planning decisions, with planners responsible for joining up strategies to manage the plethora of sustainability aims (Allmendinger & Haughton 2009). Spatial DSTs that incorporate advanced modelling techniques into the spatial planning process can potentially provide a vital aid in this process (Geertman & Stillwell 2009).

In particular, there are an increasing number of risk assessment tools which assess the probable impact of climate change induced hazards on urban areas, reporting the cost of events to aid the adaptation and the decision making process (Komendantova et al. 2014; Harrison et al. 2015; Jenkins et al. 2014). Equally, Gil & Duarte (2013) identify a range of analytical tools for assessing the sustainability of new development and measuring their sustainability, while Ibrahim et al. (2012) identify a number of tools for calculating expected emissions that may arise from implementing particular spatial development plans. Furthermore, over the past 40-years a multitude of models have been developed to simulate the spatial evolution of land use and transport planning, models which are being increasingly used to design policy with respect to limiting emissions (Waddell 2011b; Kim & Batty 2011).

Such approaches are useful to demonstrate the impacts of the different decisions. However, they are limited in scope to a single element of sustainability (i.e. climate risk, emissions, employment) (Gasparatos et al. 2008), and as a result lack information on how best to maximise the desirable outcomes of these. This is compounded by the inability of many DSTs to rank a number alternatives to aid decision makers choices (Kapelan et al. 2005a). Moreover many DSTs are hampered as they fail to resemble how decisions are taken and are too abstract from the decision making process (Uran & Janssen 2003).

It must also be acknowledged that there are limits to how much models can contribute to spatial planning process. Tinbergen (1956) identifies two aspects analytical and political. A multitude of work has considered political responses to sustainable urban development (Richardson 1997; Boland 2014). However there is significant scope for analytical tools to influence planning decisions and point decision makers towards the best decisions (Gasparatos et al. 2008; Geertman & Stillwell 2009; Jordan et al. 2011; Singh et al. 2012).

2.7 Conclusion

This chapter reviewed the sustainability issues facing urban areas and their move towards more sustainable cities. It is now commonly accepted that there are 3 pillars of sustainability; economic, societal and environmental sustainability, but that these can be extended to include aims such as being resource efficient and limiting the impact of climate change. A number of models of sustainable urban form intended to achieve sustainability are reviewed and it is found that each in their pure form have limitations. As such the text recognises the requirement to move away from conceptual ideals of what constitutes a sustainable city to developing sustainable urban development on the basis of localised evidence. A number of barriers to sustainable development in Section 2.4 are identified. Owing to the complexity and many interacting processes within cities, the transition to sustainable urban form is fraught with potential pitfalls. In particular the review identifies specific problems of conflicting sustainability efforts and dealing with uncertainty. Therefore any move to long term sustainable cities needs to consider the relationships between objectives whilst remaining flexible enough to deal with uncertainty.

Multiple sources point towards the potential and opportunity of tackling sustainability issues through sustainable urban planning. Traditional and common EIAs and SEAs are found to fail

to address a broad spectrum of sustainability issues and lack the framework to maximise the sustainability of new development. However, sustainability assessments, and sustainability appraisals in particular, provide the most opportunistic method to ensure optimal sustainable situations are obtained. However they still often fail to address the wide range of sustainability objectives found by the review in Section 2.2 and also are shallow in their application.

However, with increasing decentralisation of planning decisions there is an opportunity for the incorporation of modelling to better help support the planning process. In this regard decision support tools have the potential to significantly improve the move to more sustainable urban forms. As such, and based on the observations made in this chapter, it is proposed that a spatial multi-objective spatial planning optimisation framework is required that ultimately can provide a decision support tool for planning sustainable cities. Such a tool would comprise of the following key characteristics:

1. Consider multiple and a wide range of real world sustainability objectives in line with the definition of sustainability taken by this work;
2. Take an integrated approach by considering sustainability aims simultaneously;
3. Provide a metric of sustainability which is based on localised evidence and not on conceptual ideas of what constitutes sustainable development;
4. Assess a wide range of alternatives to ensure the best solutions are chosen; and
5. Provide flexibility to meet a range of stakeholder needs.

Chapter 3 Multi-objective Spatial Optimisation for Urban Planning

3.1 Introduction

Chapter 2 identified a need for decision support tools to aid the spatial planning process deliver more sustainable urban development. From a review, the current methodology of sustainability appraisals of future development was found to have a number of weaknesses which could potentially be improved through computational methods such as optimisation. These included a lack of considerations of multiple sustainability objectives simultaneously and acquiring an understanding of the trade-offs and cost benefits between not just alternative spatial plans but between the sought after sustainability aims themselves. Whilst a number of support tools currently exist, they are often limited to impact assessment and lack the ability to guide decision makers towards optimal setups of infrastructure in the presence of these objectives. Crucially any potential decision support tool needs to effectively assess a wide range of possible spatial development sites whilst simultaneously considering a range of sustainability objectives in order to ensure all elements of sustainability are being address efficiently.

With this in mind, analytical optimisation has been routinely used to establish an optimum configurations of infrastructure in the presence of multiple, often conflicting, objectives. Examples include the design of sewers networks (Liang et al. 2004; Berardi et al. 2009), the design of water distribution networks (Prasad et al. 2004; Kapelan et al. 2005b; Vamvakieridou-Lyroudia et al. 2005; Bieupoude et al. 2012), land use allocation (Aerts et al. 2005; Ligmann-Zielinska et al. 2008; Qian et al. 2010; Cao et al. 2011) and transit networks (Kepaptsoglou & Karlaftis 2009; Shimamoto et al. 2010). Computer modelling methods such as optimisation can assist in the planning of urban infrastructure by more effectively handling complex problems and analysing a wider number of alternatives than a human would be able (Matthews et al. 1999). In particular sources have stated there is greater scope for further inclusion of optimisation algorithms for decision support of urban planning (Kapelán et al. 2005a; Keirstead & Shah 2013) as it provides a powerful platform by which complex multi-objective problems can be solved and a number of alternatives assessed (Savic 2002; Jiang-Ping & Qun 2009).

This chapter critically reviews the use of optimisation approaches to provide optimal trade-off solutions within the analytical study of sustainable cities. In particular the review explores spatial optimisation algorithms as a method to assist spatial planners develop spatial development plans which are more sustainable for the local conditions. Generic considerations

involved in optimisation are introduced while methods at reconciling multiple-objectives are compared. A review is taken of potential spatial optimisation approaches and their utilisation in the spatial planning of infrastructure within urban systems planning is investigated. The review is then used to identify a number of recommendations for an optimisation based sustainable planning decision support tool.

3.2 Definition of an Optimisation Problem

Optimisation is a branch of applied mathematics concerned with searching and comparing feasible solutions to a problem until an optimal solution is found (Papadimitriou & Steiglitz 1998). Problems handled by optimisation can range from finding optimal production schedules for industries (Xie 2011) to finding the optimal setup of land uses and transport links (Feng & Lin 1999). The design of an optimisation problem consists of three elements; a set of objective functions to optimise, a set of decision variables to be explored and the constraints on the search.

3.2.1 Decision Variables

A complete set of variables for a optimisation problem, X , consists of m variables:

$$X = (x_1, x_2 \dots, x_m) \quad (3.1)$$

The envelope created when exploring the possible variables is called a variable space whilst the number of variables to be assessed relates to the dimension of the variable space. Variables may consist of, or a mixture of, binary, integer and discrete values. Problems where the variables set consist entirely of integer or binary values are defined as an integer programme (Aerts et al., 2002) and in a number of spatial allocation problems these have been used to represent a decision for discrete land parcels (Keirstead & Shah 2013). For example Khalili-Damghani et al. (2014) structures their land use problem by utilising binary decision variables x_{ijk} which determines if cell i, j is allocated the land use, k :

$$x_{ijk} = 0,1 \text{ for all } i, j, k \quad (3.2)$$

Alternatively discrete variables are commonly used to identify decisions or design characteristics in optimisation problems. For example Walters et al. (1999) uses a number of number of discrete variables to represent the design of their distribution network such as the diameter of pipes and the location of tanks. Meanwhile Woodward et al. (2013) encodes a number of decisions relating to flood management as discrete variables, such as raising the heights of flood defences. Problems which consist of both discrete and continuous variables can be described as mixed integer problems (Loonen et al. 2007). For example Prasad et al. (2004) formulated their water distribution network design problem to consist of investigating discrete pipe diameters as well as continuous pipe lengths. and can potentially cause problems for the method of exploration (Papadimitriou & Steiglitz 1998). Lastly problems which contain a large range of either discrete variables and or the use of both discrete and integer variables can be described as combinatorial and require advanced methods to solve due to their complexity (Reeves 1993).

3.2.2 Objective Functions

The aim of an optimisation application is to explore and configure these variables, integer, discrete or otherwise, to optimise a desirable resultant objective(s). This typically consists of finding either the minimum (i.e. minimisation) or maximum (i.e. maximisation) of a possible performance for a system. An optimisation problem can consist of a number of objectives to be optimised referred to as objective functions, f . A set of these to optimise, $F(X)$ can consist of n objective functions such that:

$$F(X) = (f_1(X), f_2(X) \dots f_n(X)) \quad (3.3)$$

The exploration of performances for $f \in F$ form an objective space, i.e. the performances in the objective functions which can be achieved. Therefore the aim of the optimisation is to identify a configuration of X which returns F in the best regions of this objective space. Figure 3.1 demonstrates how the performance of $f \in F$ are dependent on the variables selected, where in this instance the values selected for $x = \{x_1, x_2, x_3\}$ lead to the subsequent values for the objective functions of $F(x) = \{f_1, f_2\}$.

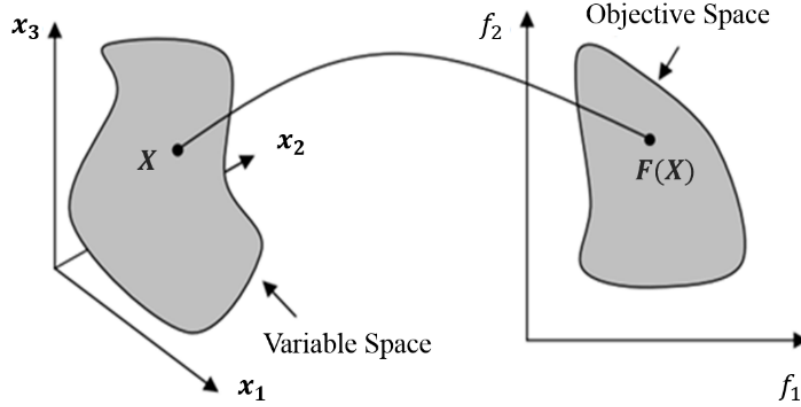


Figure 3.1 How the selection of variable set, X , in the variable space (left) leads to the performance of $F(x)$ in the objective space (right) (adapted from Deb, 2001).

Optimisation literature covers a plethora of objective functions to be optimised ranging from the design of aeroplane wings (Obayashi et al. 1997) to designing flood risk management plans (Woodward et al. 2013). For the land use allocation problem in Qian et al. (2010) the economic performance of land use set ups defined by:

$$\text{maximise} \quad Z = \sum_k^9 A_k P_k \quad (3.4)$$

where P defines the income associated with the land use k whilst A defines the area of the land use. This is set up a linear programme as the variables k and A are continuous and the relationship between them is linear. Alternatively Aerts and Heuvelink (2002) uses a more complex formulation to compute a compaction objective to maximise:

$$\text{maximise} \quad \sum_{k=1}^K \sum_{i=1}^I \sum_{j=1}^J -b_{ijk} x_{ijk} \quad (3.5)$$

where b_{ijk} is a measure of the surrounding i, j locations which are allocated the same k . As the performance of the objective is dependent on other variables (whether the local cells are assigned a specific land use) the relationship is non-linear.

3.2.3 Constraints

The final component of an optimisation problem are the constraints on the search. These can be applied directly to $x \in X$ thereby limiting the variable space, and are known as direct constraints (Deb 2001). For example Prasad et al. (2004) distribution network problem a discrete variable for the diameter of a pipe D is constrained to a set of realistic diameters:

$$\text{Subject to} \quad D_i \in \{A\} \quad i = 1, 2, \dots, np \quad (3.6)$$

where i represents a pipe in the network of which there are np , whilst A defines a set of commercially available pipe diameters. In addition constraints can be made on the entire variable set, X with for example a number of land use allocation problems present constraints on the number of different land uses assigned to within X . The land use allocation problem in Qian et al (2010) constrains the number of cells allocated to specific land uses:

$$\text{Subject to} \quad LB_k \leq \sum_{i=1}^I \sum_{j=1}^J x_{ijk} \leq UB_k, \quad k = 1, \dots, K \quad (3.7)$$

where LB_k and UB_k and lower and upper bounds on the number of cell variables, x , assigned to a landuse k . Alternatively they can be applied indirectly by restrict the possible outcomes of the set of variables. Ye et al. (2005) constraints on the lengths of transit routes L resulting from a variable set relating to the origin of a route, o , and the destination d :

$$\text{Subject to} \quad L_{min} \leq L_{od} \leq L_{max} \quad (3.8)$$

These three elements combine to define the structure of the optimisation problem. Solutions found by the search which comply with the constraints can be defined as s whilst the set of solutions found can be defined as S such that $s \in S$. The optimal solution to meet the objective functions, F , $\min(F)$ (if considering a minimisation) or $\max(F)$ (if considering a maximisation) is the solution which is found to be $s_{min} \geq s \forall s \in S$ or $s_{max} \leq s \forall s \in S$ for the respective minimisation or maximisation. The optimisation of a single objective, $F = (f_1)$ is relatively simple as a single s can be found which is $\min(f_1)$ or $\max(f_1)$. However optimisation problems rarely consist of a single objective in a vacuum (Savic 2002) and there

are normally a number of objectives to be considered simultaneously. Particularly in real world applications, these objectives very rarely coincide meaning there is no solution which is $\min()$ or $\max()$ $\forall f \in F$ (Deb 2001). Therefore in order to facilitate the optimisation of multiple objective functions there needs to be a number of considerations which are discussed in the following section.

3.3 Multi-objective Optimisation

Methods to handle multi-objective optimisation (MOO) are required in the majority of spatial optimisation applications (and optimisation applications in general) as they regularly involve competing and conflicting objectives (Jiang-Ping & Qun 2009; Mosadeghi et al. 2015) meaning there is no solution which is $\min(F)$, therefore requiring a trade-off solution (Berardi et al. 2009). To do this there are two main approaches; weighted sum (scalarisation) and Pareto-optimisation (Zitzler & Thiele 1998).

Classically weighted sum (WS) was the predominant approach to MOO (Jones et al. 2002). WS essentially entails converting the MOO problem to a SOO problem to be solved through assigning weights (preference vectors) to each objective function in order to create a composite function, F^w :

$$\text{Minimize} \quad F^w = (w_1f_1 + w_2f_2 + \dots w_nf_n) \quad (3.9)$$

A single optimal solution is then returned as the optimum which is $\min(F^w)$. It is common for the weights to add up to 1 (Maliszewski et al. 2012) and as each objective is likely to have different orders of magnitude, it is often necessary to normalise the objective functions (Eastman et al. 1995). The normalisation equation below is used to produce a f_n^{norm} value between 0 and 1:

$$f_n^{norm} = (f_n - f_n^{min}) / (f_n^{max} - f_n^{min}) \quad (3.10)$$

where f_n^{min} and f_n^{max} represent the minimum and maximum possible values of f_n . One downside of this is that these values are often hard to traduce in the absence of known range of values for f_n (Deb 2001). Efforts to bridge this exist, for example in Liu et al. (2015) a

maximum possible value for the compactness measure was unknown so instead the work utilised a proxy normalisation:

$$f_n^{norm} = f_{min}/f_n \quad (3.11)$$

Alternatively Pareto-optimisation (PO) identifies a number of Pareto-optimal solutions to a problem based on the concept of domination (Goldberg 1989). In the case of a minimisation a solution $s^{(1)}$ is identified as being non-dominated by a solution $s^{(2)}$ if no worse than $s^{(2)}$ in all objectives:

$$(f_n(s^{(1)}) \leq f_n(s^{(2)})) \forall n = 1, 2, \dots, M \quad (3.12)$$

and is strictly better than in at least one objective

$$f_n(s^{(1)}) < f_n(s^{(2)}) \text{ for at least one } n \in \{1, 2, \dots, M\} \quad (3.13)$$

A Non-Dominated Sorting Algorithm (such as those proposed by Du et al. (2007) and Mishra & Harit (2010)) are applied to the results of search, S , and use the definition above to extract a set of s which is non-dominated by all $s \in S$, N . Solutions found to be non-dominated by all other solutions are returned, $p \in N$ which are all considered to be equally optimal and Pareto-optimal as no other feasible solution $s \in S$ provides an improvement in an objective without a degradation of another objective. This can be seen in the example in Figure 3.2 of an optimisation of $F = (f_1, f_2)$ where no Pareto-optimal solution on the Pareto front (shown in red) can improve upon the performance of f_1 or f_2 without a detrimental affect on the other. In addition Figure 3.2 demonstrates how the solutions on the Pareto front out perform all $s \in S$ in at least one of either f_1 or f_2 .

An advantage of PO over WS is that it avoids the need to select weights for each of the objective functions $W = \{w_1, w_2, \dots\}$. Both Aerts et al. (2002) and (2003) used a WS method to reconcile objectives for optimising compactness and development costs during land-use allocation. However they had to elicit weights from a decision maker and apply several iterations in order to derive an appropriate weighting system. Meanwhile Liu et al. (2015) accept that the weighting system used in their study was subjective due to no prior knowledge. This is a

common criticism of WS and sources have pointed out that the derivation of a preference vector is made even harder in the absence of knowledge of the how the objective function relate and by how much they conflict (Deb 2001) whilst the final solutions are highly dependent on the initial weighting system (Prasad et al. 2004)

Alternatively the results of PO are independent of any prior subjective preferences and provide a mathematical justification of the optimality of a set solutions over the remaining solutions (Jiang-Ping & Qun 2009). Although decision makers are still required to select their final solution, WS requires higher-level information from the beginning, whereas with PO the higher-level information is needed at the end to select the preferred solution in the presence of a wide range of alternatives. Indeed there are a number of methods of identify promising solutions from the Pareto-set including k-clustering, where clusters of solutions which perform particularly well in a set of objectives are identified (Aguirre & Taboada 2011), and non-uniform weighting, where non-numerical preferences are used to shrink the Pareto-set (Carrillo & Taboada 2012).

WS method are preferable in applications which require faster productions of optimal solutions. PO is unsuitable for quick applications as the consideration of a wide range of alternatives leads to large computational expense (Sayers et al. 2014). For this reason, in their land use allocation study Stewart and Janssen (2014) utilised WS to produce baseline performances for their objective criteria in order to feed a larger scale model. In addition Cao et al. (2012) utilised WS as the diversity of solutions found by PO leads to poorer convergence. Moreover despite the wide use of Pareto-optimisation several optimisation studies (Cao et al. 2012; Stewart & Janssen 2014) have developed a refined WS methodology known as Goal Programming which dynamically changes the weights during the application (Romero et al. 1999). The problem of selecting appropriate weighting system can be offset by setting reference points for the objectives to achieve. Aerts et al. (2005) uses this to dynamically modify the weighting whilst the algorithm is running to emphasise less well achieved objectives, determined by a goal or 'reference point' which assesses how well the objectives have been achieved (Aerts et al. 2005; Cao et al. 2012; Cao & Ye 2013). As all the solutions found by WS are in fact Pareto-optimal, a number of applications use it to estimate the Pareto front by running the algorithm with several weighting systems. However this is computationally inefficient as it requires several WS runs (Kapelan et al. 2005b).

The most significant advantage of PO is the identification of a Pareto front and the information it provides decision makers in terms of the trade-offs between objectives (Kapelan et al. 2005b). Whilst solutions found by WS should lie on the Pareto front it provides only a single instance of the possible trade-offs. Alternatively as can be seen in Figure 3.2, PO provides information of the trade-off between f_1 and f_2 and what values can be achieved and at what cost and benefits to a number of alternatives. Lastly it allows for the discovery of intermediary solutions between optimally meeting specific objectives which best balance a number of objectives (Deb 1999).

Overall the PO method is best suited for the planning problem being investigated here. It is the predominate method to MOO in the literature and has been found suitable for a number of spatial optimisation application (Khalili-Damghani et al. 2014; Masoomi et al. 2012; Jiang-Ping & Qun 2009). In particular the trade-offs, which PO can provide, best meets the needs identified in Chapter 2 for an appreciation and exploration of the conflicts and synergies between sustainability objectives during the planning process (Gibson 2006). And in the lack of expert knowledge it is ideal to apply a mathematical identification of optimal solutions.

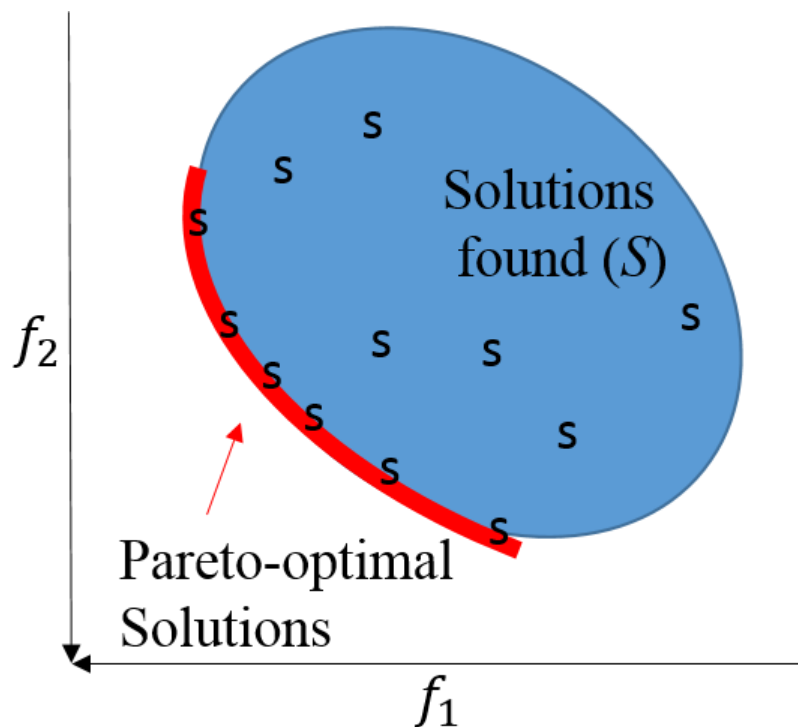


Figure 3.2 The Pareto-optimal solution set (red curve) from the found solutions, $s \in S$, in the variable space (blue) assuming minimisation of f_1 and f_2 .

3.4 Spatial Optimisation Approaches

3.4.1 Introduction

The application of optimisation to spatial problems can present a complex and non-linear problem due to the range of spatial properties which can be investigated (Loonen et al. 2007) for their incorporation of multiple objectives into spatial optimisation problems provides for very high dimensional problems (Malczewski 1999). Therefore there needs to be careful consideration of the optimisation approaches used. This section describes and discusses the major spatial optimisation techniques. Their application to spatial (and in particular urban) optimisation is critiqued in order to identify the most promising optimisation approaches which could be used to handle the problem set out in Chapter 2.

3.4.2 Linear Programming

Linear programming (LP) is the simplest form of mathematical optimisation and involves formulating a given problem in a linear fashion with continuous variables and constraints (Chuvieco 1993; Arthur & Nalle 1997; Orsi et al. 2011). Usually this involves arranging the variables as a set of integers or binary and constraints on the range of these variables (Luenberger & Ye 2008). A very simple LP approach to land use allocation could be formulated as:

$$\textit{Maximise} \quad F = (0.3R^2 + 1.6E) \quad (3.14)$$

$$\textit{Subject to} \quad R + E \leq 50 \quad (3.15)$$

where R and E are continuous variables for the number of residential and economic land uses allocated respectively and F represents a economic benefit dependant on the land uses. All possible values for R and E are then tested and as the linear problem is convex a solution is returned which is the globally optimum. Schlager (1956) was the first application of LP to land use planning applications and since then it has been used in a multitude of urban land use spatial optimisation applications (Chuvieco 1993; Arthur & Nalle 1997; Cromley & Hanink 1999; Aerts et al. 2003).

LP is often incorporated to the spatial allocation of land uses by representing each land parcel as a variable whilst assigned land uses are represented by integer values, so for L landuses $l = 1, \dots, L$ (Aerts et al. 2003). This method is known as Linear Integer Programming (LIP). LP is exclusively able to handle SOO however a number of applications have incorporated further objectives by reducing them to simple spatial constraints on the search (Baskent & Keles 2005). For example Qian et al. (2010) in their land use allocation application utilising LIP, incorporates economic objectives as the main objective to optimise whilst ecological and societal goals are handled by 13 constraints in total. These include a societal objective achieved by maintaining a number of agricultural land in proportion to residential land use and an ecological objective is achieved through a constraint on sum of soil quantity is restraint to the current land quantity. Alternatively objectives can be combined as a WS such as Aerts et al. (2003)'s application where a compactness and development cost objectives were formulated into a single objective.

Despite being limited to SOO and the limitations on continuous variables and constraints Keirstead and Shah (2013) found that LP was used in 24% of the urban planning optimisation studies they reviewed. Indeed where the problem is appropriate to be characterised as a linear problems the LP is ideal as it enables the discovery of a single optimal solution (Jones et al. 2002). Ligmann-zielinska et al. (2005) used LIP in their study of sustainable urban land use allocation by combining a number of objectives for a theoretical 20 x 20 cell grid whilst Maoh & Kanaroglou (2009) used LP to optimize the location of land use in relation to transport routes to identify baseline indicators. Indeed Loonen et al. (2007)'s study found that for a spatial allocation problem, at coarse scale a LP algorithm achieved results similar to a more complex Genetic Algorithm (see Section 3.5.5) for a small linear problem considering 235 cells whilst avoiding the need for complex constraints which the Genetic Algorithm required. However the same study found that once complexity was added to the problem LP became unsuitable. Crucially Aerts et al. (2003) found LIP unsuitable for an application for a grid of 50 x 50 cells which other approaches were able to achieve. Despite creative methods of incorporating several objectives, the majority of real world optimisation problems are in fact non-linear because of the variables considered during spatial planning (Loonen et al. 2007). Whilst a number of approaches have been developed to enhance LP in order to handle non-linear optimisation problems through non-linear programming (Fiorucci et al. 2003) and mixed integer programming (Schouwenaars et al. 2001) the increasing complexity negates the original advantage of LP approach. Moreover where the complexity of the problem means that all possible alternatives cannot be compared, these problems are best solved by non-exhaustive search methods such as heuristics (Reeves 1993).

3.4.3 Meta-Heuristics

Heuristic approaches emerged because of a need to find optimal solutions to complex problems in an realistic time frame (Reeves 1995). Where the range of variables is so complex that exhaustive search mechanisms (such as LP) are not feasible they provide an effective mechanism to narrow the search. In addition they improve upon LP as they can handle a wider formulation of variables and relationships (Loonen et al. 2007) and by allowing flexibility in constraints, the problem definition can more closely match the real world situation (Papadimitriou & Steiglitz 1998). This is crucial to facilitate the use of these tools in decision support systems (Murray & Church 1996). Meanwhile in large applications where the globally optimum solution is often too computationally extensive to find they are able to find near optimal solutions much quicker through search mechanisms based on a set of rules (Rothlauf 2011). Traditional heuristics are problem dependant and modify the search to take advantage of the specificities of the problem. Meta-heuristics on the other hand incorporate ideas from other disciplines to develop robust method for a number of potential applications (Jones et al. 2002). These have received the most interest in the literature and are proven to handle high dimensionality and a number of these are assessed below.

3.4.4 Simulated Annealing

Simulated Annealing (SA) is one the most predominant of these meta-heuristics approaches (Jones et al. 2002). First proposed by Kirkpatrick et al. (1983), SA is a method of finding the global minimum of a cost function whilst avoiding local minima by imitating the process of metal cooling (annealing) (Dowsland 1993; Luke 2009). From an initial solution, the algorithm samples the variable space by sequentially applying small random changes (as per a stochastic approach) to the $x \in X$. If these changes result in superior performances they are accepted and the search continues from this new position. However, SA is characterised by its acceptance of an inferior solution according to the probability given by:

$$e^{-\Delta F/T} > R(0,1) \quad (3.16)$$

where ΔF is the change in the objective functions F that will occur as a result of accepting the new solution, T is a synthetic temperature, and R is a random number in the interval $0 \rightarrow 1$

(Dowsland 1993). This acceptance of inferior solutions allows for a wider search of the variable space and prevents the search algorithm becoming stuck in local optimum (Murray & Church 1995). This is a vital strength over techniques such as hill climbing (Weise 2009) which don't allow for the performance of the solution to be reduced in order to continue searching different parts of the variable space (Luke 2009). This acceptance is controlled by the synthetic "temperature", T , which is initially set high to allow a high probability of acceptance. During the search this gradually restricts the acceptance probability. This aids convergence on the global optimum solutions and is an improvement over computationally intensive efforts which consider all variables (Dowsland 1993).

Whilst this method allows for wide search of the variable space the method of sequentially exploring the search space can often lead to long running times (Dowsland 1996; Weise 2009). The time of operation of the SA can be controlled by changing the initial temperature and/or the amount it reduces at each iteration (cooling factor). However the effectiveness of the SA is very sensitive to these parameters as premature convergence will prevent the convergence on globally optimal solution (i.e. leading to only a local optima) therefore care must be taken in their selection (Dowsland 1993). Throughout the search a best found solution is preserved to return as the optimal solution found throughout the search. Unlike LP approaches there is no guarantee that this is the optimal solution however it often provides a good solution in a more realistic time frame (Rothlauf 2011).

Because of its capability to handle complex non-linear problems and incorporate spatial constraints on the search effective SA has been used within number of spatial optimisation applications including resource and land use allocation (Aerts & Heuvelink 2002; Aerts et al. 2005; J. Duh & Brown 2005; Santé-Riveira et al. 2008), location modelling problems (Murray & Church 1996), transit planning (Delmelle et al. 2012) and water distribution networks (Cunha & Sousa 2001). Delmelle et al. (2012) uses SA to handle a non-linear spatial interaction problem of maximising the interaction between the demand nodes and facilities in a transit network a problem computationally intractable without an efficient search algorithm. Whilst Sabatini et al. (2007)'s investigation into land use zoning used SA to allow for the implementation of complex spatial constraints.

There are a number of variations on how the search is carried out with differing methods of changing $x \in X$ whilst continuing to utilise the generic SA algorithm to monitor the search, thereby allowing flexibility to the application. Murray & Church (1996) used SA to investigate

location planning of facilities in relation to demand by iteratively changing their locations over a grid and accepting new layouts on the basis of the acceptance criteria. Aerts & Heuvelink (2002) facilitated the 'change' step of the algorithm by exchanging the land uses of two randomly selected cells across the study area at each iteration of the SA. Alternatively Sidiropoulos & Fotakis (2009) instead of exchanging these locations over the study area for it resource allocation problem instead moves a proportion of groundwater wells being allocated within their neighbourhood at each iteration of the SA.

SA has been found to be computationally efficient when dealing with high dimension problems with Aerts & Heuvelink (2002) successfully applying to solve a land use allocation for an area of 300 x 300 cells which a subsequent LIP was found be unable to handle (Aerts et al. 2003). Additionally Santé-Riveira et al. (2008) successfully employed SA for a land use allocation problem consisting of 182,168 cells but found the optimality of the conditions were dependent on a good initialisation of land use. Despite this Aerts et al. (2005) found a SA approach required three times the time needed by a Genetic Algorithm for their land use allocation problem.

Regarding MOO, SA has predominantly been used to solve WS problems (Aerts & Heuvelink 2002; Santé-Riveira et al. 2008) and is not particularly well suited for Pareto-optimisation as it only uses one search i.e. one solution is investigated during the search. A number of studies have attempted to redress this through incorporating the search for several solutions simultaneously (Duh & Brown 2007) and goal programming to approximate the Pareto front (Czyzzak & Jaszkiwicz 1998). The former approach seems promising however the storage of multiple solutions will increase the computational time further of an already long running operation. Alternatively Nam & Park (2000) describe a method for incorporating the non-dominated sort into the acceptance criteria in Equation 3.16, whereby non-dominated solutions are accepted. The work finds that, for small problems, the Pareto front found is close to that produced by the GA whilst still allowing for the simple SA implementation. Altogether the biggest advantage of SA is its simplicity to implement (Delmelle et al. 2012) and its ability to be geared towards a number of applications whilst maintaining its core algorithm presents a significant advantage (Zhang et al. 2011).

3.4.5 Tabu Search

Another commonly used meta-heuristic is Tabu Search (TS) which was first proposed by Glover and McMillan (1986) as an addition to local search methods for optimisation. As with SA, TS sequentially assesses the solution space. The basic structure of a TS employs a memory structure called a Tabu list which dynamically records the last solutions searched (Jones et al. 2002). This is then used to prevent the same solutions being assessed again thereby reducing the number of computations. For this reason Murray & Church (1995), found TS to perform better than SA for a series of forestry spatial planning problems. Moreover, the storage of previously investigated solutions helps avoid the search becoming caught in local optima as the search will escape the local optimum once all the neighbouring solutions have been assessed.

Whilst this is effective in discrete search areas, for complex problems with continuous variables this leads to computationally extensive searches limiting application of TS. For example, Jones et al. (2002)'s study found that TS were the predominant search mechanism in just 6% of MOO applications it reviewed. Despite this sources identify that they are particularly appropriate for network optimisation (Reeves 1995) as it's mechanism to move to neighbouring variables is suitable for handling discrete-variables in the design of networks (such as pipe diameters) (Sung et al. 2007). Meanwhile there is extensive research into incorporating different search procedures alongside the Tabu list procedure. Liang et al. (2004) presents a TS method which incorporates a dynamic search mechanism approach to optimise the design of sewer networks, finding the approach finds lower cost designs than a Genetic Algorithm. Additionally Costamagna et al. (1998) finds that it can return least cost plans of communication networks as effectively as SA and Genetic Algorithms whilst avoiding having to identify the complicated search parameters necessary for SA and Genetic Algorithms. Jaeggi et al. (2008) argues that they are an underutilised approach and outlines a number of modifications to the Tabu search methodology to improve its application to problems using continuous variables. However its use is limited in the literature to applications of discrete variables such as the water network and or being coupled with other optimisation approaches to improve their local search (Zhang & Wu 2011; Khalili-Damghani et al. 2014).

3.4.6 Population Based Searches

Both SA and TS are described as trajectory searches as they incrementally alter a single solution (Khalili-Damghani et al. 2014). Alternatively with the increasing use of PO, there has recently been more interest in population based optimisation algorithms which can consider a number of solutions simultaneously, allowing for a more representative Pareto front (Deb 1999; Zitzler

& Thiele 1998; Zitzler et al. 2001). Examples of population approaches include Genetic Algorithms and Particle Swarm optimisation.

3.4.7 Genetic Algorithms

Genetic Algorithms (GA) have become one of the most prominent population based optimisation and are based on the work of Goldberg (1989) with a multitude of versions of the original algorithm having since been developed. They are a member of the Evolutionary Algorithms (EA) which includes Evolutionary Strategies (proposed by Rechenberg (1973)) and Evolutionary Programming (proposed by Fogel et al. (1966)) which utilise mechanisms based on natural evolution to evolve a set of solutions to their most optimal states. In particular, GAs use evolutionary operators of selection, mutation and crossover.

Figure 3.3 outlines a typical GA framework. A random initial population of solutions is generated and evaluated to determine for their fitness for the performance function F . From these the ‘fittest’ are selected to be ‘evolved’. For a basic GA this is facilitated by a Tournament Selection whereby each solution is compared within the population and those found to be superior are carried on (Goldberg & Deb 1991). These are then used to ‘breed’ with one another by swapping their attributes in X to produce superior offspring. Figure 3.4 demonstrates for a binary list representation the application of typical two point crossover. For the two solutions selected for the crossover, A and B , two random points along the length of their list are selected at random, cx_1 and cx_2 . Subsequently their attributes between the two crossover points are exchanged to form two new solutions A' and B' . This is repeated for the selected solutions until a new population is formed with the expectation that the new population will contain some more optimal solutions Once this new population is formed a random mutation is applied. This is shown in Figure 3.5 where two variables within the solution A'' have been mutated. In particular for the binary encoded list used a flipbit mutation operator switches attributes from 0 to 1 and vice versa. This final population that is generated is fed back to the start of the algorithm to repeat the process. This is repeated for a number of ‘generations’ until a stopping criteria is met, usually a number of iterations. By repeatedly combining the attributes of solutions found to be superior the GA intends to converge on a solution composed on the optimal set of $x \in X$ (Goldberg 1989). Meanwhile the application of the mutation operator intends to stop the solutions converging too early on a set of variables by diversifying them and also on the off chance the change of variable leads to a more superior fitness.

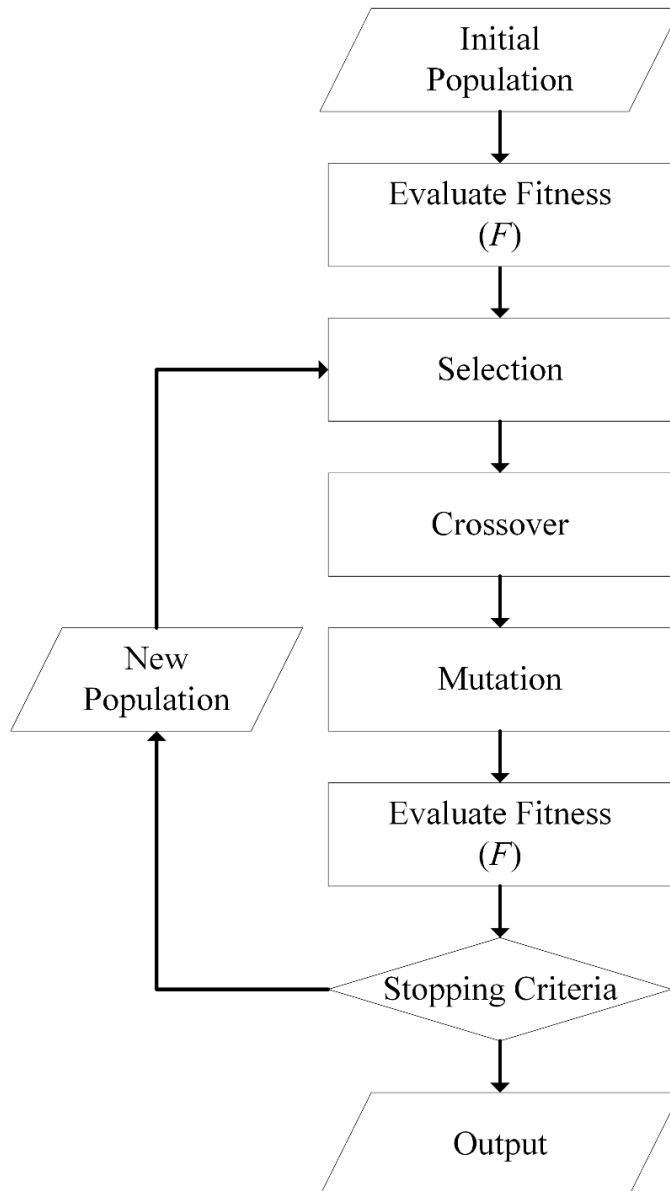


Figure 3.3 Workflow of a Genetic Algorithm.

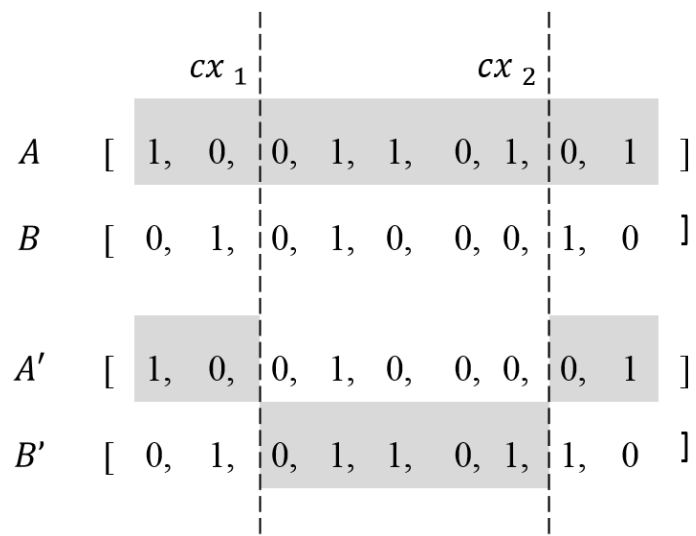


Figure 3.4 Two point crossover operator on binary list representation.

$$A' \quad [\quad 1, \quad 0, \quad 0, \quad 1, \quad 1, \quad 0, \quad 1, \quad 0, \quad 1 \quad]$$

$$A'' \quad [\quad 1, \quad 0, \quad 1, \quad 1, \quad 1, \quad 0, \quad 0, \quad 0, \quad 1 \quad]$$

Figure 3.5 Mutation operator on a binary list representation.

SA and Tabu Searches are commonly referred to as local search methods as they sequentially explore the variable space. In contrast the GA more dynamically searches the variable space with its crossover procedure. As such it has been found to outperform these other approaches in discovering the global optimum solutions to combinational problem (Reeves 1995) with consistently shorter run times (Melanie 1996). Like SA and TS, GA can handle a number of discrete, integer and binary variables. However the dynamic nature of the search leads to a number of issues. Whereas the search is more controlled in both SA and TS a number of studies have reported the difficulty of handling constraints within a GA as there is little control on the outputs of the evolutionary operators (Coello 1999; Deb 2000; Prasad et al. 2004; Konak et al. 2006). Konak et al. (2006) identifies four methods to handle constraints in GA, namely; discarding solutions which break the constraints; applying a penalty function; constructing the problem so only feasible solutions are found; and, repairing solutions during the search. Loonen et al. (2007) describes the handling of constraints as a particular problem in its land use allocation problem using a GA and argues that designing the problem so constraints cannot be broken would be the best method. This is the approach taken by Cao et al. (2012) in their land use allocation where a number of areas which were reserved for greenspace were excluded from the search space. However this isn't always possible for constraints such as ensuring a minimum number of a specific land use type. Coello (1999) provides a review of the use of constraints for EAs and found that penalty functions were the most often used. Despite being an easy method to implement on the fitness of a solution, the selection and magnitude of penalty functions is often hard to define (Deb 2000). The penalty functions chosen have a significant impact on the ability of the GA to converge on optimal solutions; a too large a penalty prevents that area of the variable space being assessed; too small a penalty allows too many unfeasible solutions to be generated, reducing computational efficiency (Michalewicz 1992; Yeniay 2005). Special dispensation must be considered when applying GA to a 2D grid encoding of the variable set, X , which are most commonly used for land use allocation problems. Simply randomly swapping the attributes as per the example shown in Figure 3.4 leads to highly

fragmented land uses (Stewart et al. 2004; Aerts et al. 2005). Indeed there is a multitude of research into the most effective methods of applying GA crossover to 2D representation (Cao et al. 2012; Stewart & Janssen 2014). Likewise a number of mutation operators have been developed to handle different encoding of the solutions (Sidiropoulos & Tolikas 2008). As well as the ‘flipbit’ mutation operator shown in Figure 3.5, boundary mutators can replace the attribute with an integer or float value from a lower and upper bound.

Despite these weaknesses the flexibility of the GA algorithm to handle different problems has led to it being extensively and widely used in contemporary literature (Feng & Lin 1999; Keedwell & Khu 2005; Sidiropoulos & Fotakis 2009; Comber et al. 2008; Stewart et al. 2004; Aerts et al. 2005). Jones et al. (2002) found that of the studies reviewed GAs were used by 70%. With regards to spatial optimisation Loonen et al. (2007) especially praises GA for its efficiency in discover optimal land use configurations for large areas as its dynamic search is particularly suitable. Where GA is most strong is its applicability to MOO through Pareto-optimisation. By considering a number of populations it is ideally placed to explore the Pareto front comprehensively. These opportunities are briefly discussed.

As a result of its efficiency there has been a considerable research into the use of GA for Pareto-optimisation. Specifically a number of evolutionary approaches have been developed of which the predominant consist of Non-Dominated Sorting Algorithm-II (Deb 2000), Strength Pareto Evolutionary Algorithm 2 (SPEA2) (Zitzler et al. 2001) and the Pareto Archive Evolutionary Strategy (PAES) (Knowles & Corne 2000). The PAES algorithm assesses the fitness of new solutions found by comparing them to an archived list of previously found non-dominated solutions. But crucially it is not a population based method so its utility with GA is limited. Instead the SPEA2 and NSGA-II are the most commonly used for GA approaches.

The NSGA-II algorithm achieves PO through incorporating non-dominated sorting into the GA’s selection operator. The previous and the newly developed population are compared simultaneously to ensure the best solutions from both generations are selected, known as elitism (Deb 2001), preventing the Pareto front regressing during the operation. From the two combined populations the next population is selected on the basis of their Pareto-rank and crowding distance operator which are demonstrated in Figure 3.6. The population is ranked into non-dominated sets shown in Figure 3.6a using Equations 3.12 and 3.13. Next to ensure diverse set of solutions in the objective space a crowding distance, ψ , is calculated based on the average distance to the nearest solution in the objective space as shown in Figure 3.6b. These two

metrics are then used to determine a solutions fitness in the selection. Alternatively the SPEA2 algorithm identifies the fitness of solutions based on their level of dominance (Zitzler et al. 2001) and a measure of their density in the Pareto front. For the minimisation of the two objective functions, f_1 and f_2 , in Figure 3.7 the solutions which are non-dominated are given the ranking of 0. Thereafter the two solutions which are dominated by two of the non-dominated solutions are given the ranking of 2. This continues until all the solutions are given a ranking. Whilst a number of studies find the two approaches are good and bad for different applications (Konak et al. 2006), sources report SPEA2 has longer running times due to its determination of density and dominance ranking (Luke 2009).

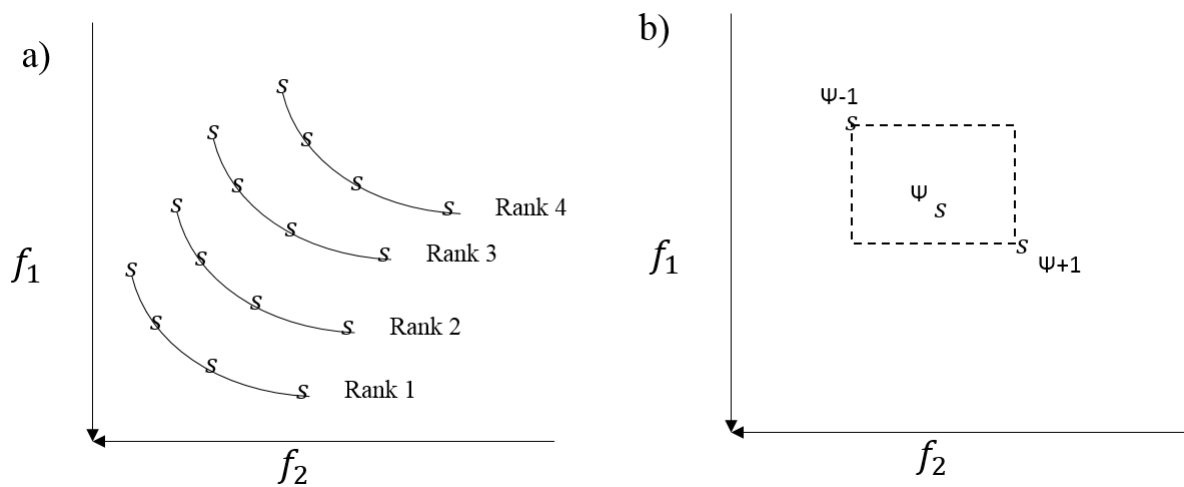


Figure 3.6 NSGA-II selection procedure consisting off a) Pareto ranking and b) Crowding distance.

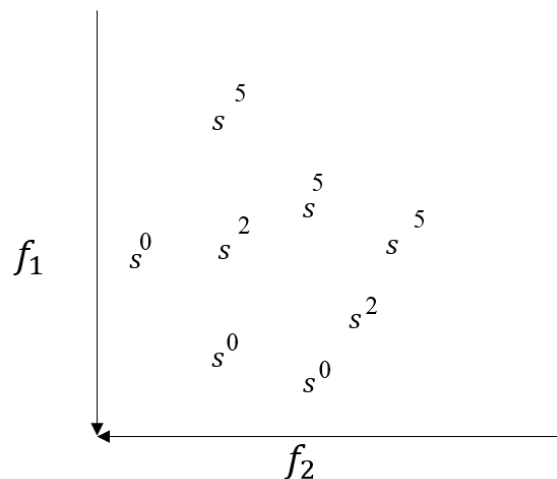


Figure 3.7 SPEA2 selection procedure of dominance ranking.

Since their inception a number of extensions to their basic algorithms have been developed to handle particular problems. For example Deb et al. (2003) developed the ϵ -NSGA-II to find well spread Pareto fronts which has been found particularly applicable in high dimensionality water resource applications (Kollat & Reed 2006). Meanwhile the time taken to assess each

solution for their non-dominance is considerable, therefore Zhang & Fujimura (2010) developed an Improved Vector Evaluated Genetic Algorithm which simplifies the determination of the fitness in order to converge faster, but with a resulting loss in performance and potentially not finding the true Pareto front.

Despite this SPEA2 and NSGA-II remain widely used to enable Pareto-optimisation as they provide a robust framework which can be adapted if needed. Indeed SPEA2 was incorporated into Khalili-Damghani et al. (2014) land use allocation problem. However of the two NSGA-II has had the most influence on spatial optimisation as it can be directly incorporated into the GA selection procedure. Shimamoto et al. (2010) utilises the NSGA-II procedure to handle the PO of passenger cost and operational cost simultaneous during investigating a bus transit network meanwhile Cao et al. (2011) integrated the NSGA-II to handle the PO of accessibilities, conversion costs and land use incompatibilities during their land use allocation optimisation.

3.4.8 Particle Swarm

Lastly consideration is given to another population based method. Like the GA approach Particle Swarm (PS) considers a population of solutions simultaneously. Originally conceived by Kennedy and Eberhart (1995) the search intends to mimic the social behaviour of birds flocking or fish schooling (Poli et al. 2007). Solutions are described as particles and during the application, particles exchange information on their location in the variable space, denoted by their variable vector X , and their fitness. Then at each iteration particles use this information to move towards the more optimal locations. A variable, $gBest$, stores the best position of the particle (i.e. the solution's X) at each iteration whilst $pBest$ records the best solutions at all iterations. For the m dimensions of variables in the search these are used to influence the direction of the rest of the particles by generating a new velocity, v_m^{new} . This can be defined as:

$$v_m^{new} = w \cdot v_m^{old} + c_1 r_1 (pBest - x_m) + c_2 r_2 (gBest - x_m) \quad (3.17)$$

where v_m^{old} is the previous velocity, r_1 and r_2 are random numbers used to ensure a sense of randomness in the search (Coello et al. 2004), c_1 and c_2 are user defined weights to influence the effect of $pBest$ and $gBest$ on the search. This is then used to move the location of the particle:

$$x_d^{new} = x_d^{old} + v_d^{new} \quad (3.18)$$

where x_d^{new} denotes the new location of the particle (Masoomi et al. 2012). As PS uses a population of particles to investigate the search space it is appropriate for PO (Reddy & Kumar 2007) however techniques to implement PO aren't as well developed as for GAs. Despite this PS also has a number of advantages over GA as the iterative search technique improves on the local search for solutions (which is often found disadvantaged by the dynamic nature of evolutionary search) and doesn't require the complicated evolutionary operators of GA allowing for much easier to implementation (Bai 2010).

A major weakness of the approach is that the variables themselves are used to direct the search, which requires the variables to be continuous. To handle this Masoomi et al., (2012) encoded land uses as continuous integer values. The method has been incorporated into a number of MOO land use allocations applications (Liu et al. 2012) but Ma et al. (2011) concede that there are issues associated with considering discrete spatial locations in the continuous search space necessary for the PS algorithm. Whilst a promising approach early in its development, there isn't enough evidence of its flexibility to a wide range of applications.

3.5 Evaluation Simulation Tools

3.5.1 Introduction

The utility of optimisation as a decision support tool for urban spatial problems is widely recognised (Loonen et al. 2007; Keirstead & Shah 2013). The previous section touched upon a number of optimisation approaches with a discussion of their relative merits. In this section a detailed assessment links the optimisation functions outlined in the previous section with their application on the planning of urban infrastructure and to urban spatial optimisation. In particular, spatial optimisation techniques have been applied to land use allocation (Ligmann-Zielinska et al. 2008; Santé-Riveira et al. 2008; Liu et al. 2012; Cao & Ye 2013), resource allocations (Sidiropoulos & Fotakis 2009; Sidiropoulos & Fotakis 2011), sewer and water distribution networks (Liang et al. 2004; Zarghami et al. 2008; Bieupoude et al. 2012), transport modelling (Delmelle et al. 2012; Shimamoto et al. 2010) which are discussed below.

3.5.2 Water Distribution Networks

A number of optimisation applications have been applied to the design of urban water distribution networks as it provides an effective way to manage the complex multi-objective problems that their design entails (Walters et al. 1999). The most common application is to minimise the cost of the system (Liang et al. 2004) however there is a move to optimising their design for a range of performance indicators (Fu et al. 2013). Sung et al. (2007) utilises both a Tabu Search investigate a set of discrete diameter of pipe of an existing network to minimise costs whilst Walters et al. (1999) outlines a GA to optimise the costs and benefits (represented by a storage capacity difference) of a network through encoding a number of decision variables. This is extended by (Fu et al. 2013) to consider six objectives which increase upon the consideration of the cost of the system to analyse the performance of the network, including objectives related to leakage and the age of water within the system. Due to water resource applications being typically high complexity problems they regularly utilise the Epsilon-Dominance Non-Dominated Sorting (ϵ -NSGA-II), an addition to the original NSGA-II algorithm which limits the complexity of the Pareto front (Kollat & Reed 2006).

Where these water distribution networks provide interesting insight is in their treatment of uncertainty. Distribution systems are subject to a number of uncertainties such as the water demand and population growth which are vital to their successful running (Vamvakieridou-Lyroudia et al. 2005). Kapelan et al. (2005) details a sampling-based approach to test how developed networks perform under uncertainty by systematically inputting randomly uncertain variables and assessing its performance. Alternatively Giustolisi & Mastroilli (2005) tests the derived solutions over a portfolio of possible input parameters. Applications to water distribution systems also reveals interesting ways of handling discrete values which related to decision variables. For example Walters et al. (1999) encodes a number of decision variables related to tank locations, depths of reservoirs etc.

Whilst water distribution systems are a common optimisation application, their application to sustainable urban development is limited to ensure a sustainable and resilient water distribution networks, which itself is becoming an increasing problem (Rosenzweig et al. 2010).

3.5.3 Transit/ Transport Networks

The design of sustainable transport networks requires good public transport coverage and efficient delivery of passengers (Mitchell et al. 2011). As a result there has been a number of applications of optimisation to investigate the efficient planning of transport networks (Kepaptsoglou & Karlaftis 2009). Applications have mainly focussed on the system cost and welfare objectives for passengers such as minimising journey costs (travel and waiting times for example) as well as coverage of service (Kepaptsoglou & Karlaftis 2009). Typically transit networks are represented as graph models with nodes representing passenger stops and arcs representing the transit lines. Shimamoto et al. (2010) is typical of these applications, with their optimisation of Hiroshima's bus network representing the problem as a series of decision variables relating to the routing of the network and utilises the NSGA-II algorithm (see Section 3.4.6 for details) to investigate different routing options by changing the alignment of nodes representing bus stops within the vector set, X . To parameterise the objectives travel time costs are estimated from previous studies and the resulting network configurations found by the NSGA-II algorithm are subject to demand parameters to evaluate them. In this instance the work identifies a Pareto front trade-off between the operational 'cost' to the service provider and the 'cost' to the passenger.

With regards to the decision support tool being investigated this type of application would be useful in the planning of transit networks to reduce emissions. However its scope is restricted as it's not suited to assess the wide range of sustainability objectives found in Section 2.2, for example climate risks to future populations, therefore failing to address the range of challenges necessary to ensure sustainable areas. Despite this, there is the possibility it could be coupled with other such applications to provide an important contribution to planning efficient public transport to compliment sustainable urban development.

3.5.4 Resource and Land Use Allocation

The most widely used application of spatial optimisation for urban areas is resource allocation problems which are concerned with the distribution of a discrete number of activities or resources over a spatial extent (Aerts & Heuvelink 2002). The resources under consideration for urban areas are predominantly the allocation of a finite number of land uses (Ligmann-Zielinska et al. 2005; Qian et al. 2010) whilst several applications also deal with the allocation

of ground water wells (Sidiropoulos & Fotakis 2009; Sidiropoulos & Fotakis 2011). These have traditionally been done for economic reasons (i.e. the most economically productive land use setups) but with the need for sustainability, the efficiency of land uses allocations is becoming increasingly prevalent in the research.

A land use allocation problem can be defined as an investigation into the location of a set of land uses subject to limited to a number/ total area of the possible land uses. Within these applications the land uses investigated can range from simple classifications of from economic, residential and industrial land uses (Ligmann-Zielinska et al. 2005) to work such as Masoomi et al. (2012) which utilises a total of 34 different land uses including low density residential and convenience retail. The former allows for a more complex consideration of the compatibility of neighbouring land uses, such as the distance of high density residential areas to convenience retail areas. Optimisation is applied to this problem through search for optimum set-ups of land uses by exchanging and assigning land uses within the problem area. For example Aerts & Heuvelink (2002) uses a SA to systematically swap the land uses within their investigation areas whilst Stewart et al. (2004) uses a GA to dynamically exchange land uses for their investigation. As this field of application is most linked to work of the thesis a thorough review is taken.

3.5.5 Urban Simulation

Urban areas are traditionally simulated spatially by either grid or vector representations, examples of which are shown in Figure 3.8. With regards to a grid representation the study area is divided into equally sized homogenous cells organised into rows and columns i, j . The size of the cell then determines the spatial resolution and detail to be assessed. In this form each cell is assigned an attribute, for example an allocated land use. Problems with this representation include it being a coarse representation of the urban system, unable to reflect the spatial variability of real urban areas (Stevens et al. 2007)

Alternatively vector representation consists of a discrete number of irregular land parcels and can be arranged as a list L of l land parcels. Representing the urban form as such is more intuitive because geographic units are often irregular (Crooks 2010) and has the advantage of more closely resembling the spatial extent. However this method of simulation this is dependent on the solution being conveniently separated into known parcels and districts (Cao et al. 2011).

A number of these instances within spatial optimisation such as Stewart & Janssen (2014) have identified agricultural fields parcels whilst Balling et al. (1999) used very high spatial resolution general land use areas. Interestingly, for their study, Masoomi et al. (2012) identified areas of specific land uses in a district of Tehran, Iran to represent a land parcel (shown in Figure 3.8b).

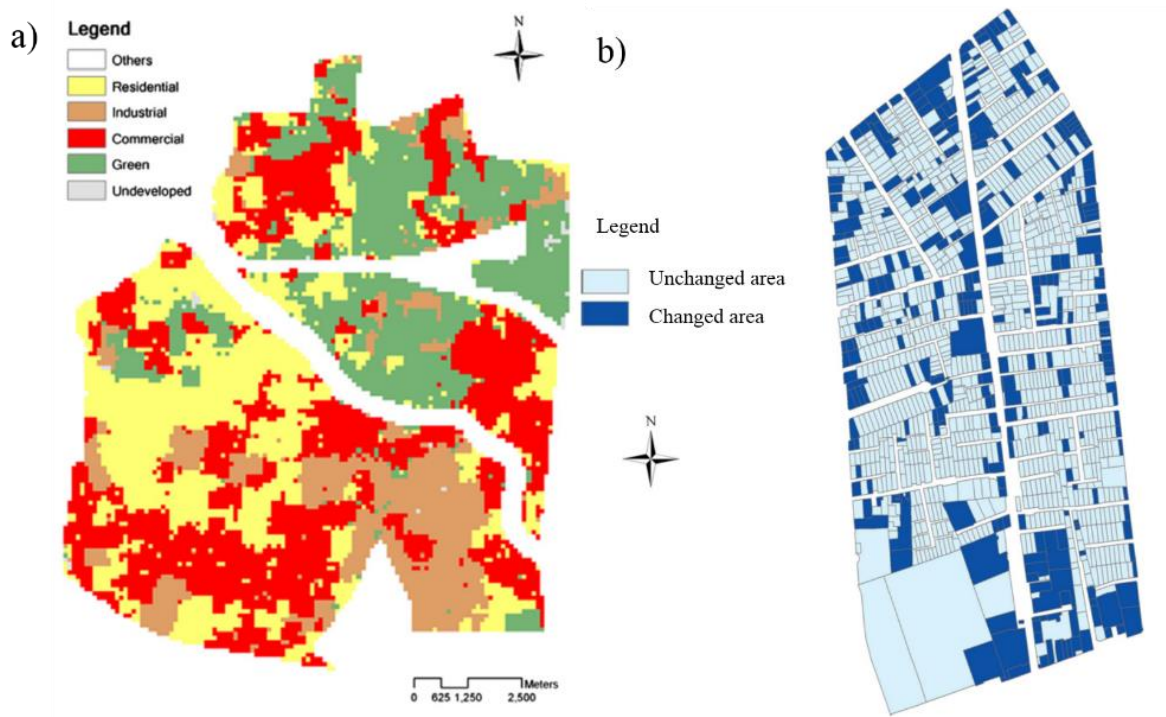


Figure 3.8 Urban landscape representations for land use allocation applications consisting of a) grids of cells (Cao et al. 2011) and b) vector parcels (Masoomi et al. 2012).

Complications in the use of vector representations arise as these polygons vary in sizes the calculation of total land uses the area of the polygons needs to be taken into account (Stewart & Janssen 2014). Moreover, the majority of spatial optimisation applications involve some measurement of proximity to the land uses of other parcels. The rigidity of grid representation allows for a comprehensive assessment of the neighbourhood of each cell, however this isn't as clear with irregular vector representations. For example the centroids of large land parcels may be far removed from the parcels edges, whilst for narrow parcels the distance to other land uses might be small. As well as the advantage of clearly defined neighbourhoods, a strength of the grid representation is that it is neatly compatible with related spatial criteria such as the cost of developing land, slope of land etc. Figure 3.9 shows a number of different types of input spatial datasets from the literature which are represented as grids in their analysis. Whilst for the vector datasets the spatial properties are aggregated over the parcel area (Feng & Lin 1999).

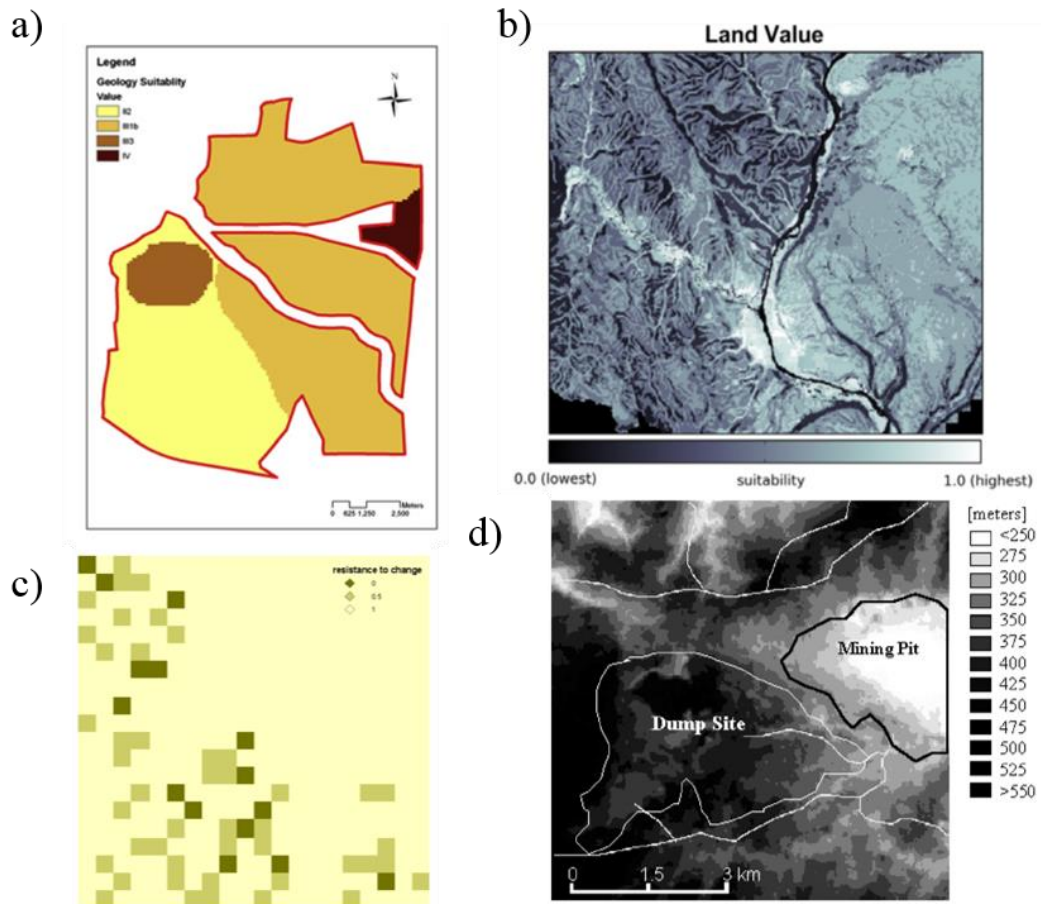


Figure 3.9 Input raster data sets from a) Cao et al 2012, b) Ligmann-Zielinska & Jankowski (2010), Ligmann-zielinska et al. (2005), and d) Aerts & Heuvelink (2002).

A widely used simulation for urban systems is Cellular Automata (CA) which are consistently used for modelling the dynamics within urban areas (Crooks 2010). Considerable early research was undertaken by White and Engelen (1993, 1994) into using CA to model urban land use patterns whilst more recently a number of more advanced CA applications have been developed (Batty et al. 1999; Torrens 2000; Kim & Batty 2011). Whilst CA represent the urban landscape as 2-dimensional grids they expand upon the grid structure by considering each cells neighbourhoods and by defining transition rules to model the spatial interaction between cells within a neighbourhood. Figure 3.10 demonstrates these neighbourhoods with Figure 3.10a demonstrating a basic Moore Neighbourhood whilst Figure 3.10b shows an extension to incorporate a wider neighbourhood. Studies have demonstrated how neighbours can be multi-scaled to model spatial reactions at different spatial scales of a city (Ward et al. 2003). Information is then passed between neighbourhoods enabling the state of cell to be affected by surrounding exogenous factors.

These transitional rules are central to the CA model and are applied at each step. For urban modelling the utility of this means that CA are able to better capture the interactions between different land uses over time. White & Engelen (1994) present a basic application where there are three rules for the modelling the growth of residential, commercial and industrial land uses:

1. Commerce is attracted to adjacent commercial and residential development but repelled by distant commerce;
2. Industry is attracted to industry whilst repelled by residential development; and
3. Residential is attracted by other residential, attracted to commerce but not adjacent to commerce and repelled by industry.

These rules are weighted, and at each iteration these transition rules are used to identify where new development is placed. This can be seen in Figure 3.11 where new land uses are assigned at each iteration based on these criteria leading to a particular type of land use pattern. The use of localised transition rules and a bottom-up approach is a much more realistic representation of how land use develops, with large scale structure evolving from local scale decision making processes, (Benenson & Torrens 2004; Liu et al. 2008).

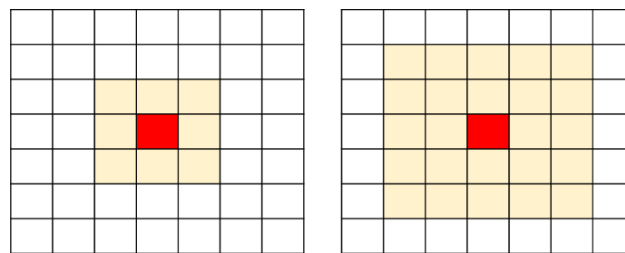


Figure 3.10 Moore a) 3x3 and b) 5x5 neighbourhood predominantly used in Cellular Automata modelling.

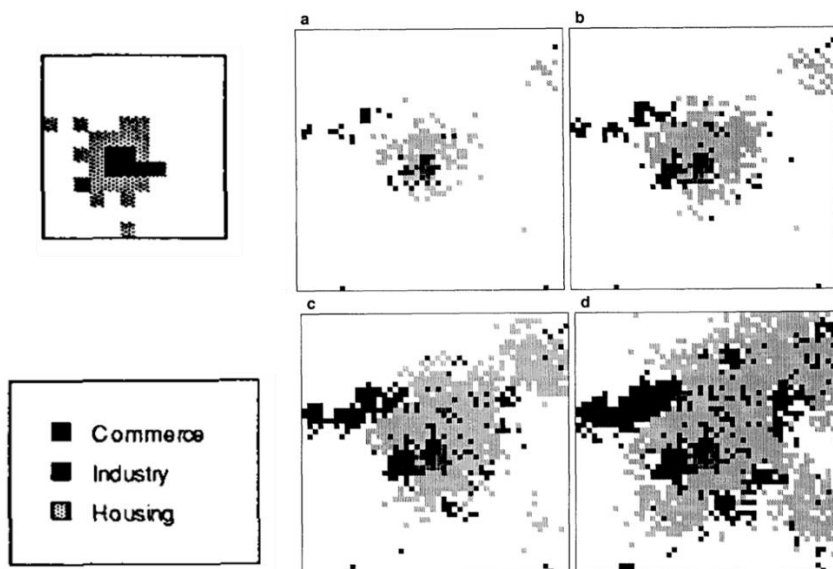


Figure 3.11 Evolution of land-use from initial state (top left) over: 10 (a), 20 (b), 30 (c) and 40 (d) iterations (White & Engelen, 1994).

Meanwhile Ward et al., (2003) additionally notes that the pattern of the urban form won't be entirely due to local decisions, and allows regional rules must be set to address this (Martin & Wu 1999). For this reason Ward et al. (2003) set a number of land use zones as per urban planning (Rossi-Hansberg 2004). Often these constraints are enforced through the transition rules to form a constrained CA (Li & Yeh 2000). However this dependence on the transition rules is a major limitation of CA as they can never be 100% accurate with regards to real world urban processes and remain a research challenge. (Straatman et al. 2004). To improve their accuracy transition rules are often calibrated using historical trends (Stanilov & Batty 2011). For example the Clarke et al. (1997) urbanisation modelling of the San Francisco bay area was calibrated using urban distribution trends ranging back to 1900.

The predominant use of CA for urban systems is to model land use growth. As such their primary potential contributor to sustainable urban development is through identifying the optimal outlays of land uses and testing different policies. Batty et al. (1999) uses a constrained CA to model urban dynamics based on dispersed or concentrated growth by constraining the speed at which development occurs. However others such as Ligmann-zielinska et al. (2005) are critical of these approaches as they have only been applied to theoretical models. Batty et al. (1999) acknowledges this and reasons that this is because the application to real cities requires such large models that traditional platforms are unable to handle it. However a number of applications have been coupled with a geographic information system (GIS) to handle the big spatial datasets required to provide real world simulation and have since then been applied to real world areas. Kim & Batty (2011) used a combined CA and GIS to simulate the future growth of the Seoul Metropolitan Urban Area in South Korea. Meanwhile (Yin et al. 2008) used CA within GIS to simulate urban growth for Changsha City in China.

A strength of using CA is that there are a number of existing CA models readily available. The SLEUTH model (an anagram of its inputs; Slope, Land use, Exclusion, Urban, Transportation and Hill Shade) originally developed by Clarke et al. (1997) has been used widely to simulate future urbanisation by modelling with the transition of undeveloped areas to developed areas (Yin et al. 2008; Al-shalabi et al. 2013). Another bespoke and widely used model, the Metronamica model (available at <http://www.metronamica.nl/>) expands upon this by incorporating up to 26 different land uses and has been widely used in a number of applications (Lahti 2008; Lauf et al. 2012; Aljoufie et al. 2013). However both these require historical trends and complex procedures to calibrate the model (Kim & Batty 2011).

Alternatively works by Benenson has developed Agent Based Models (ABM) to simulate urban dynamics (Benenson 1998; Benenson & Torrens 2004; Benenson 2004) and although they aren't as widely used as CA their use is increasing (Batty 2007). As with CA, ABM utilises a number of transition rules at each time step to represent relationships between agents to form bottom up model patterns as they emerge from local behaviour models. However where ABM differs is that these 'agents' (automata) aren't constrained to the single land unit or the grid conformity inherent in CA, allowing them to be mobile and move within the model space. Relations between neighbourhoods are also less stringent so connections can be more flexibly positioned. This makes ABM particularly suitable for modelling pedestrian flows (Schelhorn et al. 1999; Kerridge et al. 2001) and vehicles/ transport over transport networks (Rahal et al. 2010; Aschwanden et al. 2012) within cities. Within these applications each agent represents vehicles, passengers and/ or pedestrians and their motions within the system are directed by rules to react to their surroundings and other criteria (Aschwanden et al. 2012). This has been used to test the most efficient set ups of transit as well as testing the effects of impacts on transport networks (Rahal et al. 2010).

However a number of studies have extended their use to modelling residential and other land uses. Where these applications are unique are that the transition rules are based on human residential and economic preferences (Matthews et al. 2007). Any example of this would be rules which mimic the residential agents making choices for moving their residence based on criteria such as closeness to work, costs of moving etc. This is quite an innovative method of modelling behaviours and form the methodology used for UrbanSIM's urban simulation system to make economic decisions within the urban system (Waddell 2000). Despite the utility of this approach, CA remains the predominant simulation for to model urban land use growth whilst the majority of ABM applications remain concerned with processes within cities such as transport (Batty 2009). In addition the literature on ABM has been extensively applied for theoretical cities (Matthews et al. 2007) and their application to real urban areas is limited.

There are a number of optimisation applications which are utilised in-conjunction with CA. Ward et al. (2003) provide a good example of how an optimisation application can handle the allocation of land use at a regional scale, whilst a CA model organises the urban growth at a lower spatial scale within these regions. Meanwhile both Sidiropoulos & Fotakis (2009) and (2011) utilise CA to model reactions between groundwater pumps and land use at a local scale whilst an optimisation function is used to derive land use patterns. Keirstead & Shah (2013) provides an in-depth assessment of the use of spatial optimisation for urban areas. The work

concludes that rather than optimisation merely playing a part in CA systems it should instead be used to provide outlines of potential sustainable development. Keirstead & Shah (2013) reasons that with the use of more complex modelling techniques and consequential increase in the parameterisation of the models, it limits the ability of optimisation to derive optimal solutions. Instead of focusing on refining the relationships between land uses, their review suggests optimization should be used early in the planning process to identify generalised optimal planning trends.

3.5.6 Sustainable Spatial Optimisation

A number of spatial optimisation applications aim for sustainable spatial setups of development, therefore it worthwhile assessing their applications. From a review, the majority of applications intent on sustainable urban development concentrate their aims on Compact City principles (as outlined in Section 2.3.2) concerned, for example, with the efficiency of different land uses by identifying land use compatibility criteria (Ligmann-Zielinska et al. 2005; Cao et al. 2011; Masoomi et al. 2012; Khalili-Damghani et al. 2014; Chen et al. 2015). The sustainability hypothesis behind these studies is that efficient use of land is a proxy for mitigation of emissions by reducing the need to travel (Neuman 2005). To derive compatibility values, a number of applications have used Analytical Hierarchy Process (AHP) (Masoomi et al. 2012). Saaty (2008) provides a detailed explanation of their derivation but essentially an expert is employed to calculate a pairwise comparison matrix between each of the land uses based on a scale (most applications use a 1/9 – 9 scale (Eastman 1999)). This is then used to generate a series of suitability values which are calculated for the entire land use allocation to suffice an objective function.

In accordance with Compact City principles, encouraging compact development is a widely incorporated aim for sustainable spatial optimisation applications (Aerts et al. 2005; Santé-Riveira et al. 2008). Cao & Huang (2010) outline a number of methodologies for evaluating the compactness of development such as measuring the area of similar land uses in the neighbourhood of each cell; calculating the perimeter of continuous land uses; and assessing the spatial autocorrelation of the plan using the Moran's I method (Moran 1950). This varies from being an objective to be worked towards (Khalili-Damghani et al. 2014; Liu et al. 2015) to being an essential component of any spatial development plan (Aerts & Heuvelink 2002; Aerts et al. 2005; Ligmann-Zielinska et al. 2008). With regards to the latter, a number of

applications define a minimum number of neighbouring cells each designated land use must neighbour which is enforced through a constraint. Likewise accessibility is an often included objective into sustainable spatial optimisation application to further measure the efficiency of the land use set up (Ligmann-Zielinska et al. 2005; Cao et al. 2012). However, the calculation of these are often restricted to basic Euclidian distances, for example Batty et al. (1999) notes that modelling transport routes within grid based applications is often difficult as the transit network is often at a much finer spatial resolution than land parcels.. Ligmann-zielinska et al. (2005) uses a basic accessibility measure of the distance of newly assigned land uses to currently developed cells whilst Cao et al. (2012) provides a more realistic measure of accessibility taken by an appreciation of a locations proximity to the road network (see Figure 3.12). Although it has been argued that compactness provides a reasonable proxy for accessibility and therefore travel emissions, Ewing & Cervero (2010) finds that networked accessibility measures more closely resemble resulting emissions over measures of compactness (which these essentially are). Therefore there is significant scope to improve upon the calculation of accessibility in spatial optimisation problems.

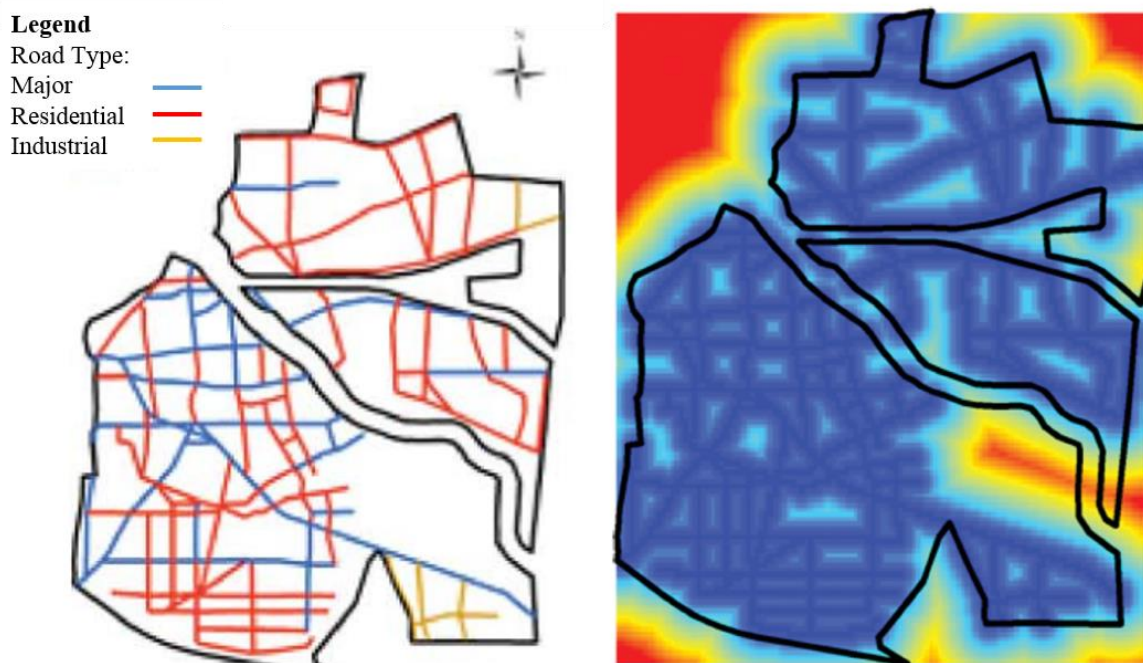


Figure 3.12 Accessibility based on proximity to the road network (from Cao et al. (2012)).

A number of sustainable spatial optimisation applications increase their scope from efficient land uses to revolve around the ‘three pillars’ of sustainable development (defined in in Section 2.2). For example Qian et al. (2010) formulates their land use problem to optimise an economic objective alongside constraining the problem to meet social and ecological sustainability.

However these are often concern sustainability on a regional scale (Chen et al. 2015) rather than specifically urban areas. For this reason economic objectives are calculated by the instance of profitable land uses such as farmland, commercial and industrial rather than any high level description of the economic activity. Although a number of climate risk related applications of optimisation exist, they're not typically spatially dependent, for example work by Woodward et al. (2013) considers flood risk, however it is defined in relation to decision variables for flood defences in set locations.

3.5.7 Evolutionary Urban Planning

Analysis of the literature suggests that any spatial optimisation technique used for urban development problems would need to be evolutionary i.e. through incremental changes to the urban environment as opposed to revolutionary where there is a major change in the current configuration, as it is would be unrealistic to expect major reshuffling of the built environment (Batty et al. 1999; Church 2005). Indeed Ligmann-zielinska et al. (2005) criticises original applications of sustainable spatial optimisation to real urban areas as they fail to exclusively consider new development. Despite this, there remains insufficient consideration of this in a number of recent applications. Instead the retention of existing land use/ development is indirectly ensured through the imposition of costs to redevelop land areas. Often this is included as an objective to optimise alongside other objectives such as (Ligmann-Zielinska et al. 2005; Liu et al. 2012). Essentially these applications consider how to improve and reorganise the current land-use arrangement which in most cases would be an unrealistic consideration. A compromise between allowing complete changes to current land uses is provided by Ligmann-zielinska et al. (2005) and (2006) who use a 'resistance to change' spatial variable to make it more likely that brownfield areas are redeveloped. Alternatively Liu et al. (2015) applies a penalty function to spatial development strategies which reallocate development on ecological area, thereby deterring these being selected by the GA to carry over into the next offspring set but fails to completely prevent redeveloped areas appearing in the resulting spatial plans. This isn't limited to grid based applications as Masoomi et al. (2012)'s land use allocation allows for land uses in land parcels to change whilst the result suggests the change of land use for a number of them. Ward et al. (2003) suggests identifying available areas for development to explore the assignment of new land uses however this hasn't been heeded by many applications.

3.6 Discussion

This section brings together the main discussion points from this chapter and Chapter 2 to outline a number of recommendations for the work carried out in the rest of the thesis. The review of urban sustainability in Section 2.2 identified that the consensus on urban sustainability centres not only on what sources identify as ‘the three pillars’ of social, economic and ecological sustainability but, with the increasing consequences of climate change, also must be incorporate mitigation and risk adaptation. As a result any decision support tool must incorporate multiple objectives. Section 3.3 reviews the methods of solving multi-objective using (i) weighted sum methods, which incorporate a number of objectives into a single objective based on preferences (weighting) to optimise, and (ii) Pareto-optimisation (PO), which identifies a multitude of mathematically determined Pareto-optimal solutions.

A potential alternative approach to Multi-objective Optimisation (MOO) is the use of Multi-criteria Decision Analysis (MCDA). There are a plethora of approaches to MCDA (Guitouni & Martel 1998) including Simple Additive Weighting (Chou et al. 2008), the Analytical Hierarchy Process (Eastman 1999) and Outranking methods (Aouam et al. 2003). Indeed so prevalent is its use in decision making that the Department for Communities and Local Government has produced guidance on their use (DCLG 2009). The strengths of taking a MCDA approach are that it provides an effective and quick method of identifying optimal solutions to multi-criteria problems. However MCDA shares many of the weakness of the weighted sum methods described in Section 3.3 including the necessity of stating preferences prior to the analysis and the identification of a limited number of optimal solutions.

The review of potential conflicts between sustainability efforts in Section 2.4 outlined a multitude of conflicts arising from the pursuit of sustainability initiatives. Whilst Section 2.4 and the review of sustainable spatial planning practice in Section 2.5 it is clear that in order to address these conflicts planners require an appreciation of how these conflicts interact in order identify the most appropriate balance. Based on these considerations Pareto-optimisation is clearly the most suitable approach to reconcile the multiple objectives which sustainable urban spatial planning entails. The trade-off information provided by the application of this approach is crucial for understanding the interactions between the objectives under consideration. In the absence of detailed priorities for planners in urban areas, identifying solutions based on their dominance as per Equations 3.12 and 3.13 is ideal for planning applications (Balling et al. 1999). These advantages outweigh the problem of long run times. Moreover Kapelan et al. (2005a)

identified a lack of PO being applied in sustainability optimisation presenting a research gap to be addressed. Despite this, MCDA could be applied after PO to aid digestion of the results.

With this in mind, Section 3.4 reviews the major optimisation approaches and identifies a number of potential approaches which have been successfully applied to spatial optimisation applications. LP is a powerful method which has been applied to a number of applications however it has the distinct disadvantage that the variables, objective functions and constraints in a linear fashion which are too far removed from the reality in spatial applications. In addition Particle Swarm appears to be a promising approach due to its speed and simplicity as well as its ability to Pareto optimisation. However as the variable list is directly utilised to guide the search (see Equation 3.17 and 3.18) it restricts analysis to continuous variables.

Instead the literature points towards the use of GA for a number of urban spatial optimisation applications due to its powerful search mechanism and effectiveness in identifying globally optimal solutions. The approach is widely used and its strengths also include its flexibility as the algorithm isn't dependent on the encoding of the problem and the dynamic nature of the search allows for the discovery of globally optimum solutions. Moreover its suitability for Pareto-optimisation makes it a very appealing for this application. For these reasons GA was chosen to be implemented by the framework.

However, the review identifies a number of weaknesses which would need to be addressed for the successful application to the urban spatial optimisation problem here. A number of studies note that the dynamic search makes the handling of constraints difficult whilst the algorithm is quite complex. Alternatively SA provides a robust methodology which is easily applied to a number of problems. Indeed SA has a number of advantages over GA in that the change mechanism at each iteration can be more closely controlled and allow for more effective constraint handling (Duh & Brown 2005) which may prove crucial in ensuring assigning of development to areas available for development (as per the requirement found in Section 3.5.7). SA has been proven to be effective for large scale urban land use allocation applications (Aerts & Heuvelink 2002; Duh & Brown 2007; Santé-Riveira et al. 2008) and whilst not typically associated with PO, Nam & Park (2000) outlines a number of modifications which incorporate non-dominated sorting into the algorithm. Therefore SA was also chosen to be incorporated within the framework. Crucially both approaches both have searches that are independent of the encoding of the variables.

More recent approaches to MOPO have been developed, for example; ϵ -NSGA-II (Kollat & Reed 2005) which utilises ϵ -dominance alongside the NSGA-II algorithm, the epsiv-dominance Multi-Objective Evolutionary Algorithm (MOEA) (Liu et al. 2007) and the Borg MOEA algorithm (Hadka & Reed 2013) which adaptively selects from a range of search operators. Whilst these show promise over current approaches (Adekanmbi et al. 2014), they haven't been as extensively used for spatial optimisation applications and there is less evidence of their successful implementation in the field.

With regards to the decision support to sustainable urban spatial planning, Section 2.5 identified sustainability appraisals as a promising method to ensure the configuration of sustainable new development. As such, if the developed decision support tool is to contribute to more effective sustainability appraisals, it is necessary that they facilitate the location solely of new development. Previous applications fail this requirement as they allow for the changing use of currently developed areas, although some attempt to dis-incentivise this (see Section 3.5.7). Therefore in order to reconcile itself with the sustainability appraisal of future development, the work carried out in this thesis must focus on new development. This could be handled by identifying areas available for development (as per the recommendation by Ward et al. 2003) and considering them as discrete locations.

The review of sustainability applications of optimisation in Section 3.5.6 identified a research gap with the majority of applications limiting themselves to themes around Compact City principles, considering objectives such as compactness and mixed land uses. The review of sustainable urban form in Section 2.3 recognised that conceptual models such as the Compact City can negatively affect sustainable development as they fail to address a range of sustainability issues. Whilst the authors are right that these are recognised sustainable interventions, the review in Section 2.3 and 2.4 found that they should instead be applied based on evidence for the localised context and with consideration to their impact in other elements of sustainability. This is crucial as Section 2.4 identified a multitude of instances of mitigation based initiatives, such as urban intensification, leading to negative outcomes in other elements of sustainability. The literature of spatial optimisation of risk adaptation are sparse and these once again fail to take any appreciation of their effects on mitigation based objectives which are important. Moreover these applications fail to consider sustainability issues faced by a particular urban area, Therefore there is scope for a sustainable spatial optimisation application to urban areas which considers a number of real world sustainability objectives simultaneously and incorporating risk based objectives alongside traditional mitigation based objectives. This

would enable assessment of future development against a number of sustainability objectives simultaneously, in line with the sustainability appraisal approach taken in UK spatial planning.

With regards to the method of urban simulation over which the spatial optimisation decision support tool would operate, the review in Section 3.5.5 identifies CA as a particularly suitable environment to simulate the interactions between land uses. However the configuration of CA requires considerable calibration based on historic trends and the determination of complex relationships between urban systems. Indeed the use of optimisation within CA is often limited to driving the choices made in the transitions at each iteration which doesn't provide the benefit of the identification of lots of alternatives which a purely optimisation approach would deliver. Moreover optimisation should instead provide robust insights into the implications of general trends of development, rather than complicate itself with determining complex and uncertain relationships in cities which stifles their effectiveness. Therefore CA is considered too abstract to be considered within a planning support tool for sustainability assessment. Instead the work in this thesis will contemplate static representations of the urban systems which more closely aligns itself with the sustainability appraisal approach set out in Section 2.5.4. Whilst vectors provide an intuitive method of representing the urban landscape, in the absence of discrete parcels, grid representations appear a suitable representation to demonstrate generalised trends of future development (Loonen et al. 2007). There are a number of advantages to this including the ease of relating this to the urban spatial properties and the majority of research into urban systems relies on this representation. Indeed analysis has recognised that vector representations aren't necessarily superior.

3.7 Conclusions

The previous chapter identified that in order to meet urban sustainability, the spatial planning of cities must be carried out in such a way to meet localised sustainability objectives and to base planning decision on contextualised evidence which considers a number of sustainability criteria. As such the assessment of a number of sustainability objectives during the spatial planning of future development provides planners with a multi-objective spatial problem. This chapter identifies a number of optimisation approaches methodologies which are potentially useful for identifying future sustainable development trends. Meanwhile the review of previous applications finds a research gap for the application of spatial optimisation to consider traditional planning objectives such as efficient land uses alongside risk based objectives.

Having now defined the concepts behind urban sustainability issues, and analysed suitable optimisation approaches, to meet the aims and objectives stated in Section 1.3 the rest of this thesis intends to develop a suite of optimisation functions to investigate and direct future sustainable development based on the recommendations on this chapter and the Chapter 2 literature review. The developed methodology is detailed in Chapter 4, whilst the remaining chapters describe the testing of the method to real world urban spatial planning applications.

Chapter 4 Methodological Framework

4.1 Introduction

Based on the knowledge gained in the previous two chapters this chapter presents the methodology of a Multi-Objective Spatial Optimisation Framework (MOSPOF or ‘the framework’ for short) for sustainable spatial planning of new residential development in cities. Section 4.2 addresses the methodology used for MOSPOF, including how it differs from previous applications. Thereafter, the sustainable spatial planning objectives employed are presented along with their parameterisation. Section 4.3 presents the software framework employed to develop the implemented MOSPOF. Section 4.4 and 4.5 describe in detail the two optimisation algorithms employed in this work; namely Simulated Annealing and Genetic Algorithms, the implementation of which are described in these sections.

4.2 Problem Formulation

4.2.1 Design Considerations

The MOSPOF approach developed in this work needs to be able to spatially optimise the location of new residential development through a resource allocation approach which concerns optimising the allocation of limited resources among competing activities (Luss 1992). Many previous studies that have focused on the simulating future development have employed grid-based land use modelling, where the primary focus is on the spatial transitions that can occur at discrete locations in terms of land use (Ligmann-zielinska et al. 2006; Qian et al. 2010; Cao et al. 2012). While powerful approaches for land use modelling, such approaches are poorly adapted with respect to accounting for wider spatial planning issues such as sustainable planning concepts and reducing the potential risks faced by new development. Thus, while many previous applications almost entirely focus on the assignment of land use they are only able to consider sustainable planning concepts based on compact city principles, such as compact development (compact land uses) and land use compatibility (e.g. proximity of residential land use to employment land uses) (Ligmann-Zielinska et al. 2005; Cao et al. 2011). However as Section 2.2 discusses, sustainable urban development shouldn’t be restricted to these ideas and should encompass a wider set of aims.

To address this limitation and to more closely resemble current planning practice in the UK (and several other countries), the developed framework must be able to optimise the location of new development with regards to real world sustainability objectives relating to sustainable cities. To achieve this the implemented MOSPOF must be able to model and represent spatially sustainable plans directly by using contextualised evidence (i.e. evidenced based on the spatial properties of the local area under investigation). This ability to employ contextualised evidence must be achievable for multiple spatial planning objectives drawn from multiple domains such as climate change risks, environmental considerations, as well as, economic and quality of life considerations.

As the implemented system must be able to address multiple-objectives, analytical optimisation approaches for resource allocation that are multi-objective and which can be adapted to work with spatial data must be employed. To this end, two potential optimisation approaches for resource allocation are investigated. Simulated Annealing (SA) is a traditional optimisation approach which has been successfully implemented and recommended for resource allocation applications previously (Aerts & Heuvelink 2002; Aerts et al. 2005; Santé-Riveira et al. 2008; Sidiropoulos & Fotakis 2009). The algorithm is easy to implement (see Section 3.5.4) and is able to escape local minima and find globally optimal solutions in a computationally efficient manner (Sabatini et al. 2007; Duh & Brown 2007). Whilst not widely used for Pareto-optimisation Nam & Park (2000) sets out a number of additions which allowed it to nearly compete with other Pareto-optimisation approaches. Genetic Algorithms (GA) are a dynamic search procedure based on survival of the fittest concepts (Dowland 1996). Previously, GAs have been used in land use allocation optimisation applications (Cao et al. 2012) and have been reported as computationally efficient approaches in a number of applications (e.g., ground water allocation (Sidiropoulos and Fotakis 2009)).

The optimisation algorithms above are coupled with a Pareto-optimisation approach in order to solve the multi-objective spatial planning problems addressed. Pareto-optimisation was used over other methods, such as weighted sum and goal programming, as the resulting optimal spatial plans are independent of initial preferences and provide a wide range of choices to planners (Jiang-Ping & Qun 2009). A further advantage of Pareto-optimisation is that solutions can be posteriorly sorted to find plans which best represent the priorities of decision makers (Deb 2001).

The method chosen to represent the spatial domain under consideration (e.g., a city) and the scale of this will influence the ability of the optimisation framework developed to robustly allocate new residential development. Raster (gridded) datasets have been frequently used in previous urban spatial optimisation applications (Cromley & Hanink 1999; Cao et al. 2012). While vector (parcel-based) spatial models have been employed in spatial optimisation its application is confined to ‘niche’ applications where the spatial domain has been tessellated previously into a set of pre-defined land parcels (for example agricultural fields (Stewart & Janssen, 2014)). As the spatial domains of the cities investigated in their work do not have pre-defined vector parcel representation in terms of the sites for allocation and to ensure the generic applicability of the method developed this study employs a raster grid data-model to represent the spatial domains under consideration.

4.2.2 Planning Problem Representation

To facilitate the resource allocation approach solutions explored by the MOSPOF are represented as a fixed length list. A proposed development plan, D , is made up of a set number of proposed development sites d each with an i, j location in the study area. Depending on the application, D requires Q number of d such that $D = [d_{i,j}^1, d_{i,j}^2, \dots, d_{i,j}^Q]$. Each proposed development d has an associated number of assigned residential dwellings, $dw_{i,j}^+$, and population, $v_{i,j}^+$, where $+$ conveys its added to the current situation, are converted to a density based on the spatial resolution of the cell. The framework focuses on residential development rather than economic development as it more appropriate to consider in the context of the sustainability challenges identified in Chapter 2; providing housing for an increasing population, reducing the risk to urban populations to climate risks and ensuring populations are located in accessible areas. These are used for the calculation of the risk based objectives and for simplicity these remain a consistent value throughout d .

In order to ensure development plans are feasible a number of constraints exist. Proposed development sites must be within the study area on a location available for development and development cannot be duplicated on a site (i.e., it can only be allocated once). Therefore the search for development sites is subject to:

$$\textit{Subject to} \quad d_{ij}^{\neq 1} \textit{ if } d_{ij} \cap a_{ij} \wedge d_{ij} \neq d_{ij}^{\neq 1} \in D \quad (4.1)$$

where a_{ij} denotes a cell available for development.

4.2.3 Selection of Objectives

To derive a set of sustainability objectives to consider for the urban planning decision support tool an extensive review was undertaken of available spatial plans, sustainability appraisals and related planning documents for large metropolitan areas such as London (Greater London Authority (2011) and DCLG (2008)), Birmingham (AMEC Environment & Infrastructure 2014) and Manchester (Atkins 2009), as well as planning authorities containing smaller urban conurbations (e.g. Essex County Council (2010)). In addition international spatial planning and sustainability practices were also reviewed, including Cockburn (2006) and American Planning Association (2000).

The results of this review are presented in Appendix A where Table A presents a comprehensive list of real world sustainability objectives. These were categorised into 6 intuitive sub-groups; Environmental, Transport, Land Use and Planning, Community and Health, Economic and Resource Use. With regards to environmental objectives, improving air quality and adapting to and mitigating against climate change were the most prominent objectives (70% of appraisals), whilst reducing flood risk/preventing development in flood plains also featured predominantly in appraisals (60%); reflecting the move towards greater consideration of climate change in the sustainable spatial planning. The protection of biodiversity also featured in 50% of those assessed; lower than expected and probably a consequence of preventions on greenbelt development being enforced at a higher national governance level.

The majority (90%) of the sustainability appraisals had improving health as one of their sustainability objectives. However, consideration of this objective with regards to spatial planning was felt to be beyond the scope of the work of this thesis. Likewise 60% of appraisals included objectives concerned with reducing or alleviating the fear of crime. Despite studies which link spatial layout to crime (Wekerle & Whitzman 1995) it was decided the objective isn't most suitably addressed through the spatial layout of development and was therefore not included in the framework. Transport related objectives concerned the provision of sustainable transport (50%), reducing automobile use (40%) and reducing emissions from transport (40%).

Lastly of the appraisals reviewed 40% regarded development on previously developed land as desirable.

Cost minimisation is a commonly associated objective in optimisation applications. However for the applications described in this thesis it was found to be infeasible to sufficiently parameterise a cost associated with differing development strategies due to a lack of data. The implications of this on the analysis are described in detail in Section 7.2.3. Instead the work focuses exclusively on sustainability objectives.

The key criterion when selecting the objectives to be included within the framework was that they had to be relevant and hence considered as important in a large proportion of the reports and literature reviewed. They also had to be considered as being feasibility parameterised and evaluated in a spatially explicit manner. For this reason objectives relating to health, education and crime, whilst commonly referred to, were excluded. Instead it was chosen that objectives focusing on the major sustainability challenges, climate risks and mitigation, would be the focus of the study. Moreover, the inclusion of too many objectives would slow and reduce the effectiveness of the optimisation. Following recommendations to employ a minimal set of planning objectives by Land Use Consultants & Royal Institute Town Planning (2008) the final set of objectives consisted of the following 5 objectives:

i. Minimizing Risk from Future Heat Waves:

Adapting to future climate change appeared as an objective in 70% of the appraisals whilst reducing population risk to future heat waves is prioritised by several national governments, including the UK (Defra 2012). Without significant redress this is estimated to result in a 257% increase in heat-related mortality in the UK by 2050 (Hajat et al. 2014).

ii. Minimizing the Risk of Future Flood Events:

Reducing flood risk and preventing development in flood plains appeared in 50% of the appraisals and is a priority policy for the UK government (Defra 2010). More recently flooding was described as the biggest adaptation challenge facing the UK by the House of Commons Environmental Audit Committee (2015). A combined property value of £200 billion and 4 million residents are currently at risk and without major interventions £20 billion of damages is estimated annually by 2080 (Office of Science and Technology 2010).

iii. Minimizing Travel to reduce Transport Emissions:

The reduction of commuting acts as a proxy for reducing transport GHG emissions (an objective which appeared in 50% of appraisals) and covers the objective of improving accessibility to services (appearing in 40% of appraisals). Reducing emissions which contribute to climate change is heavily prioritised globally, whilst the UK has stringent legislation to reduce their contribution of GHG emissions (UK Parliament 2008). The number of vehicle miles travelled in Great Britain has reduced 2.4% since its peak in 2007 (Department for Transport 2014). However, further efforts are needed to overcome pressures from increased economic activity and population growth to meet the UK's emissions reductions target.

iv. Minimizing the expansion of Urban Sprawl:

Urban sprawl (extension of city limits) is widely associated with higher commuting times, poor public transport provision (Burge et al. 2013) and inefficient land use (Speir & Stephenson 2002). Its prevention is a widely agreed sustainability principle (Johnson 2001) and a common national priority in the UK (DCLG 2011a) as well as internationally (Echenique et al. 2012) through policies encouraging development within existing urban areas (Baing 2010). This objective acts as a proxy for several sustainability objectives identified, including sustainable transport provision (as public transport is only viable in compact environments) which was prioritised by 50% of the appraisals reviewed as well as objectives for reducing GHG emissions and accessibility. Dense urban development has been found to improve building energy efficiency (Rode et al. 2014) whilst containment of urban sprawl can act as a proxy for sustainable transport as it has been found to reduce the use of private cars (Melia et al. 2011) and allow for better public transport provision (Kenworthy 2006).

v. Preventing Green-space Development:

The protection of biodiversity and improving green infrastructure was prioritised by 70% of the appraisals reviewed, whilst the UK has a national policy of protecting local green space and greenbelt by applying disincentives for loss of greenspace and restricting development on green belt (DCLG, 2011a). There is increasing pressure in cities to develop greenfield sites (Heid 2004) however urban greenspace is crucial to mitigate urban heat islands (Mcevoy et al. 2006) and provides countless health benefits for urban populations such as improved mental health and more active lifestyles (Maas et al. 2008). Greenspace development is to be restricted, rather than optimised based on the recommendations in the literature review that environmental

protection should be prioritised and not considered equally with other sustainability objectives (Morrison-Saunders & Therivel 2006).

4.2.4 Data Characterisation of Objectives

The input data of the MOSPOF consist of a series of raster datasets representing the spatial attributes required to represent and parametrise the sustainability objectives selected. In this study heat risk was represented in terms of the Crichtons (1999)'s "Risk Triangle" approach, a methodology which has been widely applied in the literature (Schneiderbauer & Ehrlich 2004) including in the calculation of heat risk (Tomlinson et al. 2011; Morabito et al. 2015). This involves characterising the spatial distribution and magnitude of heat risk as a product of heat hazard and population vulnerability. To achieve this, a heat hazard grid, $h_{i,j}$, representing the number of heatwave events per-annum was derived from future projections, while a vulnerability grid, $v_{i,j}$, comprising of the current population density per-hectare was also derived.

Although a similar risk analysis frameworks for heat risk have previously been employed for flood risk (Fedeski & Gwilliam 2007; Kaźmierczak & Cavan 2011), this study employs the UK's Environmental Agency flood zone areas (DCLG, 2009) for simplicity. In particular, the medium (between a 1 in 100 and 1 in 1,000 annual probability) and high risk (1 in 100 and above annual probability) flood zones were employed. There were used as they are the standard flood risk assessment used during UK planning (see UK Government policy statement on assessing the flood risk (Department for Communities and Local Government 2009)).

In order to evaluate the travel related objectives, a measurement of accessibility was employed as it measures have been found to be strongly related to vehicle miles travelled (Ewing & Cervero 2010) and has been used in many previous sustainable urban optimisation applications (Cao & Huang 2010). In order to calculate accessibility this work employs a full road network model (series of polylines) which were associated (joined) to CDB centroids (points). Lastly a gridded representation, generated at the same spatial resolution of the objective grids, was generated of the urban extent of the cities investigated in order to constrain spatially the location of proposed new development. Greenspace was also represented in a similar gridded manner.

4.2.5 Objective Formulation

i. Minimizing Risk from Future Heat Waves

The calculation of heat risk has a number of assumptions. Firstly the vulnerability element is based on 2011 census population so does not take into account future projected increases in population density and/or changes in the demographic profile (i.e., > proportion of >75) etc. In addition the calculation does not include any expression of exposure (e.g., no expression of building stock) due to a lack of available data. With these in mind minimising heat risk is achieved by avoiding allocating high population densities to areas expected to have high incidences of heat waves in the future and which already have a high population vulnerability. During the operation the optimisation framework attempts to minimize the objective function f_{heat} characterised by the increase in heat risk in the future:

$$\text{Minimize} \quad f_{heat} = \sum H_{ij}^{Future} \quad (4.2)$$

where H_{ij}^{Future} are defined as being the cross product of the probability of a heat hazard event ($h_{i,j}$) occurring at a particular location (i, j) and its corresponding population vulnerability, $v_{i,j}$, expressed in terms of population density (people per-hectare) and is calculated by multiplying the grids described in Section 4.2.4. As d_{ij} are being assigned spatially, the calculation of H_{ij}^{Future} is updated at each iteration of the optimisation to account for the new vulnerability that results from the increased population density of the cells $d_{ij} \in D$:

$$v_{i,j}^{future} = v_{i,j} + v_{i,j}^+ \quad (4.3)$$

$$H_{ij}^{Future} = v_{i,j}^{future} \times h_{i,j} \quad (4.4)$$

Overall the computation assumes that the risk is proportional to the population which interacts with the heat hazard

ii. Minimizing Risk from Future Flood Events

The optimization of flood risk attempts to minimize the objective function f_{flood} on the basis of reducing the number of proposed dwellings which fall within 1 in 100 and 1 in 1000 year flood zones. In the context of the UK those two zones are meaningful for planning purposes, but provide less accurate assessment of flood risk as there is a massive interpolation between just two points. The use of probability outlines such that you do not have any knowledge of the interval variability on flood depth and hence the ability of undertake a finer-scale inter-zonal flood damage calculation. The calculation assumes that the risk is proportional to the number of dwellings within each zone and is represented as:

$$\text{Minimize } f_{flood} = dw_{ij}^+ \left(10^0 \sum (d_{ij} = z_{i,j}^{100}) + 10^{-1} \sum (d_{ij} = z_{i,j}^{1000}) \right) \quad (4.5)$$

where dw_{ij}^+ is the number of dwellings associated the assignment of d_{ij} whilst Z and z are spatial grids representing 1 in 100 and 1 in 1000 flood zone extents respectively.

iii. Minimizing the Distance of Development to the Central Business District (CBD)

This objective is achieved by optimising an accessibility measure to areas of employment and services, namely the distance of new development to the current CBD. The calculation assumes that these CBDs will remain consistent in the future. The calculation is based on the distance along the road network, which likewise is assumed to be consistent in the future, however no credence is given to travel times/ costs along these routes. The optimization attempts to minimize the objective function f_{dist} which is expressed by the shortest path, $P()$, between the centroid of proposed development sites, d_{ij} , and points designated as a CBD centroid, c_{ij} , over the road network, R .

$$\text{Minimize } f_{dist} = \text{Min}(P(d_{ij}, c_{ij}, R) \forall c_{ij} \forall d_{ij} \in D) \quad (4.6)$$

iv. Minimizing the expansion of Urban Sprawl

This sustainability objective is optimized on the basis of the objective function f_{sprawl} . Originally this was calculated based on the non-linear neighbourhood method described by Cao

& Huang (2010) whereby the neighbourhood cells of each proposed development sites are assessed to see if they're within the urban extent but this was found to significantly increase the computation time. Instead f_{sprawl} is calculated as the number of proposed d_{ij} which fall outside the current urban extent. This assumes that the urban extent as defined by the data source most accurate represents the real world situation and will remain constant.

$$\text{Minimize} \quad f_{sprawl} = \sum (d_{ij} \neq u_{ij}) \forall d_{ij} \in D \quad (4.7)$$

where u_{ij} represents cells designated currently as urban. The objective is returned as a percentage.

For presentational purposes, the final objective performances of spatial strategies are normalised between 0 and 1 to provide an unbiased perspective. Once the analysis was run, normalised objective values were calculated for each solution, s , using following equation:

$$f_s^{norm} = (f_s - f_s^{min}) / (f_s^{max} - f_s^{min}) \quad (4.8)$$

where f_n^{min} and f_n^{max} represent the maximum and minimum found performances for each objective function, f .

iv. Preventing green-space development

The objective is achieved through imposition of a spatial constraint on the selection of solutions in the form of:

$$\text{Subject to} \quad d_{ij} \neq g_{ij} \forall d_{ij} \in D \quad (4.9)$$

where g_{ij} are the spatial locations (cells) of green space.

4.2.6 Pareto-optimality

Pareto optimisation is employed to solve the multi-objective optimisation of the objectives outlined in Section 4.2.5. As Chapter 3 outlines it's an approach which has been extensively

used in engineering and infrastructure optimization, including water distribution systems (Vamvakeridou-Lyroudia et al. 2005; Fu et al. 2013) and urban land use allocation (Jiang-Ping & Qun 2009; Cao et al. 2011). Its popularity rests with its ability to identify optimal solutions independently of preferences, instead allowing planners to choose their preferred solutions from a wide range of best known trade-offs reflecting multiple priorities (Jiang-Ping & Qun 2009).

With respect to the objectives under consideration, $F = \{f_{heat}, f_{flood}, f_{dist}, f_{sprawl}\}$, Multi-Objective Pareto-optimal (MOPO) development plans are determined by the formula set out in Equations 3.12 and 3.13. For planning application a development plan, $D^{(1)}$, is said to be Pareto-optimal if it is no worse than all other development plans for $f \in F$ and strictly better in at least one $f \in F$. To discern solutions defined as MOPO this work uses a non-dominated sorting algorithm based on the algorithm outlined by Mishra & Harit (2010). A set of derived development plans, D , are assembled in a list, S , and are sorted by the first $f_1 \in F$, in this case f_{heat} . The D at the top is then moved into the non-dominated set, N . Thereafter each solution $D \in S$ is compared to solutions within the non-dominated set, $p \in N$ for dominance with regards to the objectives $F = \{f_{risk}, f_{flood}, f_{sprawl}, f_{dist}\}$. If s is found to be dominated by $p \in N$ across all F it is disregarded. However if any s remains non-dominated by $p \in N$ it is added to N and if s dominates $p \in N$ p is removed. By beginning with the best performing solution for f_1 the approach ensures dominated solutions are realised quicker. Once all $s \in S$ are considered the final N set contains the Pareto-optimal spatial configurations where no other spatial configurations perform better with regards to the combination of f_{risk} , f_{flood} , f_{sprawl} and f_{dist} .

In order to evaluate and demonstrate trade-offs between each combination of pairs of objectives further sets of Pareto-optimal spatial configurations were extracted for different subsets of the sustainability objectives. Essentially, the algorithm is repeated with different combinations of F e.g., $\{f_{heat}, f_{flood}\} \subseteq F$, $\{f_{heat}, f_{dist}\} \subseteq F$ to produce Pareto-optimal sets e.g., $N_{f_{heat}, f_{flood}}$, $N_{f_{heat}, f_{dist}}$ etc. Appendix C presents the Python code developed for the non-dominated sorting based on Mishra & Harit (2010). The resulting Pareto-optimal sets for all objectives or combinations of these can be plotted against the objective functions to display a best trade-off curve.

4.3 Spatial Optimisation Software

4.3.1 Choice of Development Environment

There are several computing platforms that could be employed to develop the MOSPOF approach to sustainable residential development allocation. MATLAB is a powerful mathematical processing environment which has been used to develop a number of optimisation applications (Sigmund 2001; Lofberg 2004). It has the required mathematical programming capabilities and is highly suitable for handling the optimisation functions within the MOSPOF methodology, with modules such as the global optimization toolbox which contains both a genetic algorithm and simulated annealing (Mathworks 2015; Zhao et al. 2015). It has been widely praised for its applicability for computationally intensive optimisation approaches such as Particle Swarm (described in Section 3.4.8) (Venkataraman, 2009), as well as the ability to develop bespoke optimisation toolboxes (Brown and Hutauruk, 2007). However the software has been criticised for not being user friendly (Siauw & Bayen 2014) and is considered an inflexible language (Bröker et al. 2005) as well as being commercial software. Crucially, the platform does not facilitate easily the integration of spatial data and its GIS functionality is limited (Zhao et al. 2015). AMPL (an acronym for ‘A Mathematical Programming Language’) is another powerful mathematical software which is geared towards optimization applications (Fourer et al. 1993). It has a strong presence in the optimisation of structural components (Su & Judd 2012). However its application to spatial optimisation in the literature is limited; indeed in the standard reference book for AMPL not a single spatial optimisation is described (Fourer et al. 2003). Again, it is also a commercial software package.

Alternatively RStudio is an open source statistical programming language which has a large number of users and is extensively used by programmers. The platform carries a number of readymade optimisation toolboxes such as the ‘R Optimization Infrastructure’ (containing modules for simulated annealing (Roi et al. 2015)) and ‘GA’ which allows the use of genetic algorithms (Srucca 2014). Furthermore, the platform has the ability to handle spatial data with an adaptation of GDAL (rgdal), a widely used Geospatial Data translator library (Roger et al. 2015). However it’s not extensively used in the optimisation literature and has more prominently been used for visualisation of optimisation results (Sahnoun et al. 2012; RStudio 2013), and in support of a number of data analysis applications (Maindonald & Braun 2010; Gerrard & Johnson 2015).

Python is another open source programming language that offers a number of powerful mathematical and scientific modules (e.g. Numpy (Oliphant 2006) and SciPy (SciPy Developers 2015)), with a rich range of optimisation modules (including modules to handle genetic algorithms (Fortin et al. 2012) and simulated annealing (Perry 2015)). Although both Rstudio and Python both offer a flexible language, the Python programming platform is aligned with newest GIS (the new ArcGIS 10 platform operates on python) and has the ability to utilise GDAL's spatial library (GDAL 2012). In addition, Python has been used in a number of optimisation applications in the literature (Bröker et al. 2005; Matott et al. 2011; Hebrard et al. 2010; Beham et al. 2014), including land use allocation spatial optimisation applications (Ligmann-Zielinska et al. 2005; Ligmann-zielinska et al. 2006; Ligmann-Zielinska & Jankowski 2007; Ligmann-Zielinska et al. 2008). Python is consistently commended on its ease of use over other languages (Bröker et al. 2005; Waddell 2011a), with numerous online tutorials and help boards (Python Software Foundation 2015). Moreover extensions such as Matplotlib provide advanced plotting and visualisation through Python GUI. Therefore the Python platform was chosen to develop the framework.

4.3.2 Overall Spatial Optimisation Framework Design

Figure 4.1 shows the overall design of the Multi-objective Spatial Optimisation Framework (MOSPOF) developed. The software was designed as a modular set of routines/tools to allow for the incorporation of further elements into the optimisation framework and the robust testing of the optimisation approaches utilised. The containers indicate directories, rectangles denote Python modules which carry out specific processes, whilst rhombuses denote input/output datasets. The *Optimisation Algorithm* module drives and handles the optimisation with respect to altering spatial development plans and controlling the number of iterations. Development plans are efficiently stored as Python arrays and a number of python functions exist to modify and assess arrays.

During the search the *Evaluate* module receives spatial plans derived by the optimisation search and calculates their fitness using Equations 4.2-4.7 based on its spatial configuration in relation to the spatial datasets outlined in Section 4.2.4. Appendix B presents the source code for the *Evaluate* module. The spatial datasets used to calculate the objectives are handled in the *Data* module by the the *PyRaster* module '*RasterIO*' (Holderness 2012b). In the *Evaluate* module network analysis is undertaken using NetworkX (Hagberg et al. 2013); a powerful network

analysis python module which has been used for several network analysis applications (e.g., Barr et al. 2013). NetworkX is used to calculate shortest path distances along a road network to a CBD points from the centroid of development sites ($d_{i,j} \in D$). To reduce run time the calculation of the shortest path for all $a_{i,j}$ is carried out by a pre-processing module and stored as a lookup table for reference during the optimisation stage (see B3 in Appendix B).

The *Constraint Handling* module pulls a green space, boundary and an ‘available for development’ raster from the *Data* directory to ensure that any D meets the constraints of the problem (see Equation 4.1). Once *Optimisation Algorithm* terminates, resulting development plans, S , are handed to the *Output* module. This module handles several processes including calling the *Non Dom Sort* module which carries out the non-dominated sorting outlined in Section 4.2.6. The *Plot* module plots the Pareto-optimal sets against their respective objectives to demonstrate the trade-off curves using matplotlib¹. Resulting Pareto-optimal sets, N , sets are converted to gridded spatial plans again using *PyRaster* in the *Write Spatial Plan* module.

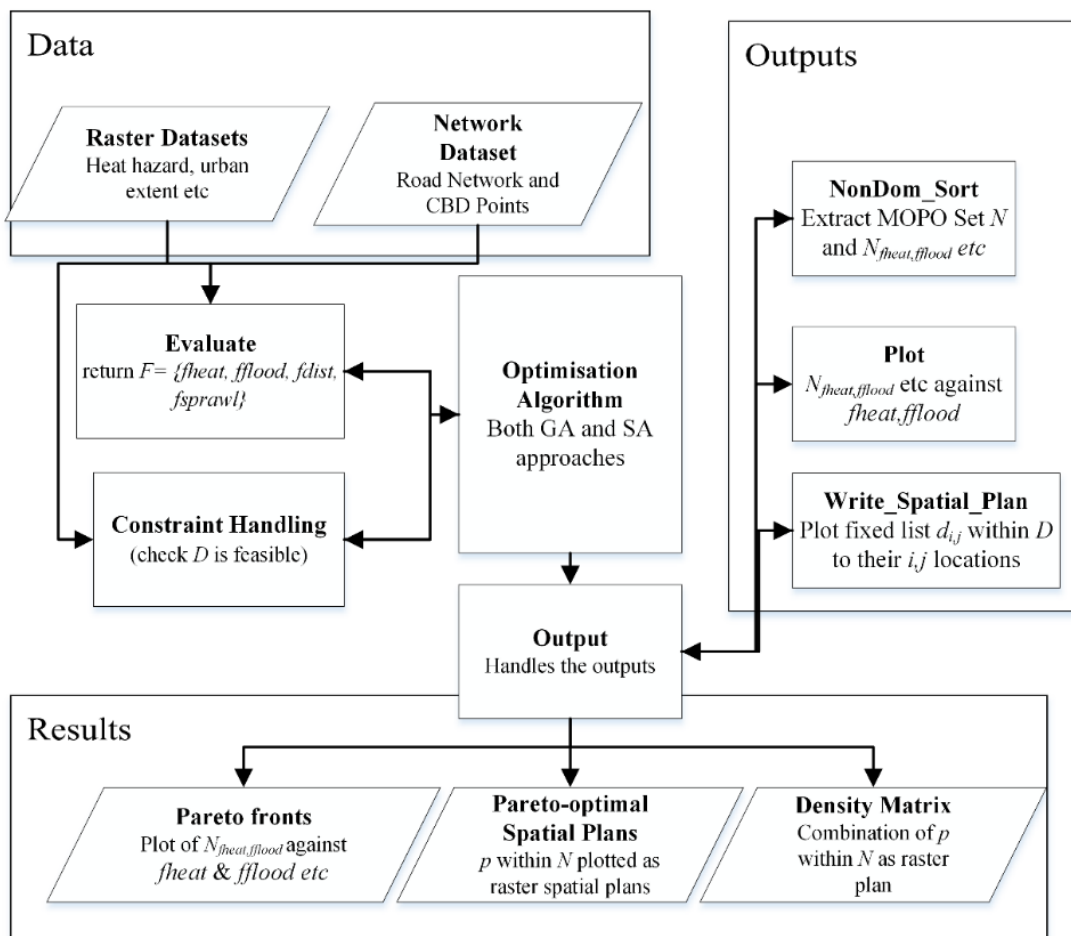


Figure 4.1 Developed Spatial Optimisation Framework.

¹ matplotlib.org

4.4 Simulated Annealing Approach

This section sets out the methodology for the Simulated Annealing (SA) approach employed. As discussed in Chapter 3, SA is a heuristic optimisation algorithm which allows for the acceptance of inferior solutions, escaping local optima in order to hopefully discovery global optimum solutions to problems (Dowsland 1993). SA employs a probability approach that iteratively searches for optimal solutions for a particular acceptance criteria (Kirkpatrick et al. 1983) and has been used for a number of optimisation applications (Czyzzak & Jaszkievicz 1998; Zhang et al. 2011; Jones et al. 2002), including several spatial optimization problems such as land use/ resource allocation (Aerts & Heuvelink 2002; Duh & Brown 2007; Aerts et al. 2005), forest planning (Murray & Church 1995), ground water allocation (Sidiropoulos & Fotakis 2009) and allocation of bus stops along a network (Delmelle et al. 2012).

Simulated Annealing is employed as it's a widely used and a simple to implement algorithm (Zhang et al. 2011). Several sources have commended its utility for resource allocation (Aerts & Heuvelink 2002), whilst it has been proven to be computationally efficient for high dimensional spatial allocation problems (Aerts & Heuvelink 2002; J. Duh & Brown 2005).

4.4.1 Simulated Annealing Operators

Figure 4.2 presents the structural components of the SA algorithm used in this study to generate a set of development plans, S , from which to determine a MOPO set, N . Spatial plans are represented as a fixed length list of proposed development plans as outlined in Section 4.2.2. The SA algorithm comprises of several distinct stages, namely;

(1) Initialisation

A random spatial plan is generated which at this stage constitutes the best found spatial plan, D_b , and its fitness, F_b . A number of random $d_{i,j}$ are used to form D , satisfying the required number of development plans, Q . This random configuration is used to seed the current spatial configuration, D_n , and its associated fitness, F_n , where n denotes the current iteration of the algorithm.

(2) Evaluation

Each spatial configuration investigated, D_n , is converted into a spatial plan by mapping it spatially over the study area and is used to calculate the performance in the objective functions

outlined in Section 4.2.5 in order to derive the associated performance scores, F_n (which comprises $f_{heat}, f_{flood}, f_{dist}, f_{sprawl}$).

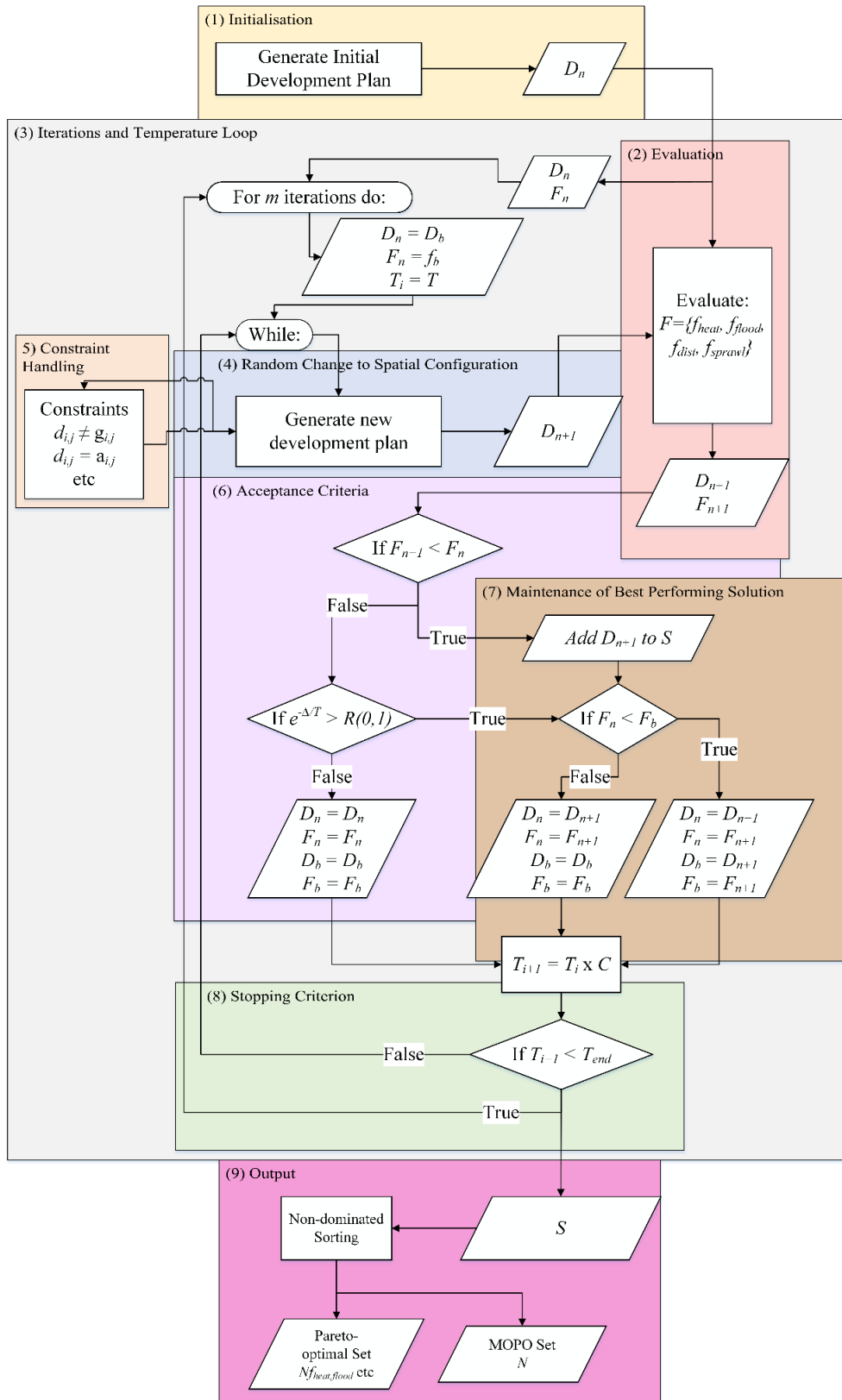


Figure 4.2 Flow diagram of the Simulated Annealing approach to spatial optimization.

(3) Iterations

In this work, the SA algorithm is applied for a user defined number of iterations, m . At the start of each iteration $D_n = D_b$ and $F_n = F_b$ to aid convergence to a global optimum spatial configuration by ensuring the algorithm is always iterating with respect the previously derived best performing spatial plan. Within each iteration the SA algorithm is carried out which consists of a while loop where at each pass through the loop a temperature variable, T , is decreased by a cooling factor C :

$$T_{i+1} = T_i \times C \quad (4.10)$$

where $0 < C < 1$. (in many simulated annealing applications C is set between 0.8 and 0.98 (Aerts & Heuvelink 2002)). As T gradually decreases it restricts the acceptance of new spatial plans which ensure the algorithm convergence on a global optimal spatial plan (see step 6 below). The SA loop continues until $T < T_{end}$, where T_{end} is a user defined threshold, ending the iteration.

(4) Random Change to Spatial configuration

At each stage in the SA algorithm a random change is applied to the spatial configuration. At each step n an existing development site $d_{i,j} \in D_n$ is moved randomly within an 8-cell Moore neighbourhood as shown in Figure 4.3a. The resulting spatial plan is stored as a new development plan D_{n+1} . As Figure 4.3b demonstrates, when adjacent cells are unavailable due to being currently developed, the Moore neighbourhood is extended to find the next available $a_{i,j}$.

(5) Constraint Handling

During stage 4, the constraint handling module enforces the constraints of the search. New $d_{i,j}$ are compared against the greenspace dataset, $g_{i,j}$ and available land dataset, $a_{i,j}$ to ensure it's a feasible development site. Moreover the new site is checked against the current allocated $d_{i,j}$ to make sure no duplicated development occurs. This evaluation loops until a feasible new $d_{i,j}$ is found.

(6) Acceptance of solutions

Newly configured spatial plans, D_{n+1} , are compared to D_n . As per the modifications set out by Nam & Park (2000) if D_{n+1} is found to be non-dominated by D_n (see Equations 3.13 and 3.14) it replaces it; $D_n = D_{n+1}$ and $F_n = F_{n+1}$. However inferior/ dominated solutions can be accepted on the basis of the Thermopolis Equation:

$$e^{-\Delta/T} > \mathbb{R}(0,1) \quad (4.11)$$

where Δ is the difference between F_n and F_{n+1} , while \mathbb{R} represents a real number between 0 and 1. Δ is calculated by normalizing all the elements f_n then calculating the difference between these normalized objective functions. The allowance of inferior solutions prevents the algorithm converging on local optima by encouraging the evaluation of a wide range of spatial development. This can be seen in Figure 4.4 where during iterations F_n takes on inferior performances in F whilst towards the end of iterations F_n begins to converge on a more optimal performance in F as Equation 4.11 restricts acceptance D_{n+1} to those which are superior. This allows for the exploration of a number of spatial configurations of D_n which ultimately leads to the discovery of better F_b . This can be seen in Figure 4.4 where F_n and F_b converge at the end of the iteration. Accepted development plans D_n are added to the set of development plans, S , from which to extract MOPO solutions at the end of the operation as per the approach set out in 4.2.6.

(7) Maintenance of f_b

The best performing spatial plan, D_b is maintained. D_{n+1} accepted by Equation 4.11 are then compared to D_b and if found to be superior $D_b = D_{n+1}$ and $F_b = F_{n+1}$.

(8) Output

The SA algorithm is repeated for the set number of iterations m . Once this is completed the SA is terminated. At this point S is returned and provided to the Output module

(9) Output

The set S is then used as the set from which to derive the MOPO and Pareto-optimal sets as described out in Section 4.2.6.

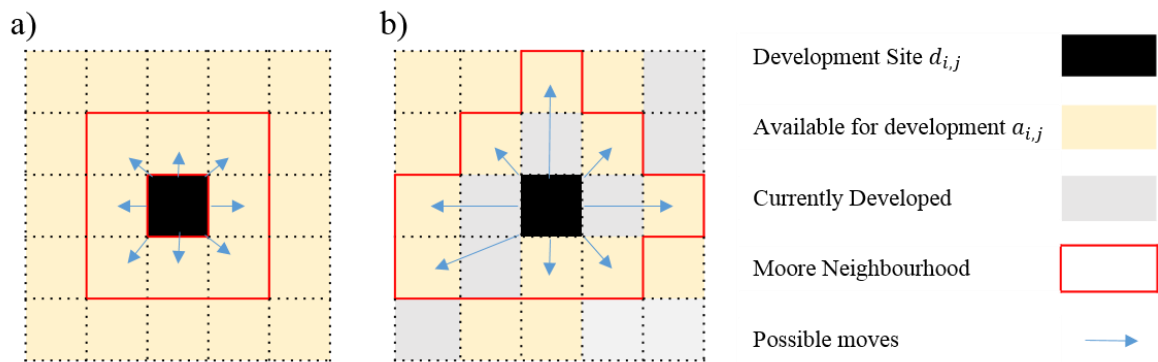


Figure 4.3 The changes to selected $d_{i,j} \in D$ at an iteration of the SA algorithm search.

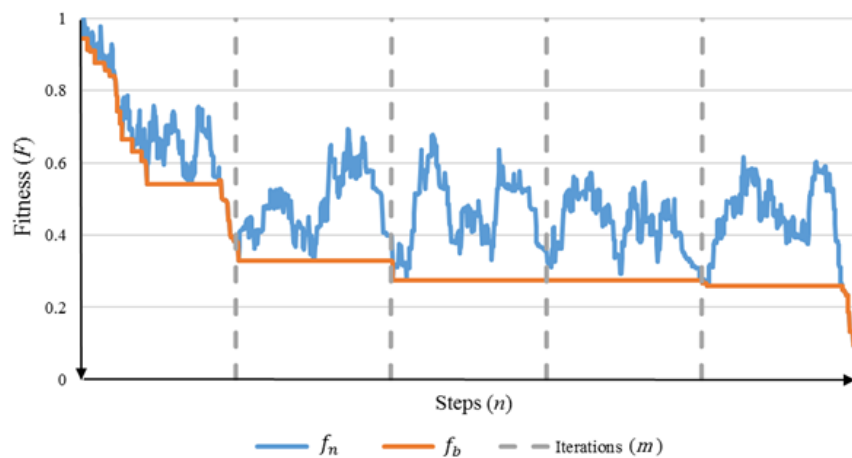


Figure 4.4 Current fitness and best fitness scores throughout the SA algorithm.

4.4.2 Simulated Annealing Implementation

Several Python modules exist for simulated annealing including SciPy `optimize.anneal` (<http://docs.scipy.org/doc/scipy-0.14.0/reference/generated/scipy.optimize.anneal.html>) a SciPy module and the `simanneal` package (<https://github.com/perrygeo/simanneal>). However, it was decided to develop in-house the SA routine so that it could be tailored to the specific requirements of this study. In particular this allowed for incorporation of the domination criteria in the acceptance procedure and the change to the spatial configuration procedure shown in Figure 4.3

4.5 Genetic Algorithm Approach

Genetic Algorithms attempt during the search procedure to converge on superior solutions to an optimisation problem by emulating the evolutionary operators of selection, crossover and mutation to identify promising solutions and recombine their attributes (Fonseca & Fleming 1993) (also see Section 3.3.6). Genetic algorithms (GA) were originally envisioned by Goldberg (1989) and have been subject to numerous versions and extensions of the original algorithm including the Non-dominated Sorting Genetic Algorithm 2 (NSGA-II) (Deb et al. 2002), the Strength Pareto Evolutionary Algorithm 2 (SPEA-II) (Zitzler et al. 2001) and more recent versions including the Improved Vector Evaluated Genetic Algorithm with Archive (iVEGA-A) (Zhang & Fujimura 2010).

GAs have recently gained prominence over traditional optimisation approaches, such as simulated annealing (Loonen et al. 2007), and have recent applications in land use planning (Stewart & Janssen 2014; Cao et al. 2011), ground water allocation (Sidiropoulos & Fotakis 2009) and risk management (Woodward et al. 2013). Indeed Xiao, Bennett, & Armstrong (2007)'s review of multi-objective spatial decision making concludes that evolutionary algorithms, of which genetics algorithms are one, are particularly appropriate for multi-objective decision making. Notably sources have noted the quicker search times and improved convergence associated with genetic algorithms. Indeed Sidiropoulos & Fotakis (2009) suggested that GA produced optimal solutions with less computations.

4.5.1 Genetic Algorithm Operators

Figure 4.5 presents the structural components of the GA algorithm used in this study. By investigating differing set ups of D , represented as a fixed length array, the GA generates a MOPO set (N). The GA algorithm is comprised of several components outlined in Figure 4.5;

(1) Initialisation

A number of initial spatial plans are needed to seed the GA from which more optimal set-ups of $d \in D$ are derived. A series of initial development plans D , equal to number $No_{parents}$, are generated and stored as an initial parent set, $parents_0$ so that $D \in parents_0$.

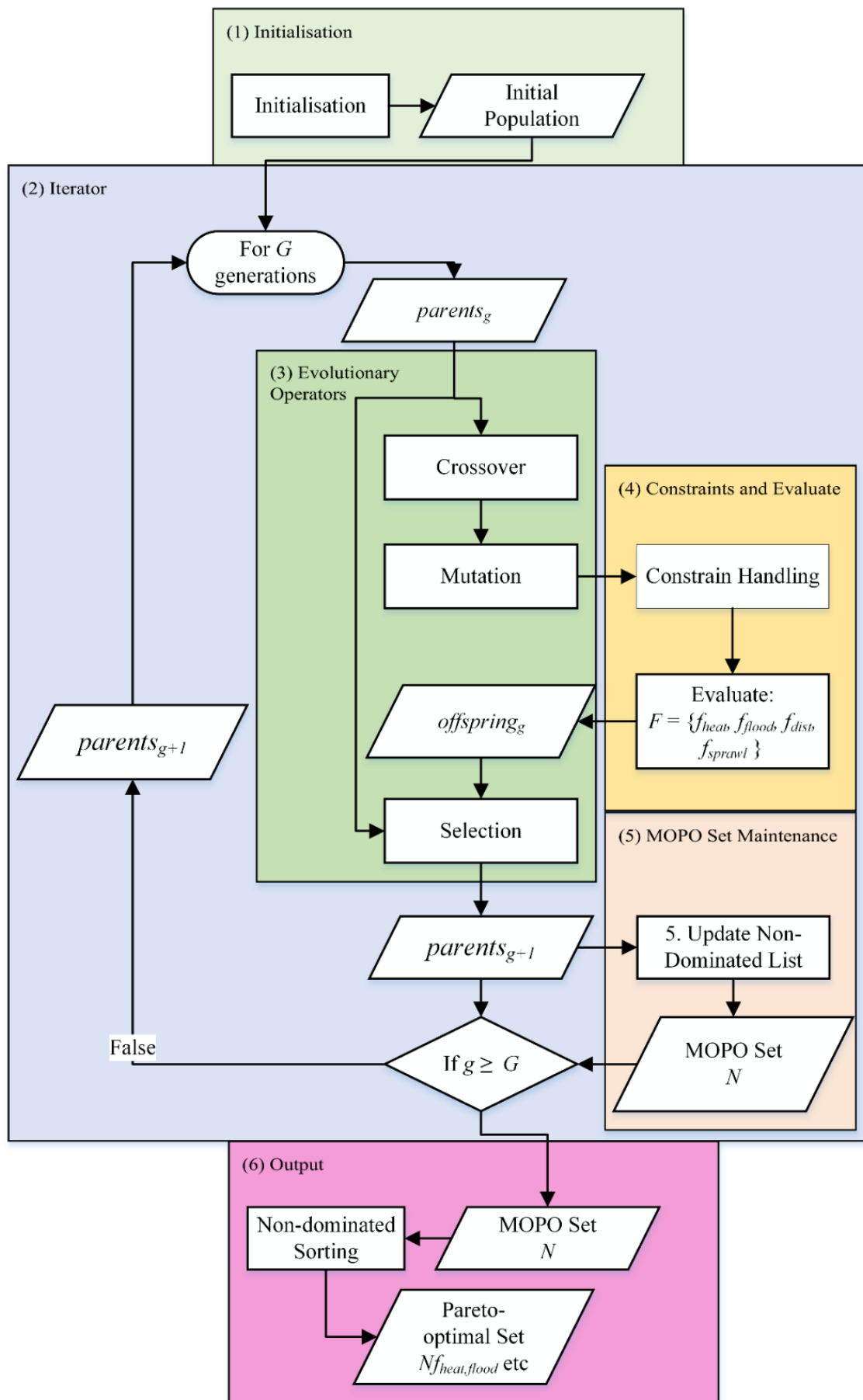


Figure 4.5 Flow diagram of the Genetic Algorithm Spatial Optimisation Framework.

(2) Iteration

The instances of D in $parents_0$ are then subject to the GA evolutionary operators for a defined number of generations (iterations) G . During each generation the $parents_g$ denotes the set of parent D for the g generation, $offspring_g$ denotes a new set of D found by the evolutionary operators applied to $parents_g$, and $parents_{g+1}$ denotes the set of D selected to continue being used for the search. At the start of each new generation $parents_g = parents_{g+1}$ so the search begins using the best set of D found during the previous g . Once $g = G$ the operation terminates.

(3) Evolutionary Operators

At each g a series of evolutionary operators are applied to $D \in parents_g$, to produce a new set of D to form the set $offspring_g$. In particular we use the Mu-plus-Lambda evolutionary strategy for the operators where solutions are subject to either a crossover operation, on a probability $p_{crossover}$, or a mutation operator, on a probability $p_{mutation}$ (Melanie 1996) as this is considered an effective strategy for escaping local optima (Rothlauf 2011).

After testing it was decided to use a two point crossover as shown in Figure 4.6. Two $D \in parents_g$, e.g., D_a and D_b have the crossover operator $p_{crossover}$ applied to generate two new plans D'_a and D'_b using crossover points cx_1 and cx_2 selected randomly along the lists of D_a and D_b such that $0 < cx_1 < cx_2 < Q$, where Q is the length of D_a and D_b . Their attributes are exchanged between the two crossover points to form D'_a and D'_b such that $D'_a[cx_1:cx_2] = D_b[cx_1:cx_2]$ and $D'_b[cx_1:cx_2] = D_a[cx_1:cx_2]$. Through this the GA aims to combine superior $d_{i,j}$ to develop optimal configurations of $D \in parents_g$.

Thereafter, sites $d_{i,j}$ within $D \in parents_g$ that were not selected by the $p_{crossover}$ probability have a mutation operator applied mutated on a small probability p_m . As variables within D are discrete i, j locations of d this is achieved using a uniform integer mutation which randomly changes the i, j location of d within a fixed range of possible i, j . This is shown in Figure 4.7 where the mutation is applied to D_c . The $d_{i,j} \in D$ selected for mutation has its i, j location changed from 3,13 to 9,33 to form a new $D; D'_c$. The mutation operator has two functions. Firstly it stops the $d_{i,j} \in D \in parents_g$ converging on a small subset of $d_{i,j}$ by introducing random $d_{i,j}$ and secondly the introduction of new $d_{i,j}$ might improve the performance of D

against the all or a number of objectives $f \in F$. Spatial plans resulting from the operators D' are stored in a new set $offspring_g$.

Next a selection operator selects spatial plans that are optimal which are used to produce offspring for the next generation. This work utilises the Non-dominated Sorting Genetic Algorithm II selection procedure proposed by Deb et al. (2002) as traditional selection methods such as tournament and roulette selection are unsuitable for multi-objective optimisation. NSGA-II is a reliable and widely used algorithm which is straightforward to implement having been shown to perform well over a range of optimisation applications (Jaeggi et al. 2008; Zhang & Fujimura 2010; Cao et al. 2011). Moreover it has been found to better estimate the Pareto front with reduced computations compared to other popular MOO GA algorithms such as the Strength Pareto Evolutionary Algorithm (SPEA) (Zhang & Fujimura 2010).

After $offspring_g$ is subject to the constraint handling module (see (4) below) and is evaluated for their F . Crucially the selection procedure is elitist as $parents_g$ is considered alongside $offspring_g$. Thus, the resulting set, $parents_{g+1}$ will consist of the best D across both sets and ensures that $parents_{g+1}$ is superior to $parents_g$. Figure 4.8 outlines how NSGA-II reduces the combined sets $offspring_g$ and $parents_g$ of length $2 \times no_{parents}$, to the set $parents_{g+1}$ of length $no_{parents}$. The combined sets of $D \in offspring_g$ and $D \in parents_g$ are non-dominated sorted to produce a series non-dominated sets of N . Firstly, the non-dominated set of the combined sets is determined, N_1 . These are removed from the combined $offspring_g$ and $parents_g$ and the remaining combined solutions are then re-sorted to determine the next non-dominated set, N_2 . This continues until all D within $offspring_g$ and are assigned to a Pareto set, $N_1, N_2, N_3 \dots$ (see Figure 3.6a for a visualisation of this). Next $parents_{g+1}$ is made up of these non-dominated sets in ascending order until there isn't enough space for the entire set of $D \in N$. So for the example in Figure 4.8 $parents_{g+1}$ inherits the D within N_1 and N_2 but can't hold the entire set N_3 and N_4 is discarded. To determine which $D \in N_3$ will be used to fill the remaining space in $parents_{g+1}$, a crowding distance, ψ , is calculated for $D \in N_3$ to distinguish which are in the least represented areas of the Pareto front. This is calculated based on the average distances to the nearest solution in the objective space (see Figure 3.6b for a visualisation). The $D \in N_3$ are sorted by this crowding distance, ψ , and those with the best performance are used to fill the remaining space in $parents_{g+1}$. This is intended to ensure a wider a representative of Pareto front is preserved in $parents_{g+1}$.

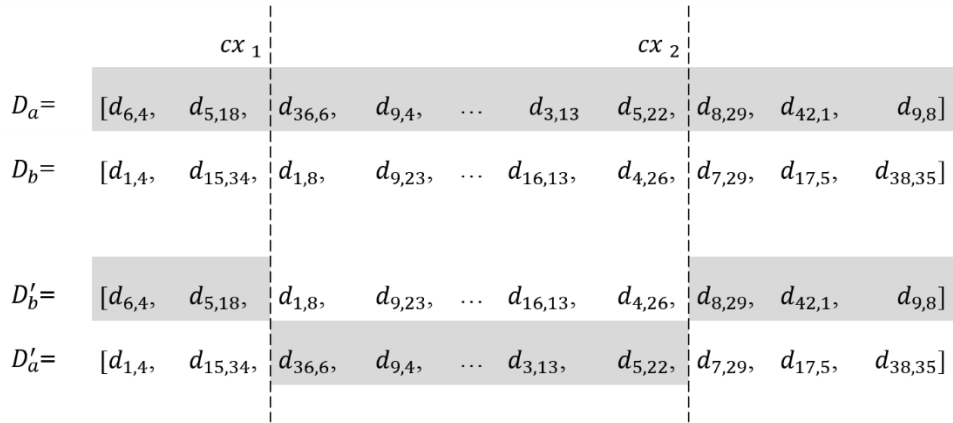


Figure 4.6 Application of the two-point crossover operator to two selected D .

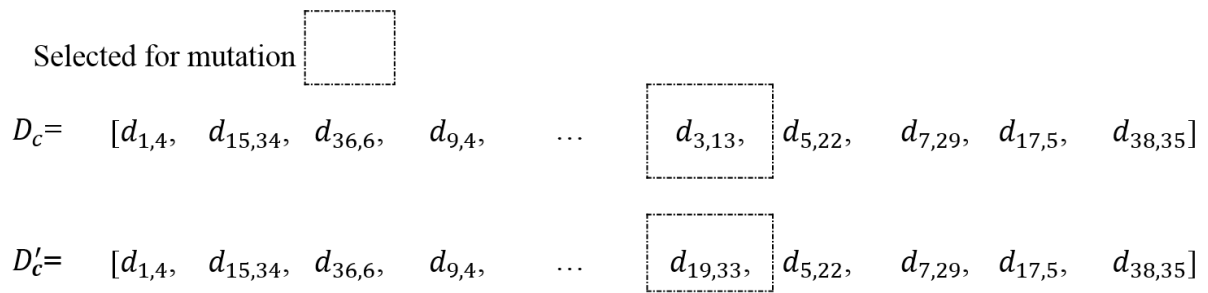


Figure 4.7 Application of the fixed integer mutation operator to a selected D .

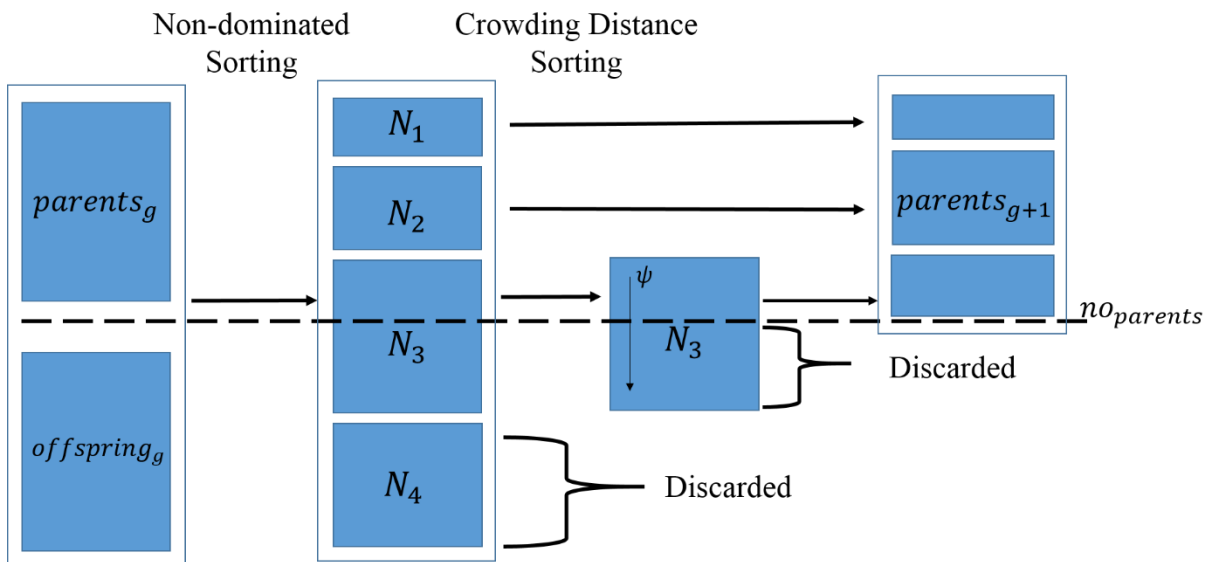


Figure 4.8 NSGA-II selection operator applied to the $parent_g$ and $offspring_g$ to form $offspring_{g+1}$ (adapted from Deb et al., 2002).

(4) Constraints and Evaluate

Before the D in $offspring_g$ are evaluated against the objective functions, a constraint handling module ensures that they are feasible spatial plans. Constraint handling in GA algorithms requires careful consideration due to the use of crossover and mutation operators (Konak et al. 2006; Coello 1999). Konak et al. (2006) identifies several methods by which to enforce constraints on a GA procedure:

1. Discarding infeasible solutions from the population;
2. Applying proportionally a penalty function to solutions which break constraint;
3. Designing the genetic algorithm problem so only feasible solutions are produced; and
4. Repairing in-feasible solutions during the algorithm.

Penalty functions are the most prominent method employed in many GA applications (Coello 1999). However they have been criticised as the determination of the penalty parameters is often complex. Liu et al. (2015) utilised a penalty function in their study to prevent the development of natural areas and acknowledged that it didn't prevent infeasible solutions being represented in the search. Loonen et al. (2007) states it should only be employed as a last resort and considers that ideally the representation should be formulated so only feasible solutions are found. Therefore the representation for the GA was formulated so proposed d were allocated spatially on the basis of a lookup value, l . Therefore $D = [d_l, d_l \dots d_l]$, where each l corresponds to an i, j location through a lookup table as shown in Figure 4.9. Figure 4.9 demonstrates how this this allows for the exclusion of i, j locations which correspond to cells designated as greenspace, currently developed land, water and cells outside the boundary. As the GA investigates the spatial allocation of d it is limited to l locations and is restricted to assigning development to cells available for development, thereby partially fulfilling Equation 4.1 (sites must be within the study area and on cells available for development) and fulfilling Equation 4.9 (not on greenspace). This mirrors the approach taken by Cao et al. (2011) where canals and greenspace in the study area were excluded from the variable space. This also has the consequence of reducing the number of variables in the search, and therefore the complexity. With respect to the example in Figure 4.9, we reduce the search from 49 combinations of i, j to 25 values for l . Unfortunately the representation couldn't be formulated to prevent duplicated $d \in D$. Instead $D \in offspring_g$ which were found to have duplicated d_l in D were discarded. The remaining $D \in offspring_g$ were then evaluated against the objectives $f_{heat}, f_{flood}, f_{dist}$

and f_{sprawl} as per the the definitions in Section 4.2.5 using the scripts listed in Appendix C to determine their respective F .

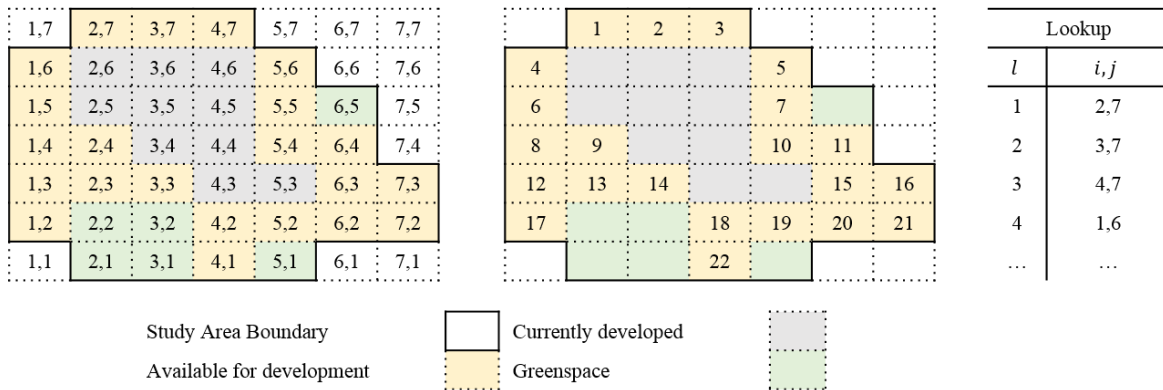


Figure 4.9 Demonstration of generating a lookup table converting cells from ij locations to a l value to excluded infeasible development sites.

(5) Update non-dominated list

During the application the GA maintains the MOPO set, N for $F = \{f_{heat}, f_{flood}, f_{dist}, f_{sprawl}\}$, based on all the D found during the search. At each g the set of superior spatial plans $D \in parents_{g+1}$ are compared to N and those found to be non-dominated are added whilst any $p \in N$ found to be dominated is ejected.

(6) Outputs

Once $g = G$ the GA terminates and returns N . This is then used to determine Pareto-optimal sets between pairs of objectives i.e. $N_{f_{heat}, f_{dist}}$ based on the formula outlined in Section 4.2.6 to form $N_{f_{heat}, f_{dist}} \dots etc$. In addition $D \in N, N_{f_{heat}, f_{dist}} \dots$ are plotted as spatial plans on raster datasets based on the spatial allocation $d_{i,j} \in D$.

4.5.2 Software Implementation

Several Python modules exist which can handle evolutionary operators. Pyevolve² is a well-documented python module with multiple scripts for mutation³) and crossover⁴ operators. Moreover it is able to handle 1D (lists) and 2D (grid) representations. However, it doesn't have

² <http://pyevolve.sourceforge.net/>

³ http://pyevolve.sourceforge.net/module_mutators.html

⁴ http://pyevolve.sourceforge.net/module_crossovers.html

the necessary selection operators for MOO Pareto-optimisation so is limited to single objective optimisation or weighted sum applications. Alternatively, Pygene⁵ is a promising approach with the necessary operators to allow for multi-objective optimisation. However there is very little associated documentation for this package and limited examples of its use.

Rather using one of the modules above, the Python module Distributed Evolutionary Algorithms in Python (DEAP) was employed (Fortin et al. 2012). DEAP has excellent online documentation. The software provides built in functions for the selection, crossover and mutation operators. In particular, the following modules were used to operate the evolutionary operators; `tools.selNSGA2` provided the necessary modules for the selection operator, `tools.cxTwoPoint` for the crossover operator and `tools.mutUniformInt` for the mutation operator. A further advantage of DEAP is that its creator function helps facilitate the creation of fixed length representations of D in the application.

4.6 Summary

This chapter has developed a Multi-objective Spatial Optimisation Framework (MOSPOF) to optimise future spatial plans of development. Specifically the framework optimises a fixed number of new residential development sites across a study area ensuring they are feasible i.e. fall in areas available for development. The novelty of the approach is that it attempts to optimise these plans against a series of real world prioritised sustainability objectives and is coupled to Pareto-optimisation to provide development plans which form best trade-off the objectives evaluated. The implementation of the two optimisation approaches employed in the developed MOSPOF have been described in detail, along with how they have been coupled with Pareto-optimisation.

⁵ <https://pypi.python.org/pypi/pygene/0.2.1>

Chapter 5 Medium Sized Urban Case Study- Middlesbrough

5.1 Introduction

In this chapter the spatial optimisation framework developed in Chapter 4 is applied to an urban planning case study to evaluate its utility to assign future residential development plans for a medium sized urban area which account for multiple sustainability objectives. The case study is undertaken for a densely urbanised local authority in the North East of the UK; namely Middlesbrough. Both optimisation approaches within the framework, Simulated Annealing and Genetic Algorithm, are demonstrated and compared in the case study in order to address in part the second research question of this thesis; the identification of the most appropriate multi-objective optimisation approach for the spatial planning of cities.

5.2 Middlesbrough Case Study

To test the utility of the developed framework for the spatial planning of residential development with regards to multiple sustainability objectives, a case study was undertaken for Middlesbrough, a local authority in the North East of the UK (Figure 5.1). Middlesbrough was selected as it is a moderately sized (land area of 54.55 km² and population of 138,400 (ONS, 2012)) highly urbanised (63% of land use) urban area facing multiple pressures from increasing population, increased incidences of future heat waves as well as at risk of flooding from the River Tees and its tributaries (Middlesbrough Council 2013c). In addition the availability of data (including climate projections over the area) and the recent publication of Middlesbrough Council's preferred options for development (Middlesbrough Council 2013a) contributed to the decision to use the local authority. Section 5.2.1 outlines the formulation of the spatial planning problem addressed by the framework whilst Section 5.2.3 presents the variable space (i.e. potential locations for new development) in which the optimisation framework can spatially allocate new residential development.

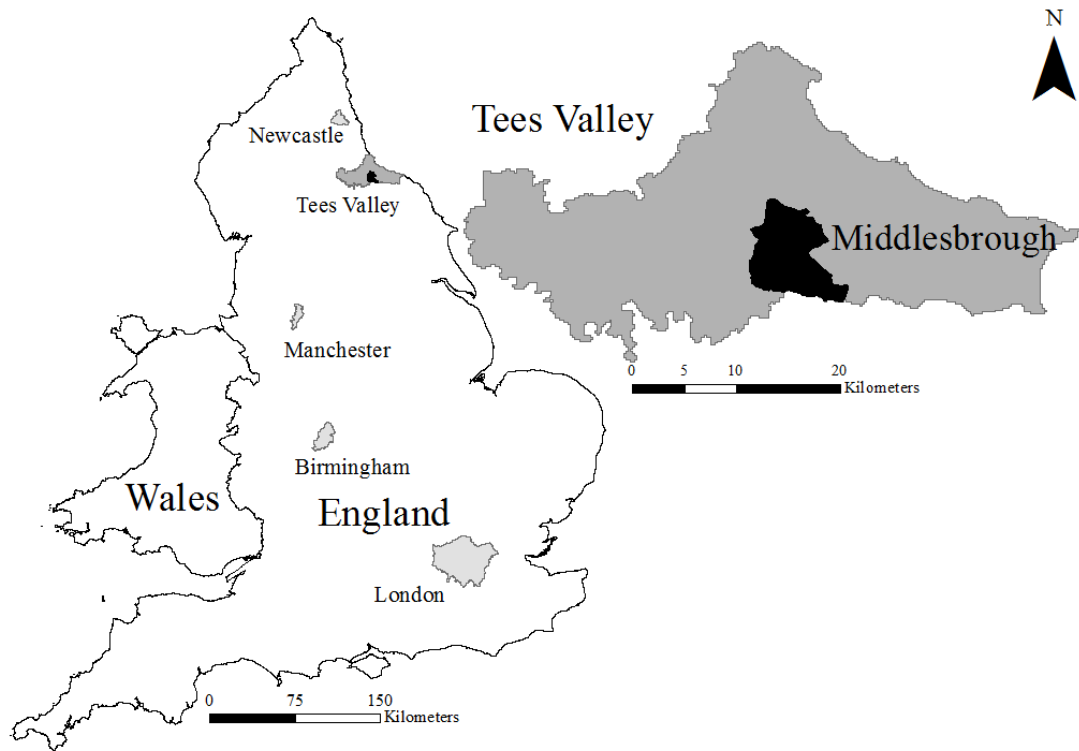


Figure 5.1 Case study area of Middlesbrough within the Tees Valley.

5.2.1 Problem Formulation

To formulate the case study several Middlesbrough Council planning documents were analysed to quantify the parameters of the search. Based on future population projections, Middlesbrough Council has laid out three planning scenarios for future development, shown in Table 5.1. Middlesbrough Council (2013a) expressly states that it is the Council’s intention is to aim for the stable (zero net migration) population scenario (highlighted in the table). Based on this Middlesbrough Council (2012) projects an increase in population of 4,890 between 2004 and 2021. This comes at a time when there will be an expected decline in the average people per household from 2.38 in 2004 to 2.17 in 2021. This leads to the amended Core Strategy in the Local Development Framework (LDF) shown in Table 5.2 which sets out the requirement of 4370 new residential developments between 2012 and 2024 (including a 20% buffer for the years 2012-2019 reflecting guidance from the National Planning Policy Framework (DCLG 2011a)). Policy CS1 in the LDF Core Strategy also sets out the provision for 85 ha of land for ‘General Employment Land’ and 100 ha of land for ‘Regional brownfield mix use land’. The mixed use site in the south of the study area (Greater Hemlington) is intended as a sustainable community of a high quality design containing up to 810 dwellings and 50,000 square metres

of employment. However the methodology is currently insufficient to handle this so it's unconsidered for this application.

Middlesbrough Council's spatial plan was digitised (steps shown in Figure 5.2) from their interactive LDF (Middlesbrough Council, 2010) to generate the spatial parameters to optimise. To reconcile this with the representation used by the framework, the resulting vector dataset was rasterised to a grid of 100 by 100 metre cells, each equalling 10,000 m² / 1 hectare (ha) in size, shown in Figure 5.2. The area and number of 1 ha cells taken up by Council proposed residential sites for the vector and rasterised datasets remains consistent, however a number of the smaller council proposed sites were lost. This spatial resolution was chosen as through testing it was found that it provided the best trade-off between the run time and effectiveness of the algorithm with a realistic spatial representation.

The optimisation aims to assign the required residential land over the time frame 2013 to 2024. Following the notation of Section 4.2.2 (Problem Representation), the 54 ha of proposed residential sites within the study area defined as forming a spatial development plan D , satisfying the series of sustainability objectives outlined in Section 4.2.5. The total number of residential dwellings to be allocated is 4370 (2013-2024, Table 5.2) and total number of people to accommodate is 4,890. Making the assumption that these are equally distributed across the 54 hectares of proposed development leads to an average of 81 dwellings per hectare and 90 residents per hectare represented by $dw_{i,j}^+$ and $v_{i,j}^+$ respectively. In this instance Q , the length of the development plan D , takes the value of 54 as each cell is 1 ha.

Table 5.1 Housing targets based on population scenarios in Middlesbrough's Local Development Framework (Middlesbrough Council 2013a)

Population Scenario	Number of Dwellings per Annum (net)	Total Dwelling Requirement
Out migration	250-380	4,250-6,460
Stable (zero migration)	410	6,970
In migration	430-570	7,310 – 9,690

Table 5.2 Amendments to policy CS1 on dwelling totals (Middlesbrough Council 2013a).

Phase	Number of Dwellings
2012-19	2,320 dwellings (300 dwellings p.a 2012/13 to 2016/17 then 410 dpa 2017/18 to 2018/19)
NPPF buffer (20%)*	465
2019-2024	2050 dwellings (410 p.a)
2024-29	2050 dwellings (410 p.a)

* Note: Requirement of National Planning Policy Framework to include 20% in first five years to ensure choice and competition for housing in the market

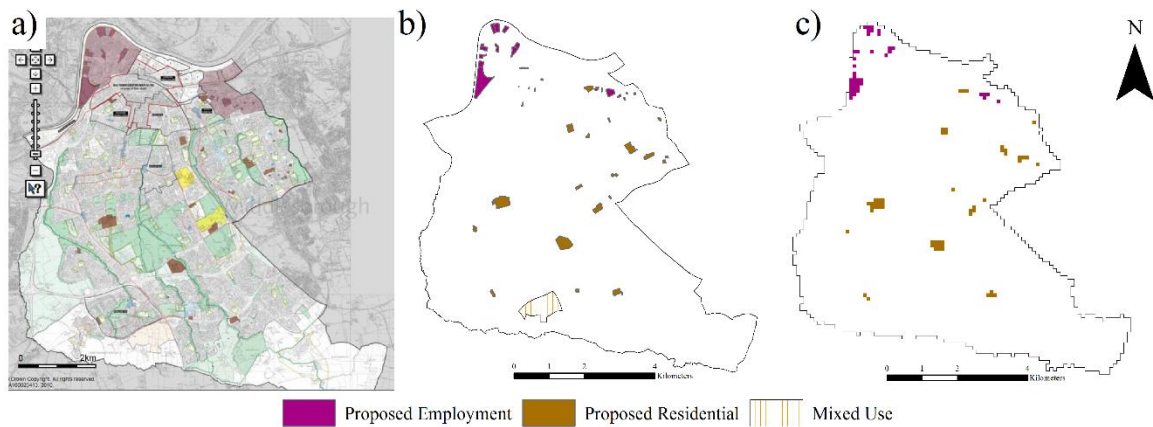


Figure 5.2 Digitisation of Middlesbrough Council's spatial plan; a) Interactive Local Development Framework (Middlesbrough Council 2010), b) digitised proposed residential, employment and mixed use sites and c) rasterised at a 100 metre spatial resolution.

5.3 Middlesbrough Datasets

To facilitate the case study a series of spatial datasets covering the study area were assembled. Using ArcGIS's Arc Map 10.1 software these were pre-processed into a set of raster datasets at 100 metre spatial resolution. Appendix D presents a series of toolbox modules which automated this process.

5.3.1 Available Land for Development

Potential locations for future residential development were identified to represent the variable space within which the spatial optimisation can search for spatial strategies of new development. Ordnance Survey (OS) MasterMap data, specifically the Topographic Area layer, was compiled for the Middlesbrough study area to provide a continuous coverage of the physical coverage of land described by the MasterMap attributes (fields) of Theme, Make and Descriptive Group. The OS MasterMap data was used to generate two constraint layers of land that cannot be developed due to the presence of water, **Water_Constraint**, or current development, **Developed_Constraint**, (Figure 5.3). The former was generated by selecting all topographic areas where the 'Theme' attribute was "Water" whilst the **Developed_Constraint** was created from a merger of polygons with the following attributes:

- i. Theme = "Land" and Make = "Multiple"
- ii. DescriptiveGroup = "Buildings" and Make = "Manmade"
- iii. DescriptiveGroup = "Rail" and Make = "Manmade"

- iv. DescriptiveGroup = “Roads” and Make = “Manmade”
- v. DescriptiveGroup = “Roads” and Make = “Unknown”
- vi. DescriptiveGroup = “Roadside” and Make = “Natural”

Both constraint layers were rasterised at a 100 metre spatial resolution as shown in Figure 5.4 which also shows the land available for development i.e. not coinciding with either of the constraint layers. It is worth noting, that the sites identified for economic and residential development in Figure 5.3 were also added to areas available for development. This dataset used in the framework to constrain the locations of $d_{i,j}$ to areas identified as being available for development through the equation:

$$\text{Subject to} \quad d_{i,j}^{-1} \text{ if } d_{i,j} \cap a_{i,j} \wedge d_{i,j} \neq d_{i,j}^{-1} \in D \quad (5.1)$$

where $a_{i,j}$ is a cell available for development. Equation 5.1 essentially ensures that proposed sites are not duplicated on the same location/area of available land.

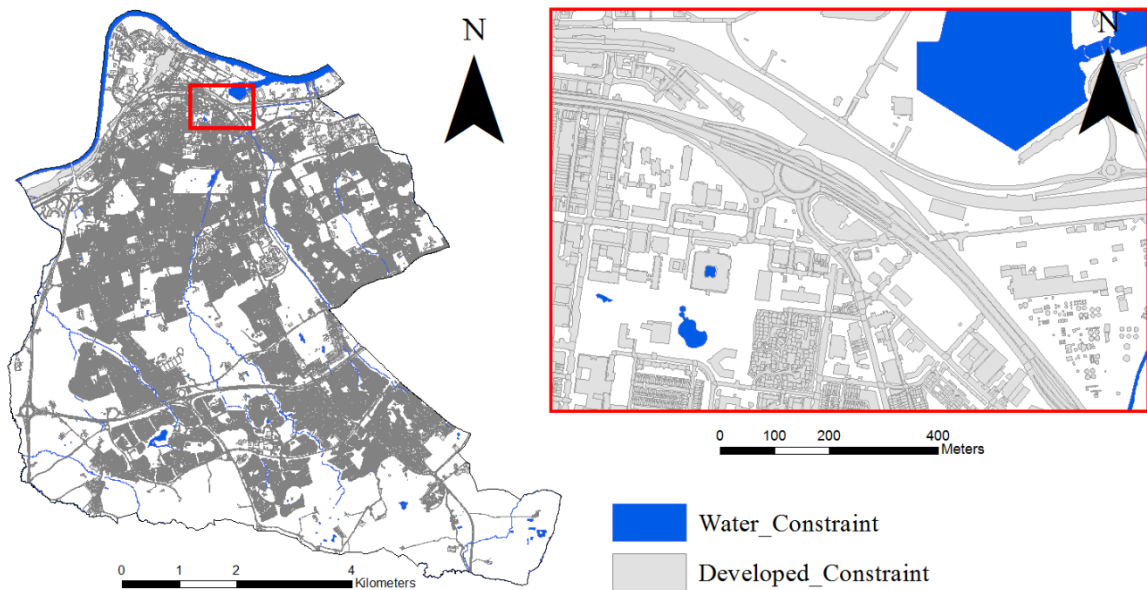


Figure 5.3 Currently Water and Developed Constraints shapefiles extracted from OS MasterMap topographic area layer.

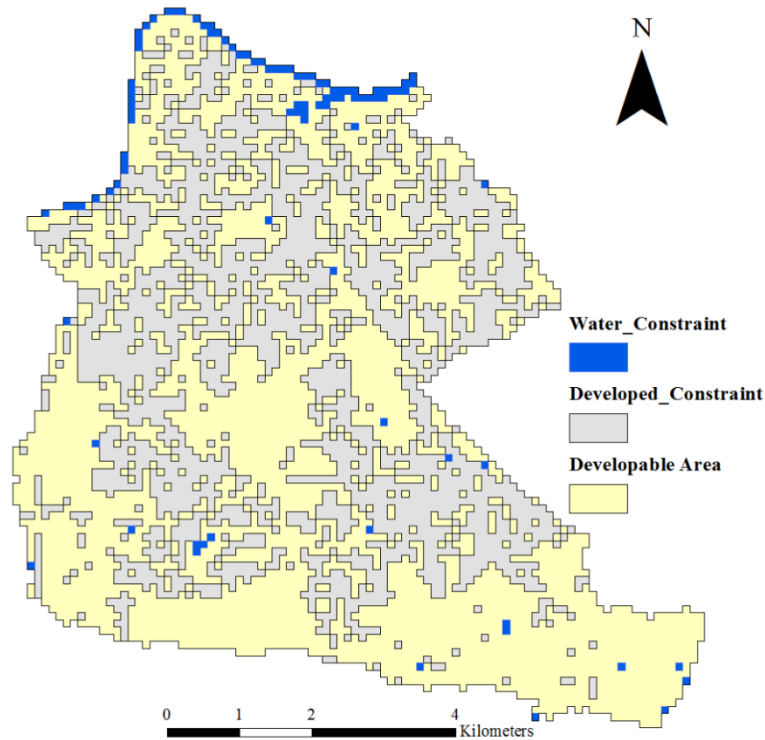


Figure 5.4 Rasterised water and developed constraints at 100 metre spatial resolution.

5.3.2 Data for Objective Formulation

Figure 5.5 sets out the spatial datasets used to quantify the sustainability objectives explored by the framework. Figure 5.5a presents the spatial representation of the hazard constituent, h , attained from the medium emissions scenario of the UKCP09 projections (Jenkins et al. 2009). The UKCP09 medium emissions climate projection change factors are at a 25km spatial resolution for 30-year periods. This was used as an input into a spatial weather generator (Jones et al. 2009). The spatial weather generator disaggregates UKCP09 data to estimates of daily T_{max} (daily maximum) and T_{min} (daily minimum temperatures) at a 5km spatial resolution. The spatial weather generator is a recent extension of the a-spatial weather generator that has been widely employed in several UK heat and heat wave impact studies ensuring that both predictions temporally and also spatially for a study area are consistent (correlated) (Jones et al. 2009; Kilsby et al. 2007). From this data the heat wave frequency per annum was extracted using the heat wave thresholds from the UK Heatwave Action Plan for the North East (Department of Health (DoH) 2010) for two consecutive days and interceding night; $T_{threshold}^{day} = 28 / T_{threshold}^{night} = 15 / T_{threshold}^{day+1} = 28$. This annual frequency for the period 2020 was normalised over study area to values between 0 and 1. Whilst this is a short horizon to

analyse future heat risk, it is in line with the planning process which tends to be restricted to ten year periods.

Figure 5.5b presents the population vulnerability constituent, v , and is spatially represented by a population density per hectare figure. The source for the data was Census 2011 (Office of National Statistics 2012) figures at super lower output area level. Output level is a sub-ward geography averaging approximately 309 people and designed specifically to contain a similar population size (although crucially the spatial extent varies) and to be as socially homogenous as possible (Cockings et al. 2011) and rasterised to a 100m resolution. Figure 4.6c presents the floodzone areas over the study area, $z_{i,j}^{100}$ and $z_{i,j}^{1000}$, representing 1 in 100 and 1 in 1000 floodzones, sourced from the UK's Environmental Agency's (EA) Flood zone 2 and 3 maps. Figure 5.5d presents the urban extents for the study area, $u_{i,j}$. This was sourced from Ordnance Survey Meridian 2 Developed Land Use Areas (DLUA).

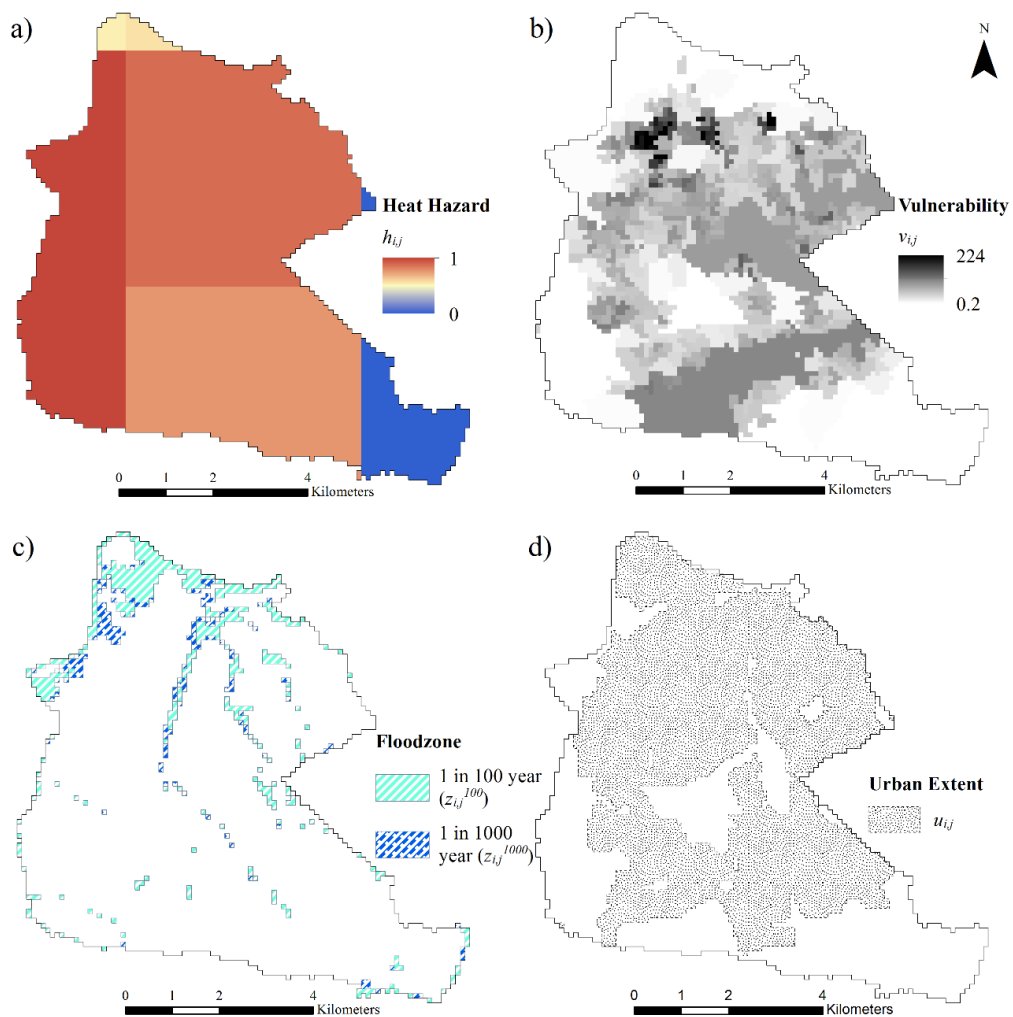


Figure 5.5 Spatial datasets for the Middlesbrough case study.

Middlesbrough's Central Business District (CBD) ($c_{i,j}$) in the study area was represented by a centroid calculated from the Council's definition of Middlesbrough's town centre (Figure 5.6a) which was digitised from Middlesbrough's interactive Local Development Framework (Figure 5.6b and 5.6c). The road network, R , used in the calculation of f_{dist} , was represented as the major roads in the Ordnance Survey Meridian 2 dataset. For the spatial constraint outlined in Equation 4.9 (preventing development on greenspace), a greenspace dataset (Figure 5.7a) was collated from Ordnance Survey MasterMap data. From the Topographic Area layer, all features with Theme = Natural were extracted before conversion to a raster dataset (Figure 5.7b).

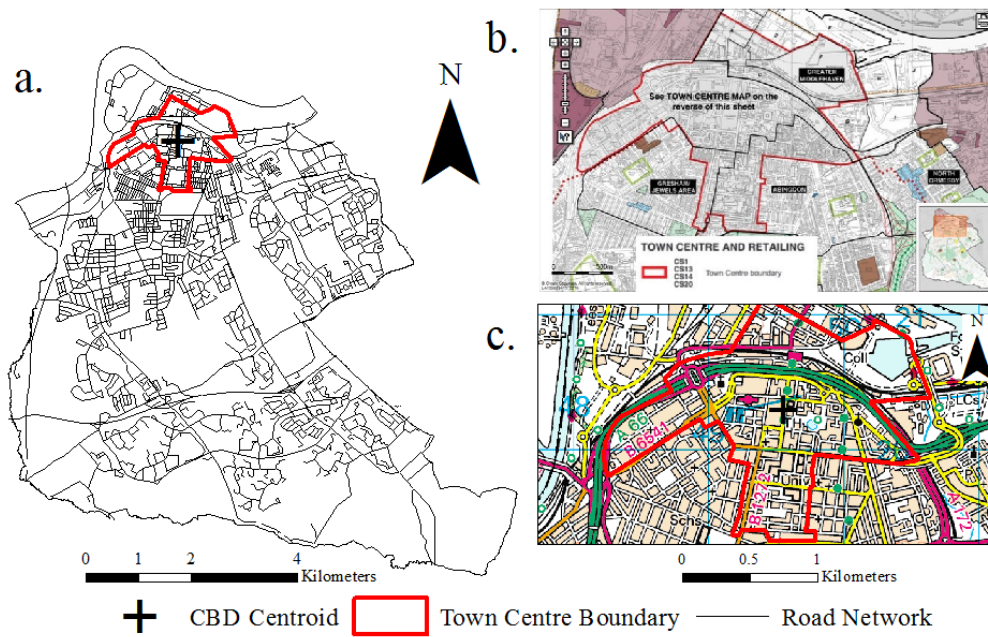


Figure 5.6 a) Middlesbrough's town centre boundary and CBD centroid ($c_{i,j}$), road network (R) and b) & c) digitisation of Middlesbrough town centres boundary from Middlesbrough's interactive LDF (Middlesbrough Council 2010).

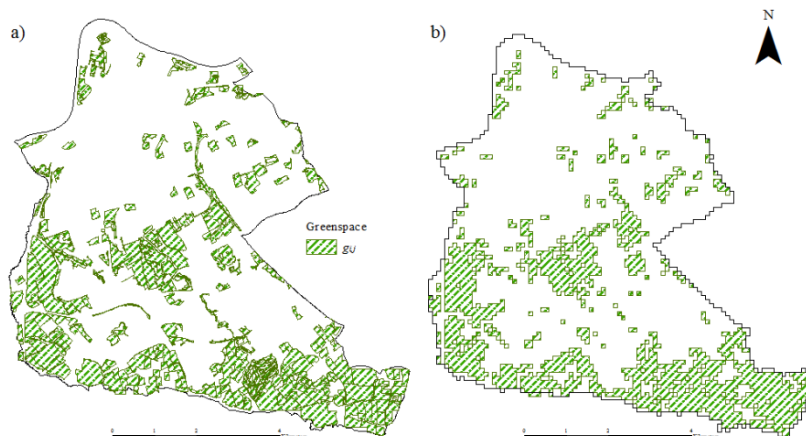


Figure 5.7 Middlesbrough greenspace in a) vector format and b) rasterised at a 100 metre spatial resolution.

5.4 Optimisation Parameters

5.4.1 Simulated Annealing Parameters

As several sources have noted, the success of a Simulated Annealing algorithm search can be highly dependent on initialisation parameters of the search (Dowsland 1993; Aerts & Heuvelink 2002; Delmelle et al. 2012). Therefore great care was taken in the selection of the input parameters in order to assure the best opportunity to discover optimal solutions including the initial and ending temperatures, T and T_{end} . Testing was carried out with random initial development plans however these performed extremely poorly, with low convergence at each iteration. Therefore the councils own plan, shown in Figure 5.2 was used as the initial spatial configuration of new development, D_n .

The cooling parameter, c , was set to 0.85 as recommended in the literature (Aerts & Heuvelink 2002) whilst a very small figure, 0.0001, for T_{end} was utilised to maximise convergence at the end of each iteration. This means a number of steps are taken at the end of the iteration which only accepts superior fitnesses. To determine a suitable initial temperature, T , and number of iterations, m , a series of possible parameter values were investigated shown in Table 5.3. Figure 5.8 demonstrates the convergence of F (made up of normalised performances for f_{heat} , f_{flood} , f_{dist} and f_{sprawl}) for a series of SA searches under different runtime parameters (search A-C) outlined in Table 5.3. The figure presents the F_b , and, F_n performance at the n th step against the F value normalised throughout all three searches. Note that F_n represents the fitness accepted by the Thermopolis equation (Equation 4.11) otherwise it represents the fitness value of the previous spatial configuration ($f_n = f_{n-1}$).

Figure 5.8 shows that by accepting inferior solutions of D_n , (demonstrated by the poor f_n performances in-between iterations (blue line)), it allows the optimal performances of f_b to be found. Table 5.4 outlines the statistics of the convergence for each of the searches. In all cases, there is a significant improvement in the first iteration with, for example in search A, a 66.8% improvement in f_b by the end of the first iteration ($m = 1$), whilst there is 26% improvement in f_b between $m = 1$ and $m = 10$. Thereafter convergence slows with improvements of 15% between $m = 10$ and $m = 20$ and 2% improvement in f_b between $m = 20$ and $m = 30$. There's an anomalous higher percentage improvement for f_b between $m = 30$ and $m = 40$ (40%) as a result of the randomness of the search however within final 10 iterations the improvement reduces to 7%.

In comparison search B, with a lower initial temperature, has a lower initial improvement in f_b (50% compared to search A's 67%). However, thereafter the search improves considerably with improvements of 41.4%, 45.6% and 38.0%. This results in search B reaching a better performance in f_b despite 50% less computations. In addition a higher percentage of iterations resulted in an increase in f_b (76% compared to 64% for search A). This suggests that a smaller period of accepting of inferior solutions improves the convergence as the spatial plan doesn't become too convoluted. For example the average performance for f_n in search A is 0.18 compared to 0.15 search B. To test this search C utilised the same temperature value and reduced the iterations (m) to 3. Despite carrying out a 3rd of the computations as search A, the best performance in f_b was only marginally higher, 0.16 compared to 0.11. Conversely search A finds double the number of MOPOs compared to B, suggesting a longer search is need to present a diverse Pareto front and range of Pareto-optimal spatial configurations. Based on these findings the final set of initial parameters utilised for the Middlesbrough case study are presented in the final column of Table 5.3 . A lower initial temperature value was used to ensure better convergence whilst a increased the number of an iterations was employed to ensure a sufficient number of MOPOs are found. The results from this search are presented in Section 5.5.

Table 5.3 Parameters for the testing the Simulated Annealing approach.

Parameter	Testing Search			Application Search
	A (Figure 5.8a)	B (Figure 5.8b)	C (Figure 5.8c)	
Starting temperature (T)	1000	500	500	500
Iterations (m)	50	50	30	400
End temperature (T_{end})	0.0001	0.0001	0.001	0.001
Cooling Factor (C)	0.85	0.85	0.85	0.85
Steps within an iteration	1474	766	766	766
Total Steps (n)	73,700	38,300	22,979	153,200
Running Time (hr.min)	12.23	6.25	4.13	15.23
MOPOs Found	268	138	80	272

Table 5.4 Performance of the Simulated Annealing search at different stages during testing.

	Iteration (% denotes percentage improvement)													
	m=0		m=1		m = 10		m = 20		m= 30		m = 40		m = 50	
	fb	%	fb	%	fb	%	fb	%	fb	%	fb	%	fb	%
Search A	0.98		0.31	67.9	0.23	25.6	0.20	15.0	0.19	2.2	0.12	39.7	0.11	6.6
Search B	0.95		0.48	49.5	0.28	41.4	0.15	45.6	0.09	38.0	0.01	88.1	0.00	100.0
Search C	0.98		0.38	61.6	0.22	42.8	0.15	30.7	0.14	7.2				

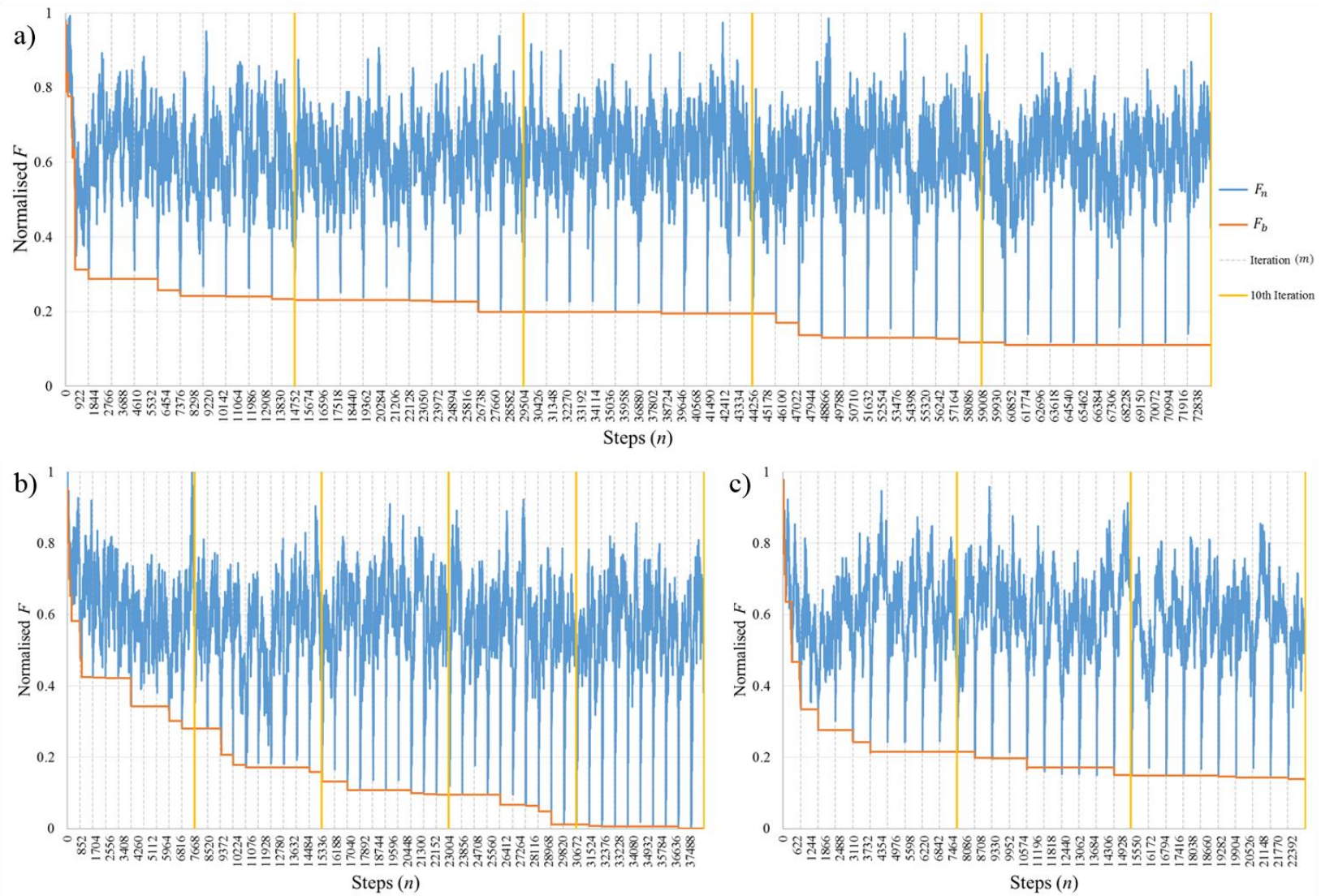


Figure 5.8 Convergence during the Simulated Annealing runs (a-c) using the input parameters set out in Table 5.3.

5.4.2 Genetic Algorithm Parameters

Table 5.5 outlines the input parameter values for the GA application. Selecting the initial parameters presented several challenges. Firstly a sufficient population size to represent a wide range of development sites was required. This is crucial as the GA creates new development plans from the attributes of previous development plans so if potential development sites aren't represented they won't be investigated (Cao et al. 2011) potentially missing the opportunity to find the most optimal sites. The mutation operator can potentially redress this as it randomly brings new development locations into the $parents_g$ set however as this is done in a random manner it can't be assured to ensure all development sites are assessed. Through testing a figure of 1500 for $no_{parents}$ (number of spatial plans represented in the initial parent set) was found to sufficiently cover the 1729 possible development sites in the initial parent set. This can be seen in Figure 5.9 which demonstrate the wide coverage of potential sites in the initial parent set (5.9a) before it convergences on optimal sites (Figures 5.9b - d).

In order to allow for the sufficient convergence on the best approximate Pareto front a suitable parameter for the number of generations is necessary. However too many generations will lead to redundancy, whilst too few restrict the convergence on the approximate Pareto front ignoring potentially more optimal plans. The Figure of 200 generations was reached after several tests to ensure optimal convergence. Figure 5.10 demonstrates the convergence of the Pareto front of newly produced $offspring_g$ during stages of the Genetic Algorithm between f_{heat} and f_{dist} (it should be noted that they are taken before the selection operator to solely demonstrate newly developed solutions). Figure 5.10a demonstrates the significant improvement in the convergence between the 1st and 50th generation with an average improvement across the Pareto front of 24.4%. This occurs as the algorithm is able to expunge non-optimal spatial plans and development sites ($d_{i,j}$) from the $parent$ set whilst retaining those in optimal locations. This can be seen in Figure 5.9b where the potential sites present in the $parent$ set reduces from 1729 to 621 between $g = 1$ and $g = 50$. Thereafter the convergence is much less significant, with an 8.4% average improvement in the Pareto front between the 50th and 100th generations, which becomes more than half again between the 100th and 150th generations (3.1%) and 150th generation (3.2%).

Figure 5.10b demonstrates marginal improvements in the convergence of the Pareto front of new offspring in the final 50 generations during the GA application with improvements of 0.7%

between $g=150$ and $g=160$, 1.1% between $g=160$ and $g=170$, and 0.5% between $g=170$ and $g=180$. The marginal improvements are a result of the algorithm converging on a set of optimal spatial plans from an already near optimal set, demonstrated in Figure 5.9c and 5.9d where the development sites represented *parent* set at $g=150$ and $g=200$ is reduced marginally from 115 to 102. Indeed the Pareto front regresses on average 1% between $g=180$ and $g=190$ (which can be seen in the inset in Figure 10b) as the process of crossover and mutation can lead to inferior spatial plans in the hope that it leads to optimal solutions in the future. However due to the elitist nature of the NSGA-II algorithm (see Section 4.5.1 and Figure 4.8) the search in fact continues from the previous superior positions on the Pareto front. Thereafter, there is a 2% improvement between the parent set at $g=190$ and the final Pareto front which contains the best set of spatial plans found throughout the application.

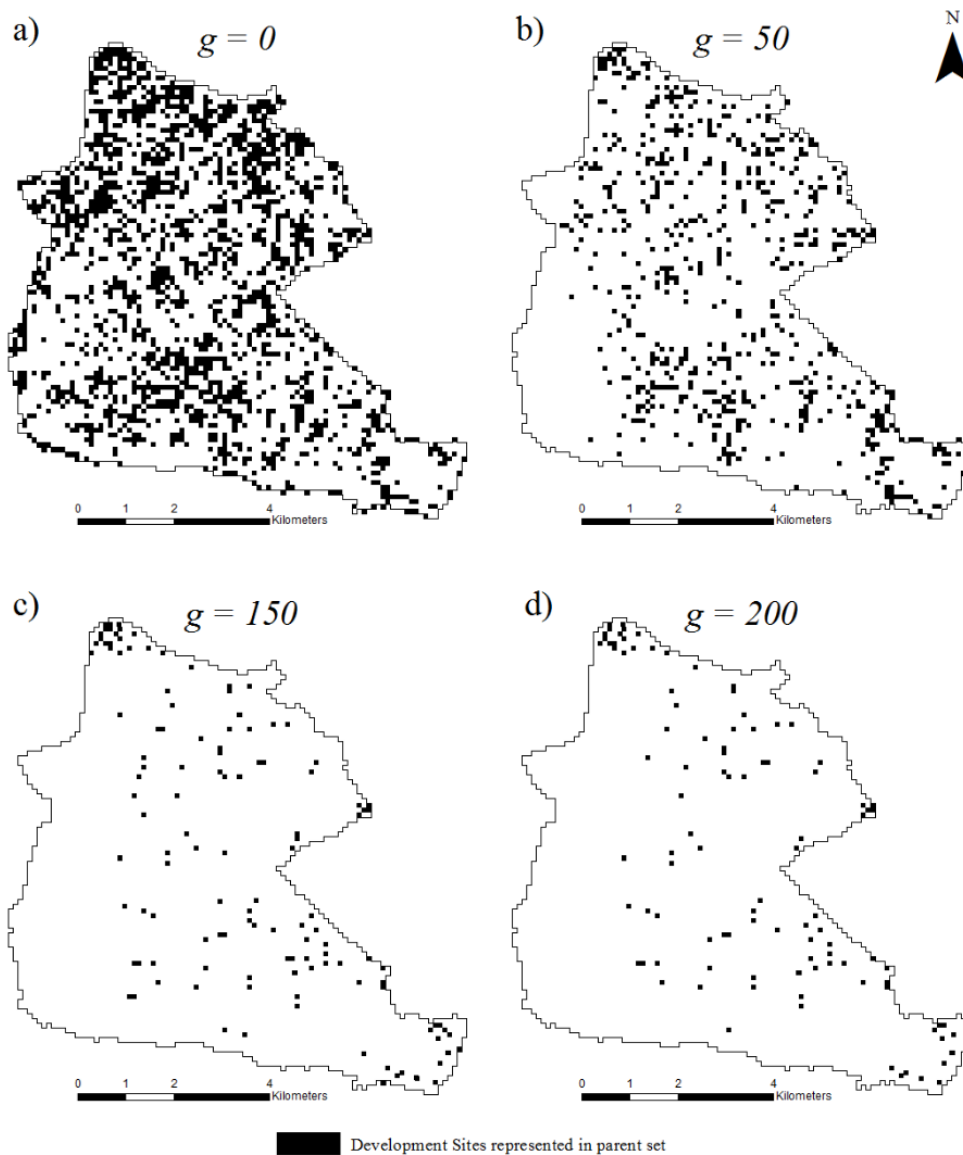


Figure 5.9 Proposed development sites represented in the *parent* set at stages of the GA operation.

Table 5.5 Genetic Algorithm Search Parameters for Case Study Application

Parameter	Description	Value
G	Number of generations	200
$No_{parents}$	Number of individuals to select for the next generation	1500
$p_{crossover}$	Probability of applying a crossover to two individuals	0.7
$p_{mutation}$	Probability of mutating an individual	0.2
p_m	Probability of mutating an element within an individual	0.05
Total Run Time		10hr 25m
Number of Computations		251313

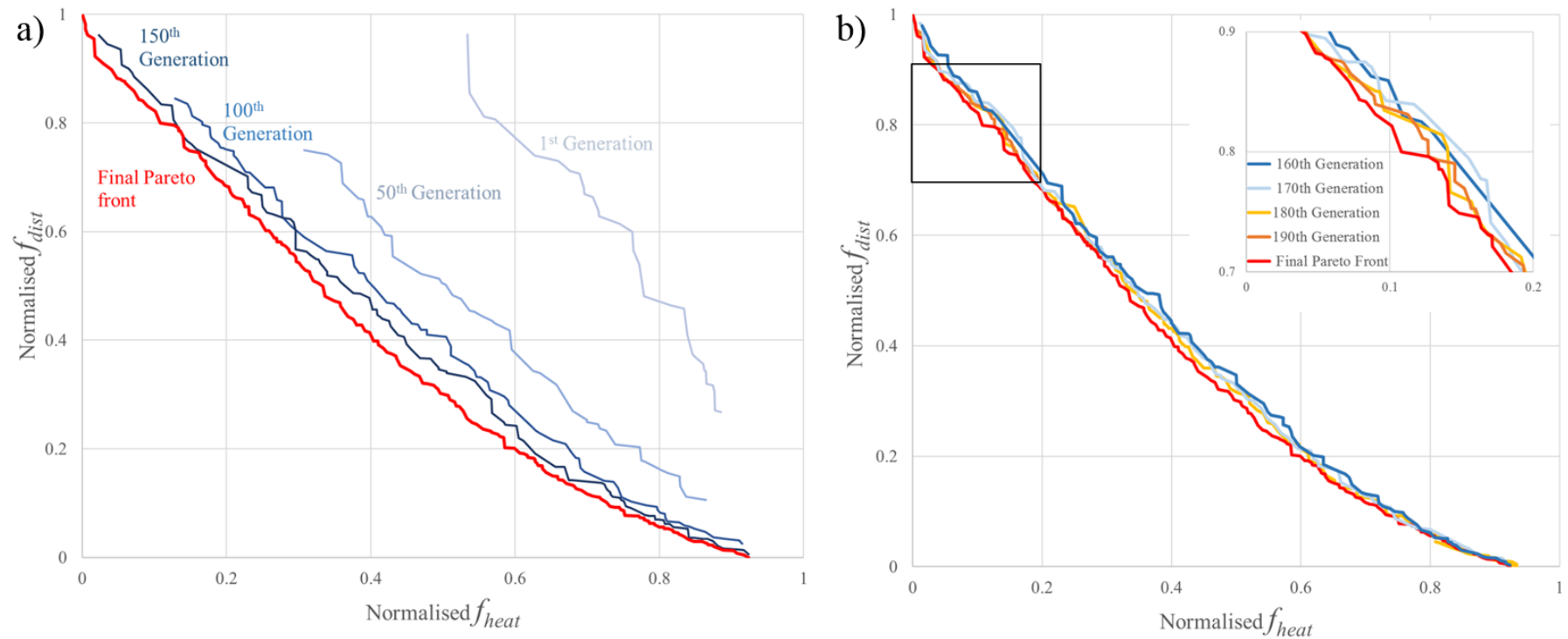


Figure 5.10 Convergence of Pareto front of $offspring_g$ during the Genetic Algorithm search with a) every 50th generation and b) between generations 160-200.

5.5 Middlesbrough Optimisation Results

5.5.1 Pareto-optimal Fronts between Pairwise Sustainability Objectives

Figures 5.11 and 5.12 present the results of the optimization framework using the SA and GA approaches. The figures show the normalized performances of Pareto-optimal fronts against the solutions found by the optimization framework, whilst Tables 5.6 and 5.7 quantify the statistical properties of each Pareto front. In addition Figure 5.11 displays the sub-set of solutions that are optimal for multiple sustainability objectives (MOPO) for the SA approach (they are not shown for the GA results due the quantity (568 MOPOs compared to the SA's 272) which visually obfuscates the Pareto front). The performance of the current development plan (Middlesbrough Council 2010) is highlighted for comparison (yellow triangle) revealing that both approaches are able to discover development strategies which substantially improve upon the proposed spatial plan with regards to the objectives under consideration (discussed further in Section 5.5.7). The periodicity apparent in Figures 5.11 and 5.12 a, d and e is as a result of flood risk being parameterized in three discrete values: 1 in 100 floodplain, 1 in 1000 year floodplain and areas of no flood risk.

The results of both the SA and GA application demonstrate that there is a clear conflict between f_{heat} and both f_{dist} and f_{sprawl} whilst planning new residential development in Middlesbrough. With regards to the SA approach, the best performance for f_{heat} , $\min(f_{heat})$, comes at a compromise of a normalized value of 0.63 for f_{dist} i.e. $\min(f_{heat}) \Rightarrow^6 f_{dist} = 0.63$, and $\min(f_{heat}) \Rightarrow f_{sprawl} = 0.49$. Whilst $\min(f_{dist}) \Rightarrow f_{heat} = 0.59$ and $\min(f_{sprawl}) \Rightarrow f_{heat} = 0.5$. This degree of conflict is also mirrored in the results of the GA application (Figure 5.12b and 5.12c) however it is much more pronounced with 210 and 42 spatial plans in $N_{f_{heat},f_{dist}}$ and $N_{f_{heat},f_{sprawl}}$ respectively compared to 31 and 10 found by the SA approach and the conflict appears more linear. With regards to the results of the GA approach, $\min(f_{heat}) \Rightarrow f_{dist} = 1$ and $\min(f_{heat}) \Rightarrow f_{sprawl} = 1$ demonstrating that the best performance in f_{heat} is found when development is located the furthest possible distance away from the CBD and with 75% of new development outside of the current urban extent. The conflict is intuitive as areas close to the CBD and within the current urban extent have higher population densities, as well as higher than average heat hazard leading to higher heat risk. Alternatively $\min(f_{dist}) \Rightarrow f_{heat} = 0.92$ and $\min(f_{sprawl}) \Rightarrow f_{heat} = 0.65$ shows that the

⁶ The symbol \Rightarrow is used to denote the resulting performance of a spatial plan in an objective.

algorithm is able to strategically locate development close to the CBD and within the urban extent in lower heat risk areas leading to better trade-off compared to the worse development plan for f_{heat} . Therefore it is easier to optimise both f_{sprawl} and f_{dist} with f_{heat} than vice-versa.

The SA approach is able to reconcile optimising f_{flood} and f_{sprawl} , i.e. $\min(f_{flood}, f_{sprawl})$ (therefore the Pareto front isn't visible in Figure 5.11e) as the algorithm strategically locates development within the urban extent which avoids the floodzone. Meanwhile Figure 5.11a and e demonstrate the conflicts found between minimising f_{flood} and f_{heat} as well as f_{dist} . For example $\min(f_{flood}) \Rightarrow f_{heat} = 0.26$ and $\min(f_{heat}) \Rightarrow f_{flood} = 0.46$, whilst $\min(f_{flood}) \Rightarrow f_{dist} = 0.57$. The GA is able to reconcile a spatial plan which is optimal for both f_{sprawl} and f_{flood} , $\min(f_{flood}, f_{sprawl})$, however the conflicts found by the GA between reconciling f_{flood} alongside the other objectives are much less pronounced with $\min(f_{flood}) \Rightarrow f_{heat} = 0.05$, $\min(f_{flood}) \Rightarrow f_{dist} = 0.15$, and $\min(f_{heat}) \Rightarrow f_{flood} = 0.16$. Both approaches are unable to simultaneously entirely reconcile f_{flood} with other objectives due to the presence of several flood zones in close proximity to the CBD and the presence of low population density/ heat hazard areas in the far north and south of the study area.

As the CBD is located within the urban extent it is perhaps surprising that the SA analysis highlight a conflict between f_{dist} and f_{sprawl} , with $\min(f_{sprawl}) \Rightarrow f_{dist} = 0.33$ whilst $\min(f_{dist}) \Rightarrow f_{sprawl} = 0.42$. This is caused by the spatial layout of Middlesbrough, where there are undeveloped areas west of the CBD which are not within the current urban extent. Alternatively the GA is able to reconcile the two objectives, i.e. $\min(f_{dist}, f_{sprawl})$ (see Figure 5.12f) by strategically locating development within the urban extent and within close proximity to the CBD. Based on the convergence (demonstrated by the generated solutions (green crosses)) the objectives are optimized simultaneously during the GA application.

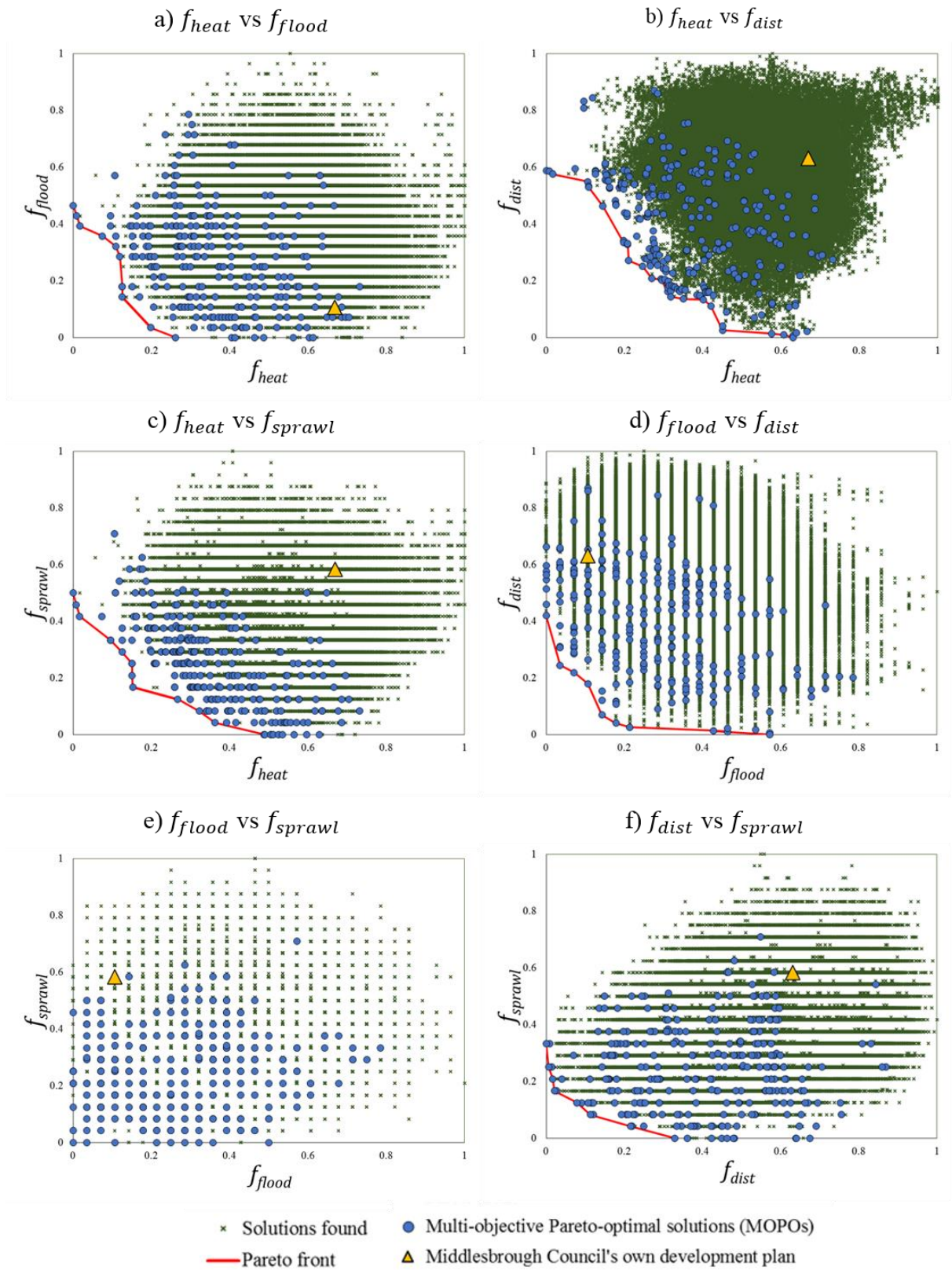


Figure 5.11 Pareto-optimal solutions between sustainability objectives found by the SA approach.

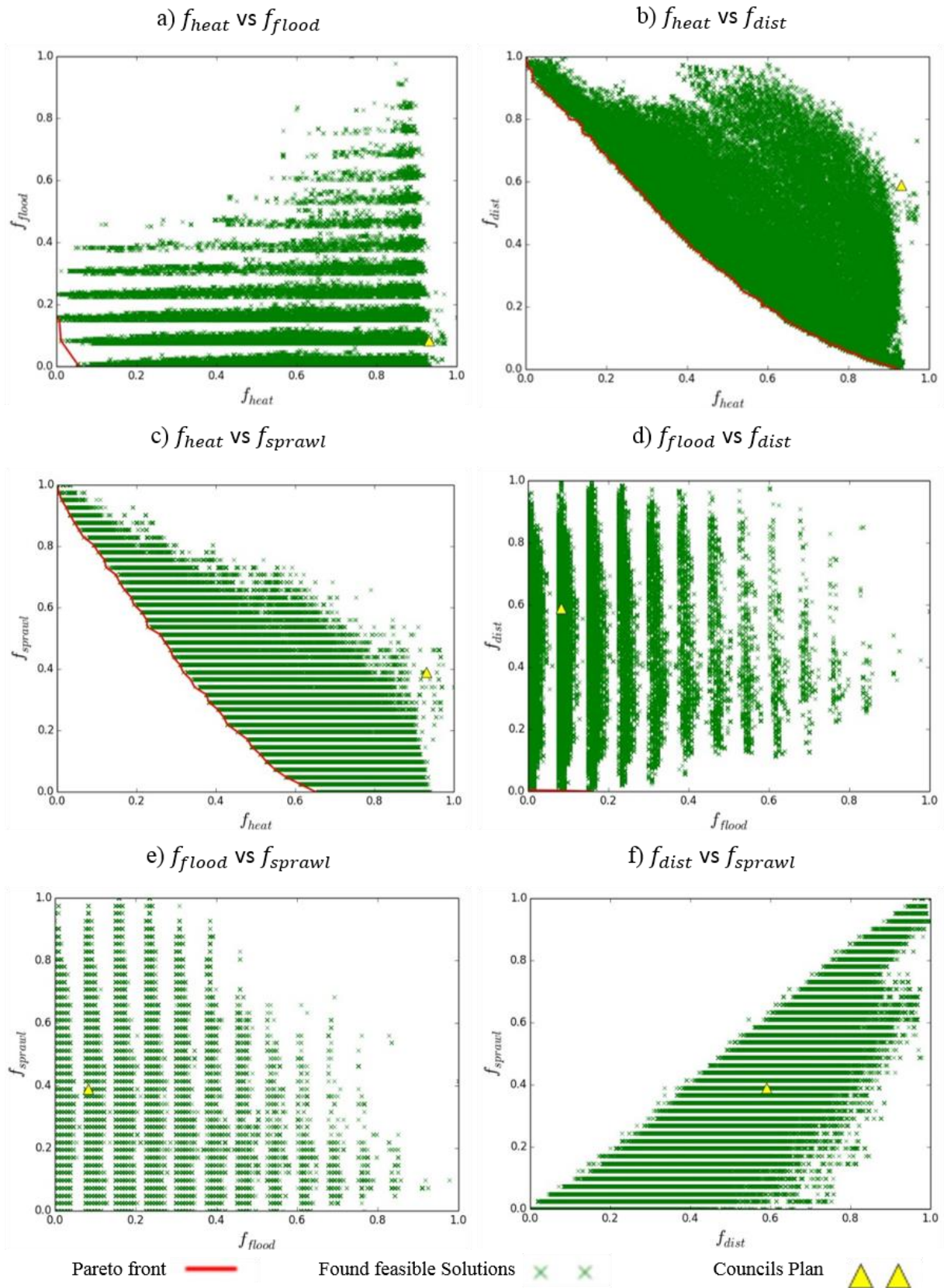


Figure 5.12 Pareto-optimal fronts found between sustainability objectives utilising the GA approach.

Table 5.6 Normalised Pareto front trade-off matrix from SA results (see Figure 5.11).

		Best Trade-off in corresponding objective.			
		f_{heat}	f_{flood}	f_{dist}	f_{sprawl}
Optimised objective: $\min(\cdot)$.	f_{heat}	NA	0.46	0.63	0.49
	f_{flood}	0.26 (10)	NA	0.57	0
	f_{dist}	0.59 (29)	0.42 (10)	NA	0.42
	f_{sprawl}	0.5 (10)	0 (1)	0.33 (8)	NA

(Number of Solutions in Pareto front)

Table 5.7 Normalised Pareto front trade-off matrix from GA results (see Figure 5.12).

		Best Trade-off in corresponding objective.			
		f_{heat}	f_{flood}	f_{dist}	f_{sprawl}
Optimised objective: $\min(\cdot)$.	f_{heat}	NA	0.16	1	1
	f_{flood}	0.05 (5)	NA	0.01	0
	f_{dist}	0.92 (210)	0.16 (4)	NA	0
	f_{sprawl}	0.65 (42)	0 (1)	0 (1)	NA

(Number of Solutions in Pareto front)

5.5.2 Comparison of Pareto front Convergence

Several of conflicts found by both optimization approaches are consistent. However the GA was able to discover a spatial development strategy which is $\min(f_{dist}, f_{sprawl})$ in addition to $\min(f_{flood}, f_{sprawl})$. Figure 5.13 presents a comparison of the resulting Pareto fronts from both approaches, normalised throughout all solutions illustrating the much superior convergence of the GA approach. Table 5.8 quantifies the statistics of each approach's Pareto fronts in comparison to all the solutions found by both approaches.

Figure 5.13a demonstrates the GA approaches' better convergence and its wider spread of solutions (210 compared to SA's 23) on the Pareto front $N_{f_{heat}, f_{dist}}$. In particular the SA performs very poorly in $\min(f_{heat})$ compared to the GA with a normalized value of 0.75 compared to 0. However, the difference in performance is much less for the SA's $\min(f_{dist})$ 0.16 compared to the GA's 0, indicating the SA algorithm is much better at optimising f_{dist} than f_{heat} . Although the GA result for $\min(f_{heat}) \Rightarrow f_{dist} = 1$ compared to the SA's $\min(f_{heat}) \Rightarrow f_{dist} = 0.57$ this comes at the expense of a much improved $\min(f_{heat})$ performance (0 compared to 0.75). Throughout, the GA's Pareto front is much better and has an average 29% improvement in performance.

Likewise, Figure 5.13b also demonstrates the superior convergence of the GA approach with an average 22% improvement in the performances in $N_{f_{heat},f_{sprawl}}$. Although both approaches are able to fully optimize f_{sprawl} , the SA's $\min(f_{sprawl}) \Rightarrow f_{heat} = 0.86$ compares unfavourably to the GA value of $\min(f_{sprawl}) \Rightarrow f_{heat} = 0.65$. This demonstrates that the GA is better able to simultaneously optimise the two objectives by locating development in lower risk areas within the urban extent.

This is shown again in Figures 5.13c and d where although both approaches are able to optimize f_{flood} , the GA is able to achieve a much better performances in corresponding objectives. This is most pronounced in Figure 13c where $\min(f_{flood}) \Rightarrow f_{heat} = 0.82$ for the SA compared to the GA's $\min(f_{flood}) \Rightarrow f_{heat} = 0.05$. As a result the GA's Pareto front is on average 92% better. Although the SA has a better optimal converge on f_{dist} , the GA is able to convergence on both f_{dist} and f_{flood} simultaneously resulting in a 83% average improvement in $N_{f_{flood},f_{dist}}$. Interestingly, in order to fully maximise f_{dist} the GA is forced to place development in the flood zone reducing its performance in f_{flood} to 0.13 and shows the proximity of floodzones to the CBD.

Table 5.8 Comparison of Pareto front statistics between the Genetic Algorithm and Simulated Annealing approach.

Pareto front (Figure)	No. of Pairwise		Minimum value				Maximum value		Overall % Improvement
	Pareto-optimal		(normalized performance)						
	GA	SA	GA	SA	GA	SA			
$N_{f_{heat},f_{dist}}$ (5.13a)	210	33	f_{heat}	1925.7	3586.8 (0.75)	3977.20 (0.92)	4055.3 (0.95)	29%	
			f_{dist}	1005.2	2014.8 (0.16)	7236.1 (1)	4556.6 (0.57)		
$N_{f_{heat},f_{sprawl}}$ (5.13b)	42	10	f_{heat}	1925.7	3586.8 (0.75)	3371.0 (0.65)	3832.9 (0.86)	23%	
			f_{sprawl}	0	0	75.9 (1)	37.7		
$N_{f_{heat},f_{flood}}$ (5.13c)	5	13	f_{heat}	1925.7	3586.8 (0.75)	2040 (0.05)	3754.9 (0.95)	91%	
			f_{flood}	0	0	168 (0.13)	688 (0.53)		
$N_{f_{flood},f_{dist}}$ (5.13d)	4	10	f_{flood}	0	0	168 (0.13)	432 (0.33)	83%	
			f_{dist}	1005.2	2014.8	1051.2 (0.01)	2595.8 (0.26)		
$N_{f_{flood},f_{sprawl}}$	1	1	f_{flood}	0	0	0	0	NA	
			f_{sprawl}	0	0	0	0		
$N_{f_{dist},f_{sprawl}}$	1	8	f_{dist}	1005.2	2014.8 (0.16)	1005.2	2590 (0.27)	NA	
			f_{sprawl}	0	0	0	20.4 (0.27)		

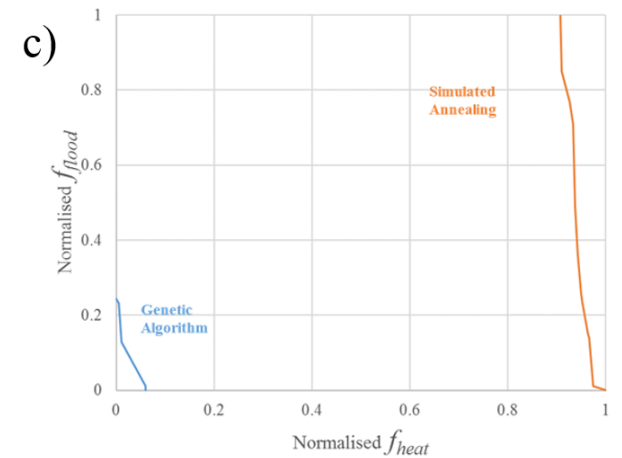
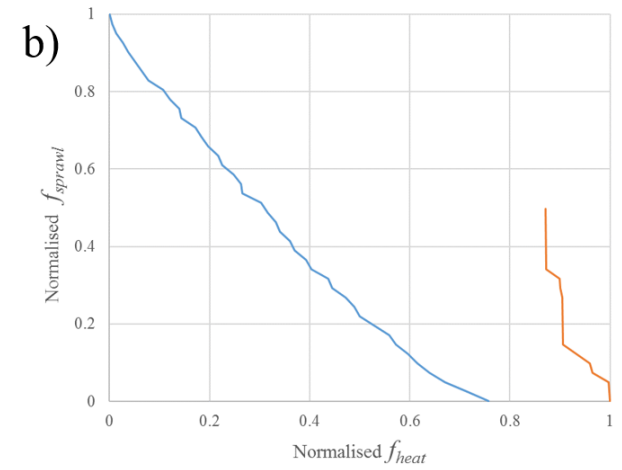
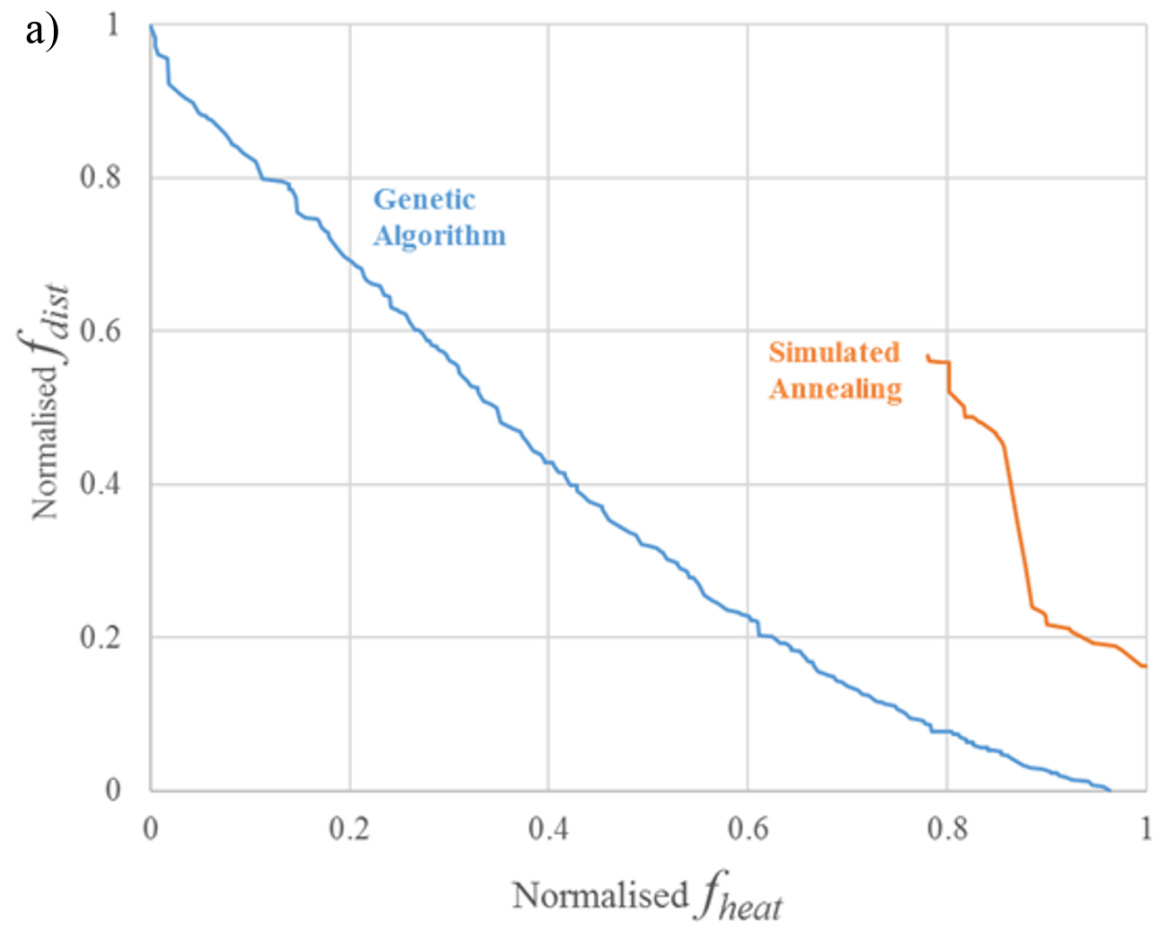


Figure 5.13 Comparison of the Pareto fronts from the GA and SA approaches (normalised through all solutions found).

5.5.3 Pareto-optimal Spatial Configurations

Figure 5.14 and 5.15 show the spatial development strategy of the best performing configurations for each individual sustainability objective in the Pareto-optimal set resulting from the SA and GA runs respectively. In addition Figure 5.16 presents a parallel line plot of their performances against the objectives assessed. Plotting performances in this way allows for simultaneous comparison of performances across the spectrum of objectives. Comparison of the spatial configurations reveals why the performances of the two approaches are so dramatically different. Figures 5.14a and 5.15a demonstrate the spatial plan for $\min(f_{heat})$ for both approaches. The best performance in f_{heat} is achieved at the expense of locating development outside the urban extent and away from the CBD to take advantage of the lower incidence of heat hazard and low vulnerability due to sparse populations. As a consequence their performance in f_{dist} and f_{sprawl} is negatively affected as can be seen in Figure 5.16. This is quite striking with regards to f_{dist} where the performance is 1; the worse possible. Likewise, by locating development in areas that are far outside the currently defined urban extent the solution has a normalised performance of 1 in f_{sprawl} with 76% of proposed development occurring outside the urban extent. The degree to which development is located away from the urbanised centre of the study area varies significantly between the SA and GA. Whilst the SA strategically locates development in low risk areas on the outskirts of the developed area, the GA develops the south east of the study area. This demonstrates spatially the gulf in performance and suggests the SA approach is becoming stuck in local optima and unable to reach the more optimal areas in the far south-east of the study area. The conflicts with f_{flood} occur due to the flood zone coinciding with the low risk areas in the north of the study area (for the SA's spatial plan) and south edge of the study area (for the GA's spatial plan).

Figure 5.14b and 5.15b demonstrate both $\min(f_{flood})$ spatial plans avoid all floodplain development (i.e. $f_{flood} = 0$). Both approaches find several MOPO spatial plans which are $\min(f_{flood})$ (21 by the SA and 11 by the GA) and are able to find plans which are $\min(f_{flood}, f_{sprawl})$ (shown in Figure 5.14b and 5.15b). However Figure 5.16 demonstrates the plan $\min(f_{flood}, f_{sprawl})$ found by the GA outperforms the equivalent plan found by the SA in the other objectives.

Both $\min(f_{dist})$ spatial plans concentrate development predominantly in close proximity to the CBD (Figure 5.14c and 5.15c) resulting in a poor performance in f_{heat} (see Figure 5.16).

However, in comparison the SA's spatial plan is less compact with development occurring along transport routes further from the CBD. This results in the worse performance in f_{dist} compared to the GA's plan and causes a negative effect in f_{sprawl} . The spatial allocation of development questions the ability of the SA to converge all the development sites within optimal locations. Lastly the poor performance of $\min(f_{dist})$ in f_{flood} for the GA application is due to locating three of the 54 proposed development sites in flood zones (one in $Z_{i,j}^{1000}$ and two in $Z_{i,j}^{100}$) to ensure all development is as close as possible to the CBD.

Both approaches identify several spatial plans which are $\min(f_{sprawl})$. Figure 5.14d and 15d demonstrate the spatial plan $\min(f_{sprawl}) \in N_{f_{heat}, f_{sprawl}}$ from the SA and GA approaches respectively. Interestingly in order to reconcile $\min(f_{sprawl})$ with $f_{heat} = 0.63$ the spatial plan in Figure 15d develops the north of the study area which is within the urban extent but also corresponds with lower heat risk, demonstrating a spatial trade-off location. As a result the spatial configuration is able to achieve a performance in f_{heat} of 0.65. Whilst in Figure 5.14d the spatial plan $\min(f_{sprawl})$ found by the SA achieves $f_{heat} = 0.82$ as it less successfully to locate development in lower risk areas within the urban extent, in this case the south east of the study area. Overall the resulting spatial plans offer an interesting perspective on the difference in performance of the optimisation approaches. Specifically, they show that the SA falls into local optima and it is poor at converging on spatial plans in optimal areas, especially for f_{heat} .

Figure 5.17 presents the ranked Pareto-optimal locations of sites designated by the MOPO solutions from a) the SA approach and b) the GA approach. This highlights spatial locations in the study area which are more suitable for development. Areas consistently spatially assigned by the MOPO solutions include the north and north west of the study area due to the proximity of the CBD and lower heat risk whilst there are strategic areas away from floodzones. Moreover there is a consistent assignment of sites in areas of the south east and south central of the study area which are within the urban extent whilst retaining a lower than average heat risk. The areas with the highest rank are within the far north of study area as well as central north due to the strategic areas which balance all of the objectives. Significantly the GA Pareto locations are more spatially concentrated/clustered in the north of the study area, while the SA Pareto locations are more spread out suggesting the SA wasn't as able to converge on optimal areas. This demonstrates why the GA performs better as development has escaped areas that are local optimum in the east and north central parts of the study area.

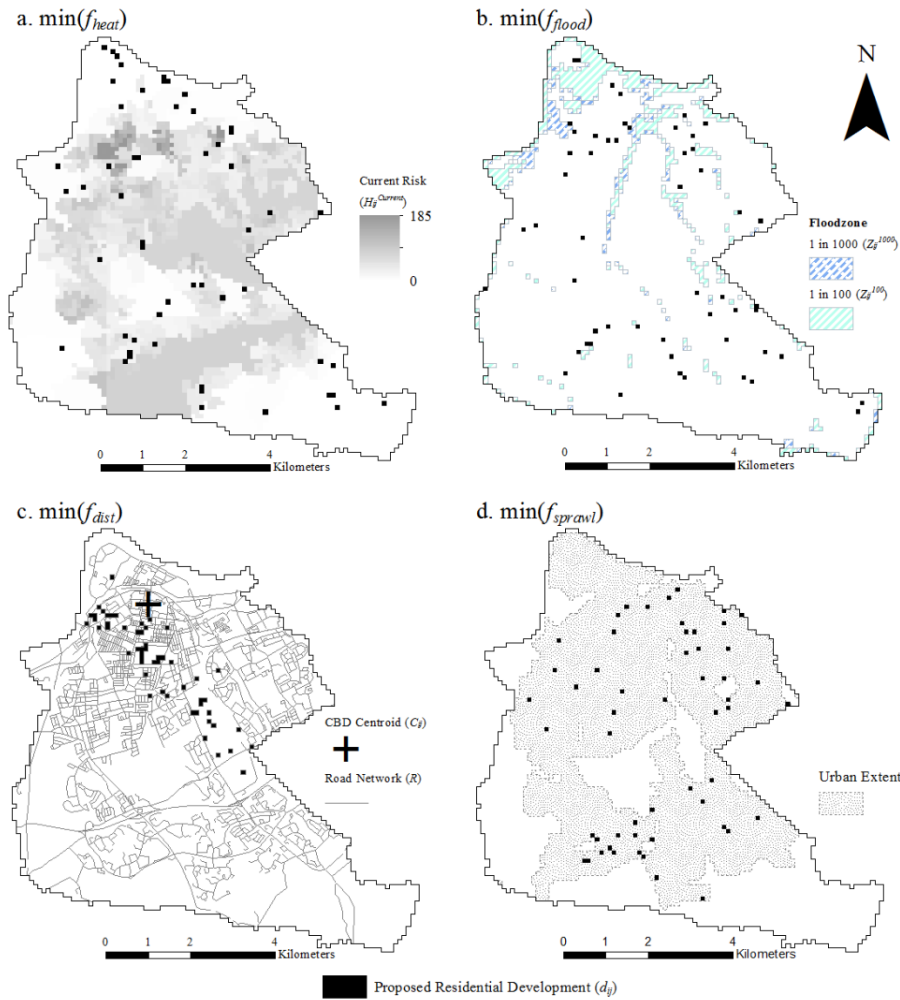


Figure 5.14 Best performing spatial configurations resulting from the SA investigation for a) $\min(f_{heat})$, b) $\min(f_{flood}, f_{sprawl})$, c) $\min(f_{dist})$ and d) $\min(f_{sprawl}, \in N_{f_{heat}, f_{sprawl}})$.

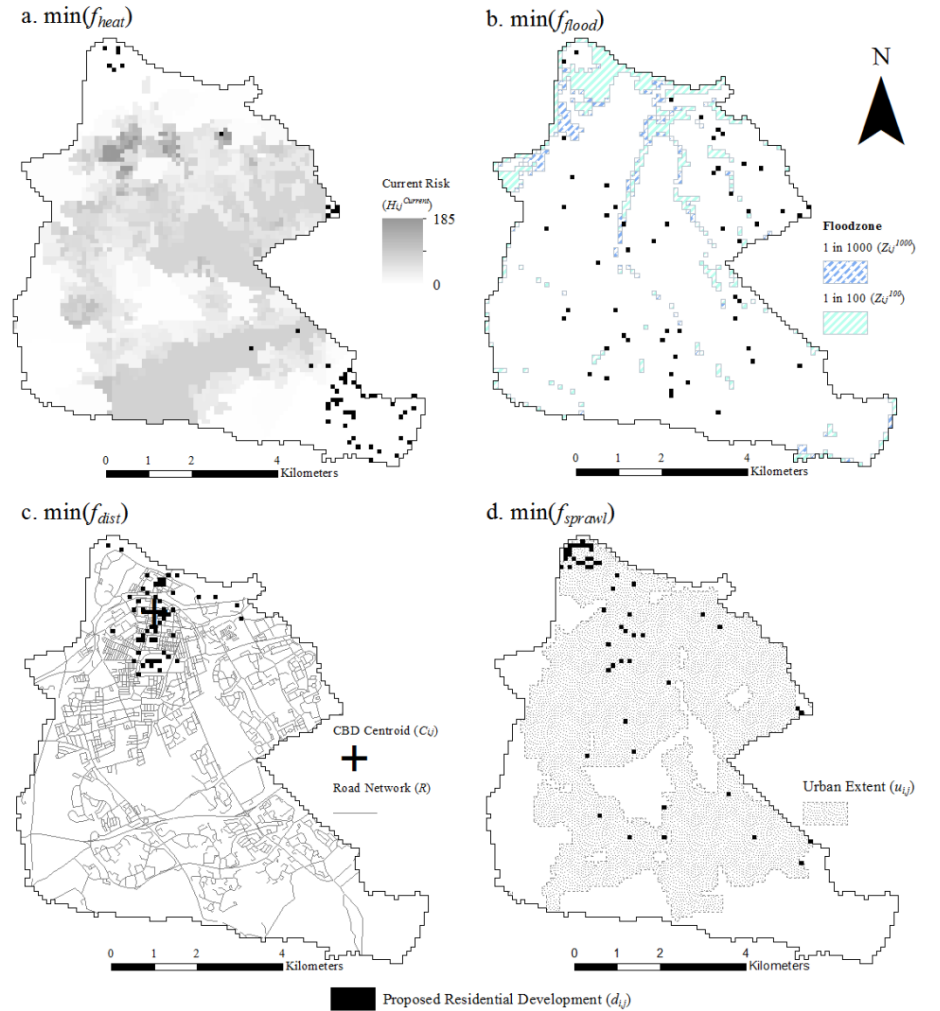


Figure 5.15 Best performing spatial configurations resulting from the GA investigation for a) $\min(f_{heat})$, b) $\min(f_{flood}, f_{sprawl})$, c) $\min(f_{dist})$ and d) $\min(f_{sprawl}, \in N_{f_{heat}, f_{sprawl}})$.

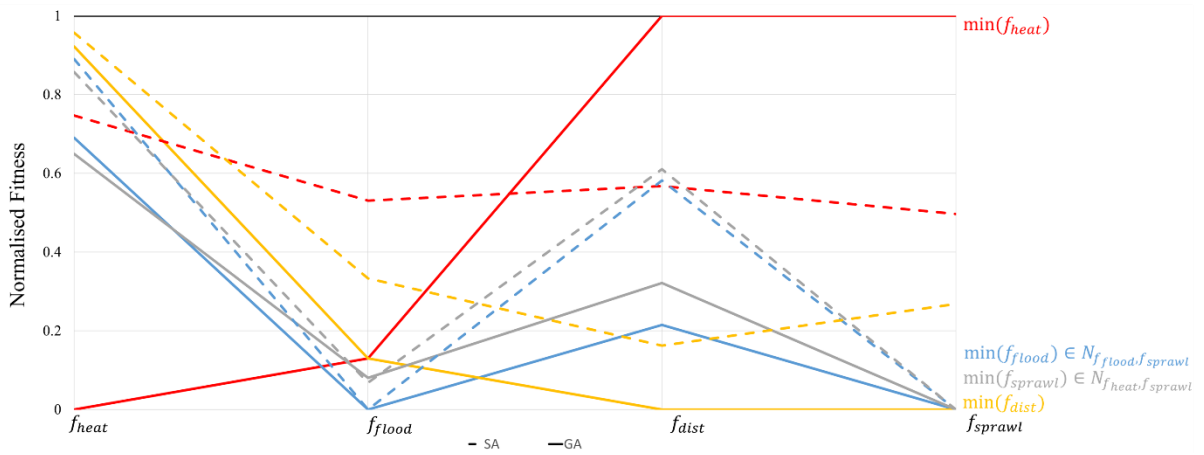


Figure 5.16 Parallel line plots of best performing Pareto-optimal spatial plans from the SA (hatched) and GA investigation (Figure 5.14 and 5.15) normalised throughout the solutions found.

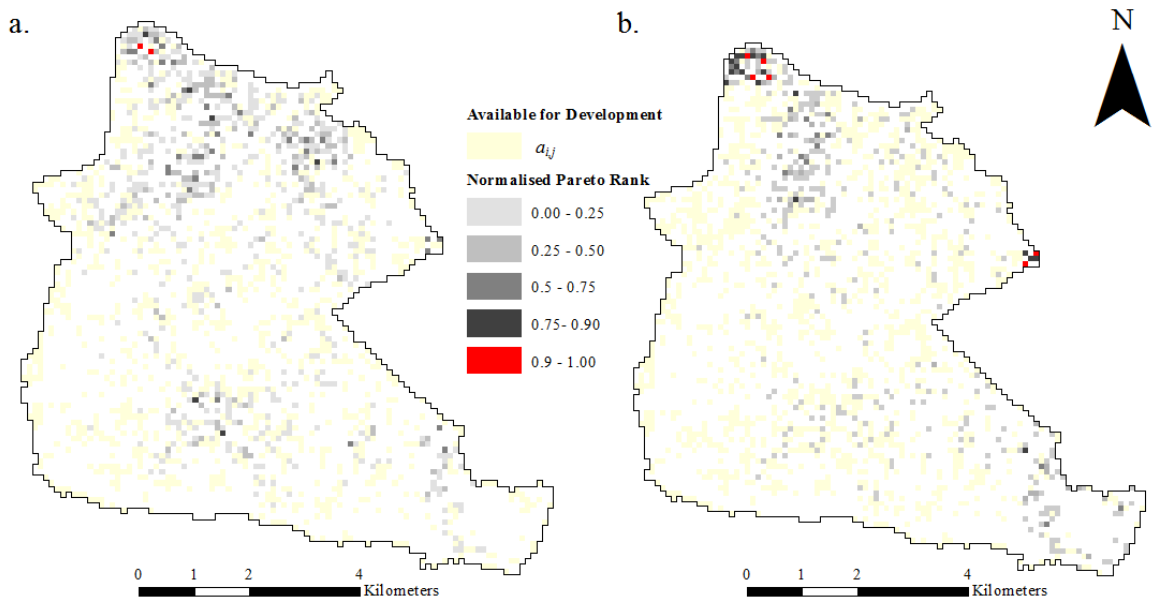


Figure 5.17 Spatial frequency of site assignment based on the resulting MOPO solution from a) the SA investigation and b) the GA investigation.

5.5.4 Multi-objective Pareto-optimal Solutions

Figure 5.18 shows a parallel line plot demonstrating the range of Multi-objective Pareto-optimal (MOPO) solutions resulting from the GA application across the four sustainability objectives normalised with respect to all the solutions found by both approaches. Altogether the GA discovers 568 MOPO spatial plans whose performances range from 0 through to close to 1 for the objectives f_{heat} , f_{dist} and f_{sprawl} . The framework is able to ensure MOPO spatial plans that perform well for f_{flood} (normalized performance of less than 0.4) as the algorithm was able to reconcile locations for development outside of floodzone with the other objectives.

The best un-weighted Pareto-optimal solution (presented in Fig 5.22b) is plotted to provide a comparison to see how an unbiased Pareto-optimal plan performs. Notably it performs poorly in f_{heat} due to it performing well in both f_{dist} and f_{sprawl} . Despite being the best unweighted solution, inspection reveals that it is out performed in at least one objective by all of the other many objective Pareto-optimal solutions.

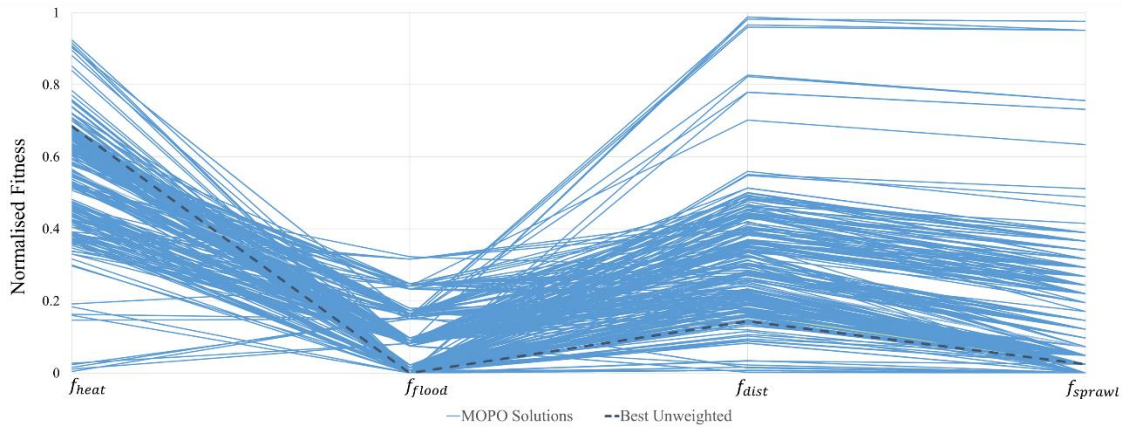


Figure 5.18 Parallel Line plots of the normalized objective score of the MOPO solutions ($F = \{f_{heat}, f_{flood}, f_{dist}, f_{sprawl}\}$) against the best performing un-weighted Pareto-optimal solution.

5.5.5 Findings for Middlesbrough

Having established that the GA provides the best performing optimal spatial configurations the conflicts found by the application are examined closer. Overall, whilst the Multi-Objective Spatial Optimisation Framework is able to successfully develop spatial plans which reconcile the objectives under investigation, significant conflicts exist between f_{heat} and both f_{dist} and f_{sprawl} . Figure 5.19 presents a series of spatial configurations which lie on the Pareto front between f_{heat} and f_{dist} , $N_{f_{heat}, f_{dist}}$. In particular it presents the spatial plans which are $\min(f_{heat})$, $\min(f_{dist})$ and the median of the set $N_{f_{heat}, f_{dist}}$. It demonstrates how significantly different the spatial strategies for $\min(f_{heat})$ and $\min(f_{dist})$ are with the former predominantly developing the far south east of the study area whilst the latter develops close to the CBD. However interestingly the median solution develops large amounts of land in the north of the study area. This corresponds with the spatial pattern identified in the density matrix presented in Figure 5.17. Figure 5.20 shows how these spatial plans perform across the range of objectives. The median spatial configuration performs relatively well across the objectives and is able to improve performance in f_{dist} from $\min(f_{heat})$ from a normalised performance of 1 to 0.37,

whilst improve the performance in f_{heat} in $\min(f_{dist})$ to 0.45 from 0.96. This demonstrates that although the planning dispute is severe, the possibility to develop the north of the study area allows for a reasonable trade-off between the two objectives. Notably all three spatial plans conflict with f_{flood} due to the presence of flood zones in low heat hazard areas and in proximity to the CBD however they are all able to reconcile $\Rightarrow f_{flood} < 0.2$.

Figure 5.21 presents a density matrix of the spatial configurations within the Pareto front, $N_{f_{heat},f_{sprawl}}$ showing cells that are assigned to 20 or more times demonstrating a series of sites which are attributed to consistently by the spatial configurations within $N_{f_{heat},f_{sprawl}}$. These are highlighted in red and have a significant presence in the north and far east of the study area. Interestingly these areas coincide with Pareto-optimal spatial locations (Figure 5.17) due to the correlation between f_{sprawl} and f_{dist} . This demonstrates the best trade-off areas that balance the need to minimise heat risk whilst not significantly extending the extent of the urban area or increasing the distance to employment and service areas. Although there are areas developed in the far south east of the study area, due to their lower flood and heat risk which appear but these attributed to $< 50\%$ of the spatial plans because they perform poorly in f_{dist} .

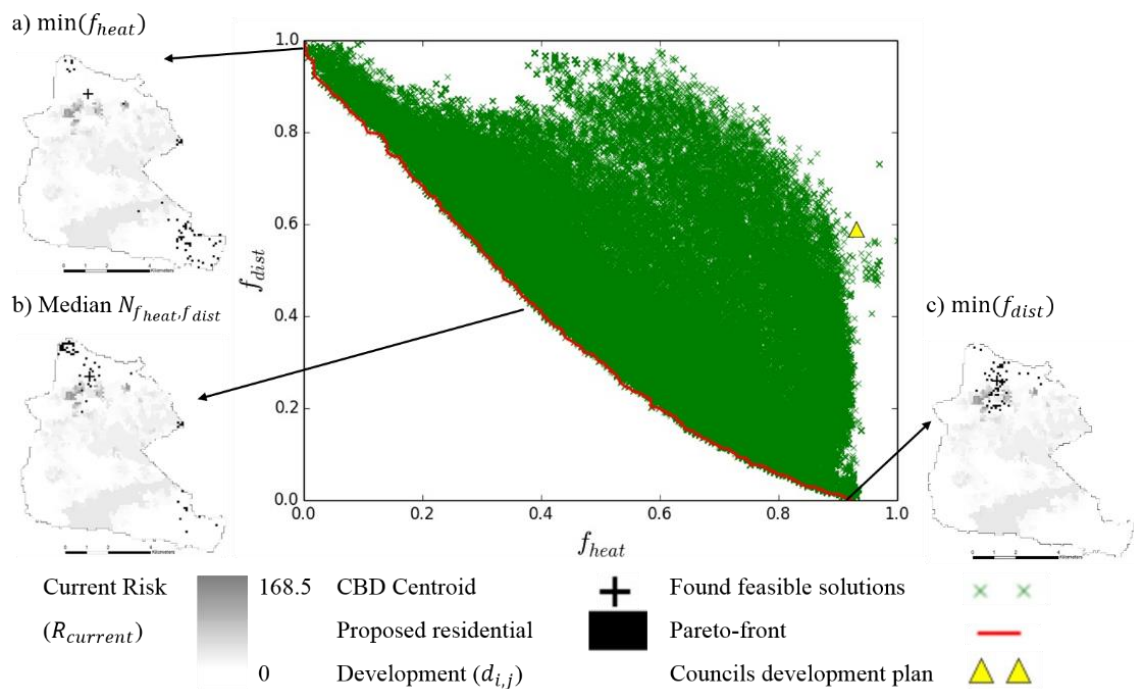


Figure 5.19 Pareto optimal spatial configurations within $N_{f_{heat},f_{dist}}$.

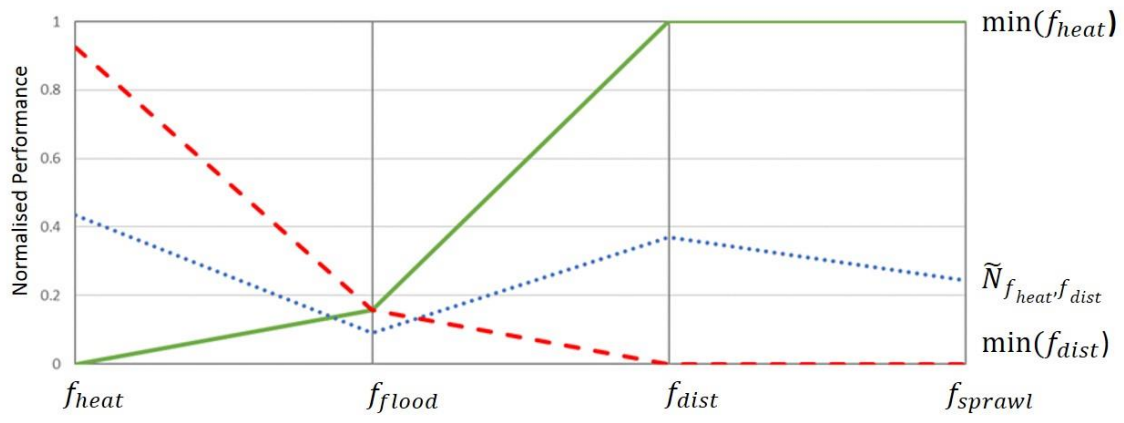


Figure 5.20 Parallel line plots of Pareto-optimal spatial configurations in $N_{f_{heat}, f_{dist}}$.

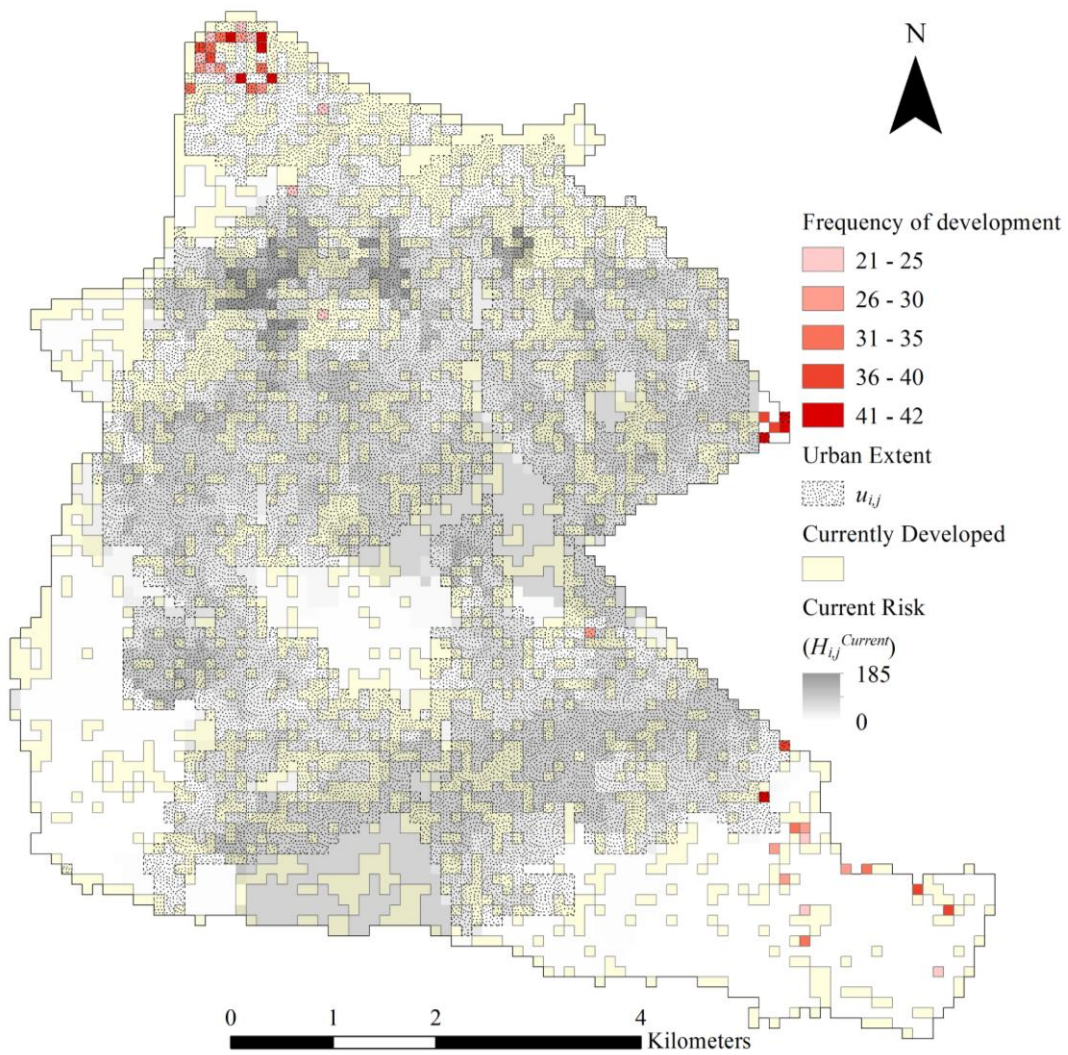


Figure 5.21 Density matrix for spatial configurations within $N_{f_{heat}, f_{dist}}$.

5.5.6 Comparison to Middleborough's Current Development Plan

In Figures 5.11 and 5.12 the current development plan performs significantly worse than the best trade-off curve for both the SA and GA approaches. Figure 5.22 presents a spatial comparison of the council's currently planned spatial strategy for residential and economic development with the best unweighted Pareto-optimal spatial plans found by both approaches. Table 5.9 quantifies the difference in performance of the current development proposal against the optimized solutions. It demonstrates that the multi-objective spatial optimization framework is able to identify spatial strategies that are far superior to the Middleborough plan.

The selected optimized spatial plans outperform the council's development strategy in all objectives. For example the best unweighted spatial configurations from both approaches are able to improve accessibility by 71% and 40% (the GA and SA plans respectively), as development is located in close proximity to the town center whilst simultaneously eradicating flood risk. Furthermore, close to 100% of the potential spatial plans found during the GA search outperform the council's development plan with regards to minimizing in f_{heat} . This is due to the majority of resulting spatial plans avoiding the area to just west of the center of the study area where the councils proposed development areas coincide with a higher heat hazard value and higher population vulnerability.

Of all the feasible plans found by the GA, 71.7% and 67.8% outperform the current plan in f_{dist} and f_{sprawl} respectively, as development is more strategically located on transport routes within the current urban extent. Significantly, the Middlesbrough plan proposes to develop 24 ha of designated greenspace, whilst all the optimised spatial plans could not utilise these spaces as they formed a spatial constraint layer.

a) Middlesbrough Council's own development plan (Middlesbrough Council 2013b) b) Best unweighted GA Pareto-optimal spatial plan c) Best unweighted SA Pareto-optimal spatial plan

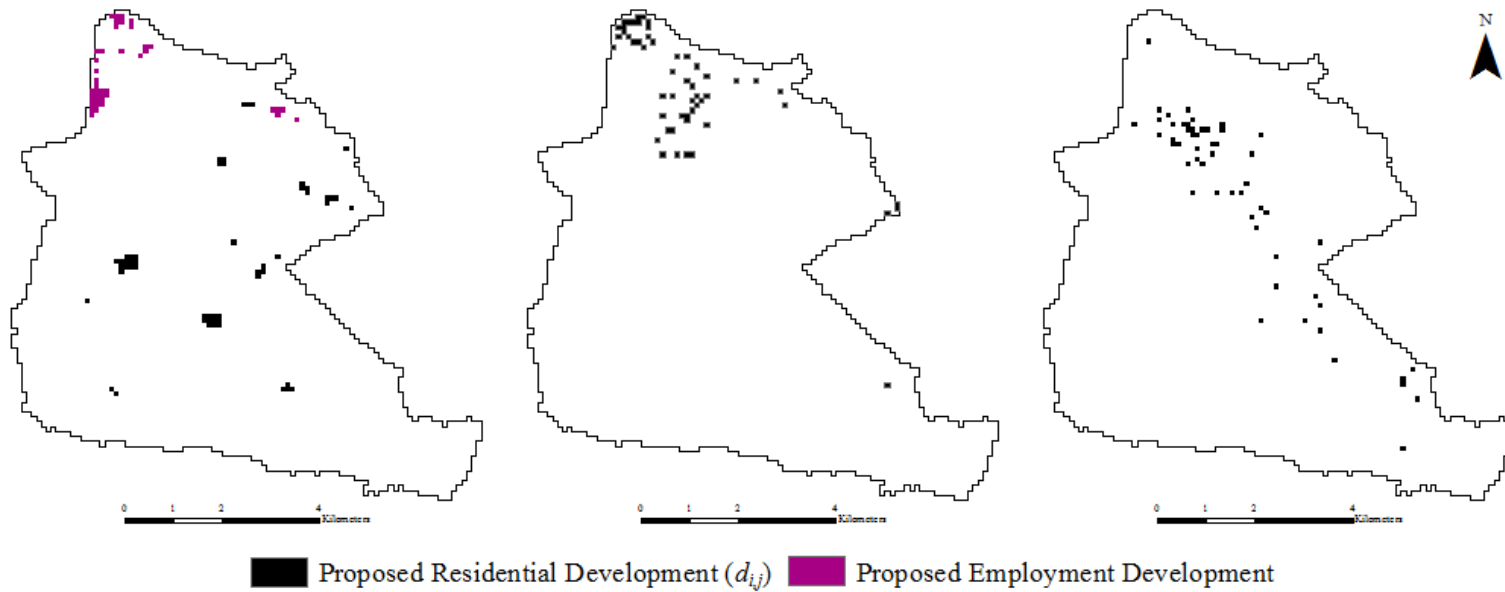


Figure 5.22 Comparison of a) Middlesbrough's current spatial plan and Pareto-optimal spatial configurations selected on the basis of equal priorities for b) the GA run and c) the SA run.

Table 5.9 Performance of the best un-weighted Pareto-optimal result (Figure 5.22) against Middlesbrough Council's development plan.

	Middlesbrough Development Plan (5.22a)	Genetic Algorithm Approach			Simulated Annealing Approach		
			(Figure 5.22b)	% of found spatial plans	(Figure 5.22c)	% of found spatial plans	
	Fitness	Fitness	% improvement	which outperform	Fitness	% improvement	which outperform
f_{heat}	3991.8	3445.1	14%	100%	3754.9	6	85
f_{flood}	88.0	0	100%	55.3%	0	100%	0
f_{dist}	4679.3	1899.7	59.4%	71.7%	2633.5	44	68
f_{sprawl}	29.6	1.9	93.7%	67.8%	7.4	75	88
Green space	24ha	0	(NA)	100%	0	Na	100

5.5.7 Post Pareto Analysis

A frequent criticism of the Pareto-optimisation approach is that high number of resulting Pareto-optimal results place a heavy cognitive burden on decision makers (Xiao et al. 2007). Although the Pareto fronts clearly illustrate the conflicts and associated trade-offs of different spatial strategies final decisions needs to be taken on the basis of priorities. Deb (2001) describes the strategy of using Pareto-optimisation to elicit a series of Pareto-optimal solutions before the final solution is chosen based on higher-level knowledge (ideally influenced by the results of the Pareto-optimal analysis). To test this a series of weighting systems were derived and applied to the MOPO set to aid digestion of the results:

1. **Risk heavily prioritised:** The local authority prioritises reducing the risk of hazard events to the future population whilst not concentrating on mitigation efforts.
2. **Risk marginally prioritised:** The two risk objectives are still prioritised but the priority isn't as pronounced and more emphasis on mitigation is made.
3. **Equal Priorities:** To investigate which plan is most optimal in the absence of any preference.
4. **Mitigation marginally prioritised:** Due to small likelihood of hazards over the Middlesbrough area, the local authority decides to concentrate efforts on energy mitigation.
5. **Mitigation heavily prioritised:** Decision makers decide to heavily emphasise the pursuit of energy mitigation over the risk based objectives.

These scenarios were used to develop a series of preference vectors outlined in Table 5.10 (each set of preference vectors sum to 1 following Eastman (1999)). These were applied posteriorly to the normalised performances of the MOPO solutions using Equation 5.2 to calculate a composite function, F^w , based the normalised objective functions of each solution in the MOPO set, f^{norm} , and the objective functions weight, w_f :

$$F^w = (w_{heat} * f_{heat}^{norm}) + (w_{flood} * f_{flood}^{norm}) + (w_{dist} * f_{dist}^{norm}) + (w_{sprawl} * f_{sprawl}^{norm}) \quad (5.2)$$

The composite function is calculated for all solutions before the solution which is $\min(F^w)$ is extracted. Figure 5.23 shows the performance of the derived spatial plans across the range of sustainability objectives whilst Figure 5.24 demonstrates their spatial configurations. Notably

Figure 5.23 shows that all of the prioritised Pareto-optimal spatial plans perform very well in minimising f_{flood} reiterating its correspondence with the other objectives. Moreover spatial plans for scenario 2 and 3 in Figure 5.24b and c heavily develop the north of the study as it is a trade-off location (as demonstrated by the density matrix in Figure 5.17). A significant weakness of this approach is that the weights don't sufficient reflect the conflicts resulting in poor performance in f_{heat} ; spatial plan which is b) Risk Marginally Prioritised $\Rightarrow f_{heat} = 0.4$. This is a result of the conflict with the remaining objectives. Therefore an improved weighting system requires a more intuitive calculation which takes into account conflicts between objectives. In further applications a more advanced multi-criteria decision assessment method should be used.

Table 5.10 Preference vectors for prioritised spatial plans.

Scenarios	Preference Vectors			
	w_{heat}	w_{flood}	w_{dist}	w_{sprawl}
a) Risk Heavily Prioritised	0.4	0.4	0.1	0.1
b) Risk Marginally Prioritised	0.35	0.35	0.15	0.15
c) Equal Priorities	0.25	0.25	0.25	0.25
d) Mitigation Marginally Prioritised	0.15	0.15	0.35	0.35
e) Mitigation Heavily Prioritised	0.1	0.1	0.4	0.4

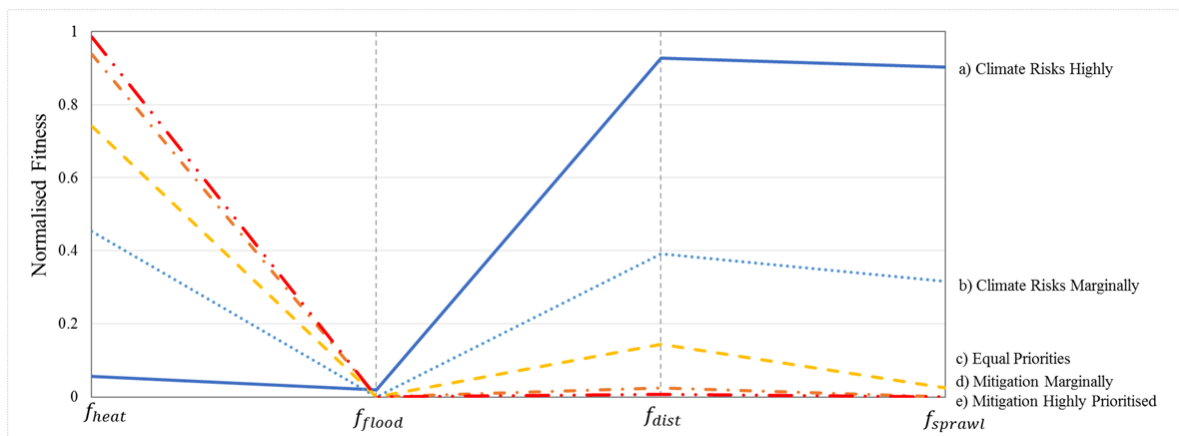


Figure 5.23 Parallel line plot of the prioritised Pareto-optimal spatial configurations.

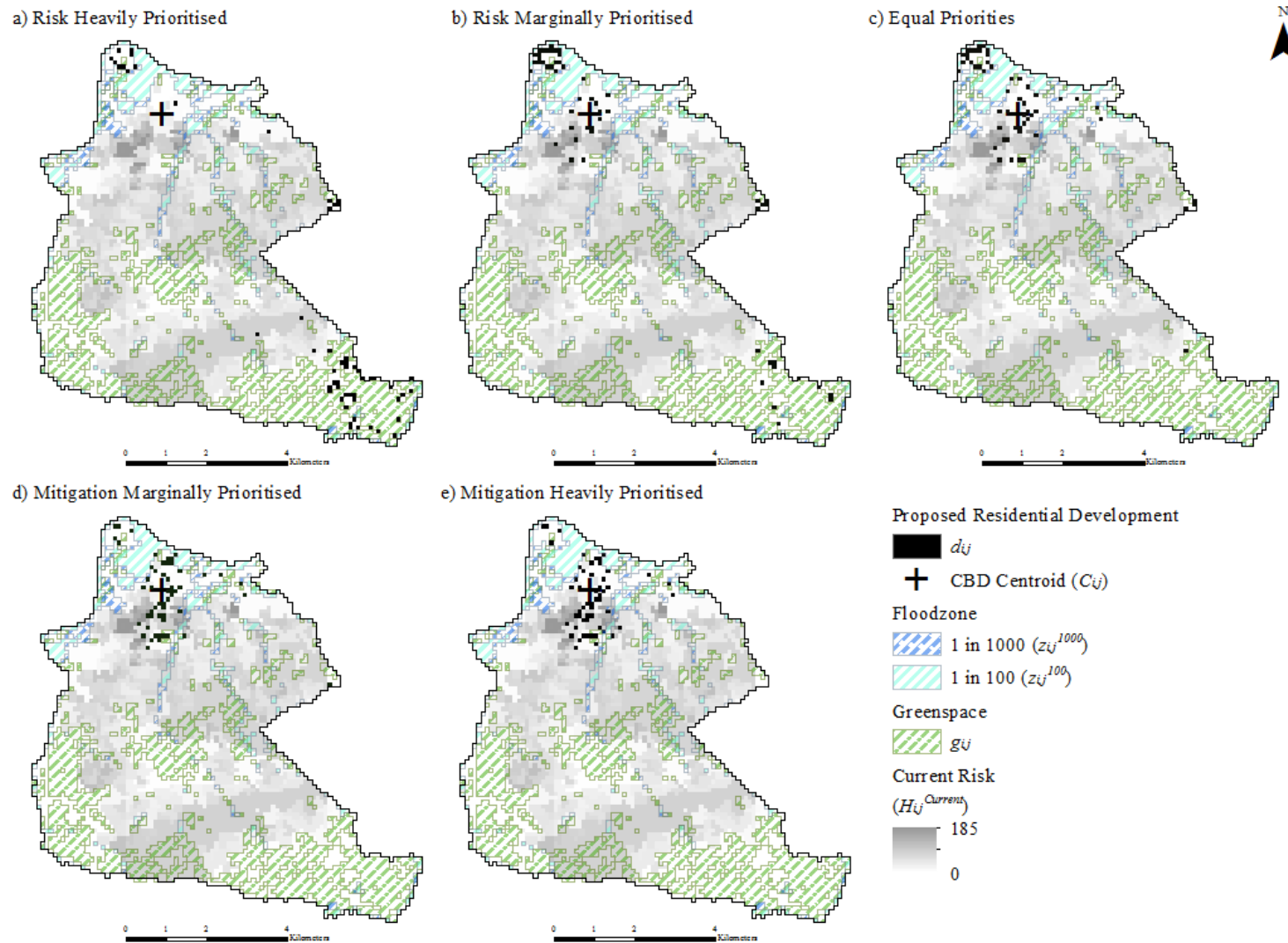


Figure 5.24 Prioritised Pareto-optimal spatial configurations.

5.6 Discussion and Recommendations

In this section we discuss the performance of the MOSPOF methodology, including the performance of the two optimisation approaches before outlining a series of recommendations for the framework to handle a more complex and larger spatial planning problem.

5.6.1 Performance of the Optimisation Approaches

The results of the spatial optimisation framework are greatly improved when utilising the GA approach compared the SA approach. From exploring the results there are several reasons the approach is superior. A significant difference is the GAs uses of a series of modifiable solutions which are simultaneously explored allowing for improved pursuit of a range of Pareto-optimal spatial plans. This can be seen by the 6.4 and 4 times as many Pareto-optimal spatial plans found for $N_{f_{heat},f_{dist}}$ and $N_{f_{heat},f_{sprawl}}$. On the other hand the SA's singular modifiable spatial configuration is hampered by the competing objectives and doesn't allow for investigations of radically different spatial configurations of development. This can be seen in the spatial configurations for $\min(f_{heat})$ where development hasn't reached the most optimal areas for development in the far south east of the study area because of the need to reconcile a single spatial configuration against a number of competing objectives simultaneously. Moreover the results demonstrates that the modifications to SA by Nam & Park (2000) wasn't sufficient to facilitate Pareto-optimisation which competes with GA for this planning application.

There are several ways this could be addressed including systematically adjusting the associated parameters for the calculating the difference between fitnesses, therefore assigning a proportion of the processing time to optimising objectives individually. However, by doing this there is the potential for the MOSPOF to overlook important solutions especially when the Pareto front is concave and results in a discontinuous Pareto front (Xiao et al. 2007). Other methods include the approach taken by (Czyzzak & Jaszkiwicz 1998) who's study coupled Simulated Annealing with the use of a set of interchangeable solutions. These sets of solutions would occupy the current solution variable in the approach used in this chapter. However this would require a significant redevelopment of the MOSPOF.

One of the few strengths of the SA approach over the GA is the more straight forward application of the optimization algorithm. Whilst the SA was developed fully in-house while the GA uses third-party modules to handle its operators. Due to this and the simpler SA algorithm, the search is more easily controlled particularly with respect to ensuring any spatial constraints are accounted for such as currently developed areas. Alternatively the GA approach required more technical modules and innovation to handle the constraints on the search is more dynamic. However this is negated by the difficulties in selecting the search parameters for the SA as can be seen in Section 5.4.1. Both optimisation approaches suffer from uncertainty over in the selection of parameters for the search. However the GA was much less sensitive to these and was able to determine optimal spatial configurations from random initial spatial plans, whilst the SA required a reliable initial spatial configuration. The GA's evolutionary operators move towards optimal spatial configurations in a more intuitive way by recombining/ splicing spatial plans which are found to be superior resulting in a much faster convergence than the SA approach. Meanwhile the SA makes small minor changes which are at first completely random. As the Pareto-optimal spatial plans demonstrate, it is clear that the SA is failing to find globally optimum spatial locations and is instead becoming stuck in local optima. This is compounded as the allowance of moving through inferior solutions needs to be carefully controlled so it's not too extensive (as found in Figure 5.8a) whilst allowing for a wide enough search. This was demonstrated in Section 5.4.1 were increases to the initial temperature variable results in poorer convergence. The sensitivity of the input parameters is a major weakness of this approach.

To improve this the SA search could be streamlined by incorporating a Tabu search approach to prevent the reassessment of recently assessed spatial configurations (Glover & McMillan 1986). Although this exhaustive search might be satisfactory over a small-to-medium spatial scale such as Middlesbrough, more complex objectives (multiple integer values for example) or larger spatial extents will increase computational intensity exponentially (Xiao et al. 2007). This also questions whether such a sequential exploration of the search space is efficient for larger applications. Sources who have utilised SA have concede that faster search algorithms will return optimal solutions in a much faster time (Delmelle et al. 2012). However several have commented on its applicability to carry out localised searches in conjunction with other approaches such as GAs (Sidiropoulos & Fotakis 2011). Some of the problems encountered might not be encountered in the literature as a number of applications utilise synthetic grids where the solutions are relatively linear whilst the complexities of real world problems might make it too unsuitable. Indeed Aerts & Heuvelink (2002) found that when they increased the

size of the grid it vastly increased the processing time. This mirrors experience in this work when moving from smaller synthetic datasets to real data applications such as the Middleborough case study.

5.6.2 Effectiveness of the Pareto Optimisation Approach

The extraction of Pareto-optimal sets of solutions demonstrates the best-trade-offs achievable between sustainability objectives. By visualising these Pareto fronts it provides a valuable demonstration of the inherent conflicts between achieving sustainability objectives whilst the quantitative summation of the Pareto sets provides useful knowledge of the conflicts.

A major strength of this is that it provide planners with wide variety of alternative spatial plans to choose from with knowledge of the trade-offs necessary to reach certain performances. However with regards to utilisation of the framework to aid the spatial planning decisions, as section 5.5.7 discusses the large number of Pareto-optimal configurations found suggest it would place a substantial cognitive burden on decision makers. This is true with the application covered in this chapter with the GA approach identifying 568 MOPO spatial plans for a relatively small urban extent. Section 5.5.8 tests the simple application of preference vectors to elicit prioritised spatial plans but it falls foul of the conflicts between f_{heat} and the rest of the objectives due to their conflict. This proves the utility of the PO approach as using a weighted sum approach in the absence of knowledge of the conflicts would produce solutions which fail to reflect the priorities of the decision maker. For the utility of eliciting final solutions from the MOPO set a more intuitive method is needed which utilises the diagnostic information of the conflicts and better interprets planner's preferences. Potential applications include the use of fuzzy reasoning (Vamvakeridou-Lyroudia et al. 2005) or analytical hierarchy process (Saaty 2008) to generate more intuitive preference vectors

5.6.3 Spatial Planning Problem Representation

In terms of the definition of the spatial planning problem presented the application is restricted by only considering a set number of homogenous residential developments. When in reality development often differs in density depending on its location (higher density closer to transport links, lower density in the suburbs). Therefore to better represent the spatial planning problem it would be valuable to test the inclusion of different densities of development. This also lets us assess the amount of land needed to meet certain objectives and further examine the effects

development densities have on the ability to achieve objectives. This would further enhance the uniqueness of the approach as no previous applications of optimisation in the literature distinguishes between different densities of residential development. This isn't possible under the current methodology of a fixed list representation of development sites, as variable densities would require fluctuating number of development sites to fulfil a target number of dwellings. Options include variable length representations or a partial move back to grid based representations.

5.7 Summary

This chapter demonstrates the utility of a Multi-Objective Spatial Optimisation Framework for a real world planning problem of preparing spatial plans of residential development for a local authority. The framework was successfully able to recognize potential development patterns that are potentially more sustainable than those planned whilst the diagnostic information contained within the results provides an evidence basis to assist planners and decision makers to better meet sustainability objectives and achieve broader sustainable patterns of development. Overall the results demonstrate the possibilities of spatial optimisation to contribute to sustainable spatial planning.

Two optimisation approaches are assessed for their suitability for inclusion in the spatial optimisation framework. Crucially, both are able to improve upon the currently planned situation however the GA approach is found to be superior with better convergence on the Pareto front (demonstrated by its ability to reconcile f_{dist} and f_{sprawl}) and results in a wider spread of spatial plans across the front. SA is rejected as the main methodology for further optimisation framework as the case study identified several weaknesses such as it being computationally exhaustive and it being highly dependent on the initial parameters. Significantly the chapter sets out a series of recommendations based on the results of the case study for an improved spatial optimisation framework including increased complexity, with further variables related to development density for example, and further objectives to optimise.

Chapter 6 Large Urban Case Study- London

6.1 Introduction

This chapter describes an improved Multi-Objective Spatial Optimisation Framework (MOSPOF), based on the recommendations of the previous chapter (Chapter 5), and its application to a more complex and larger spatial planning problem than the case study presented in Chapter 5. In particular, this chapter modifies the GA approach presented in Chapter 4 and employed in Chapter 5 such that it can handle the more complex optimisation of land development under spatially variable development densities, a greater number of objectives and a greater number of spatial planning constraints. To test the utility of this improved framework Section 6.3 onwards presents a detailed case study of assigning optimised land development for Greater London.

6.2 Modifications to the Multi-Objective Spatial Optimisation Framework

On the basis of the results of Chapter 5 several significant improvements to the initial multi-objective spatial optimisation approach developed were recommended. On the basis of these recommendations, the following changes are implemented for the analysis undertaken in this chapter:

- i. Changes to the spatial plan representation to incorporate further complexity (Section 6.2.1);
- ii. Updating the constraint handling to deal with increased complexity (Section 6.2.2);
- iii. Changes to the objective functions employed (Section 6.2.3)

6.2.1 Planning Problem

The methodology was investigated to accommodate different densities of residential dwellings within development plans to bring the planning problem more in-line with the planning system (see plans such as Greater London Authority (2011e)). This is facilitated by assigning proposed development sites a housing density. Other studies have investigated low, moderate and high residential density land uses (Ligmann-zielinska et al. 2006; Masoomi et al. 2012) but haven't quantified the number of dwellings for the purposes of calculating risk etc. Instead this work defines a finite set of discrete density values $dens = \{1,2, \dots\}$ which equate to a number of

dwellings assigned, dw based on the area of a cell; $dw = area \times dens$. In this way every proposed development site has a proposed number of dwellings, d_l^{dw} where l continues to refer to an i, j location via the use of a lookup table (see Section 4.5.1 (4) and Figure 4.9).

The current representation of a development plan with proposed locations of development is dependent on a set number of sites to allocate and for the purposes of parameterisation assumes a consistent number of dwellings at each site. The move to incorporate different densities of residential dwellings within the representation would necessitate a shift from optimising the spatial allocation of a fixed number development sites to optimising the spatial allocation of a set number of dwellings. The fixed length arrays which represented development plans for the Middlesbrough case study are insufficiently flexible to accommodate the variable number of dwellings that may be associated with different development densities assigned to development sites. Consider the two development plans shown below, D_1 and D_2 ;

$$D_1 = [d_l^{200}, d_l^{200}, d_l^{200}]$$

$$D_2 = [d_l^{100}, d_l^{100}, d_l^{100}]$$

The first development plan, D_1 , consists of higher densities of development than D_2 and as both development plans have the same number of development sites, D_a has a much higher number of total dwellings: $D_1^{dw} = 600$ compared to $D_2^{dw} = 300$. Therefore to ensure sufficient number of dwellings are reached, development plans consisting of low density development will require more proposed development sites compared to a development plan consisting of high density development

A potential solution is the use of a variable length list representation (Brie & Morignot 2005) whose length varies to accommodate a sufficient number of dwellings. To ensure the number of dwellings in each development plan are consistent, $D^{dw} = 600$ for example, the two development plans, D_1 and D_2 , could be derived using varying length representations:

$$D_1 = [d_l^{200}, d_l^{200}, d_l^{200}] : D_1^{dw} = 600$$

$$D_2 = [d_l^{100}, d_l^{100}, d_l^{100}, d_l^{100}, d_l^{100}, d_l^{100}] : D_2^{dw} = 600$$

To accommodate a higher dwelling density, D_1 , has double the number of development sites as D_2 , which has half the average dwellings assigned to each development site. This method of variable list has been used previously, for example (Walters et al. 1999) use it in their study to

handle a number of decisions related to a water supply network. However they and other studies (Brie & Morignot 2005; Wagner & Neumann 2012) point out that the application of the GA crossover operator is complicated when dealing with different length lists as the resulting *offspring* are often infeasible. So for the example of D_1 and D_2 shown above a crossover product of the two development plans could potentially lead to plans D'_a and D'_b which contain too few or too many dwellings. This would require complex procedures to increase or reduce the number of development sites in generated development plans leading to further computations.

Alternatively the inclusion of different development densities could be facilitated by a move back to the grid representation utilised by several other urban planning optimisation applications (e.g., Cao et al., 2011; Ligmann-Zielinska, Church, & Jankowski, 2008) (also see Section 3.5.5). Although previous applications haven't considered different development densities, discrete variable density values could replace the discrete land use variables usually utilised. This would generate a representation such as:

$$D_a = \begin{bmatrix} [0, & d^{dw}, & d^{dw}, & \dots & 0, & 0], \\ [0, & d^{dw}, & 0, & \dots & d^{dw}, & 0], \\ [d^{dw}, & 0, & d^{dw}, & \dots & 0, & d^{dw}], \\ [0, & d^{dw}, & d^{dw}, & \dots & d^{dw}, & d^{dw}] \end{bmatrix}$$

Where each element of the grid relates to a i, j location within the study area, noting that cells can remain undeveloped as per-previous applications (this is represented by a '0'). The advantage of this approach is that there are enough potential development site locations to meet the dwelling targets therefore avoiding the need to vary the lengths of the lists. Moreover a number of studies have developed GA crossover operators specifically to handle grid representations (Cao et al. 2012; Stewart & Janssen 2014).

However this representation is still subject to a number of the weakness identified in Section 3.5.5. This approach would lead to the incorporation of currently developed areas into the representation. In the Middlesbrough case study this would have increased the size of the representation of D from 54 to 5465 variables to cover the number of i, j locations within the study area substantially increasing the run time computational intensity. Moreover it would require the use of penalty functions to disincentivise development plans which alter current

development being searched and run contrary to the evolutionary approach of only considering the placement of new development which Section 3.5.7 found to be necessary.

Instead, the inclusion of different development densities into the representation of a single development plan D is handled via the use of a sparse matrix indexed via the use of a lookup table. In this method D has length equal to the number of cells available for development. Each element of D then relates to a coordinate i, j within the study area via the use of a lookup table. This is shown in Figure 6.1 where each element of the D corresponds to a cell identified as being available for development $a_{i,j}$. As development sites, d , are allocated within D , their corresponding number of dwellings, dw is allocated to the i, j location the element of D is linked to. Meanwhile elements with no development sites retain a 0 value. In the example given, dw totals of 50, 100 and 200 are assigned to the development plan meeting the target of 600. This method it improves on the grid based representation as it dis-considers cells currently developed, which also reduces the computational complexity (56 total variables to 11 for the example in Figure 6.1).

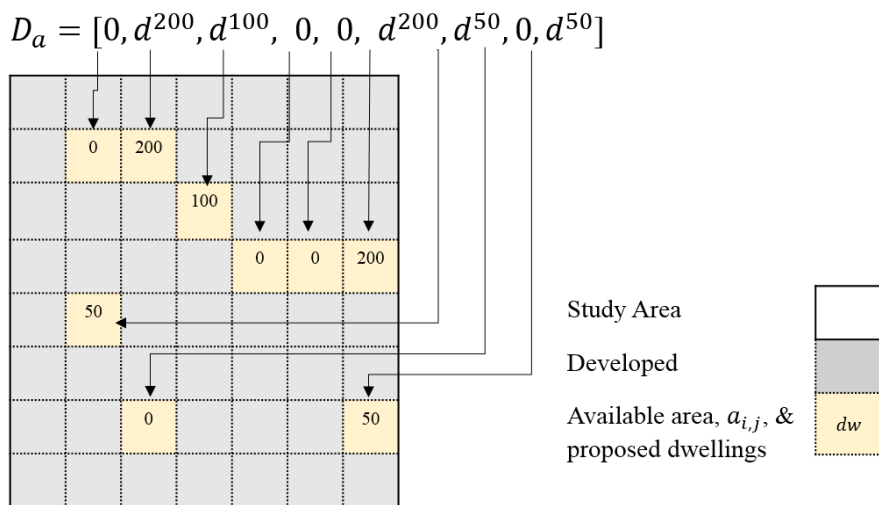


Figure 6.1 Mapping how development sites within a development plan, D relate to cells designated as available throughout the study area.

6.2.2 Modifications to Constraint Handling

Modifications in the constraint handling were necessitated by the new representation above, i.e. optimising the spatial allocation by number of dwellings rather than sites. A constraint was needed to ensure development plans have a sufficient number of dwellings. In the previous

methodology a target number of development sites was controlled. However as the new methodology allows for a varying number of development sites and densities, it was found that a single dwelling target would mean a high number of found development plans would slightly fail to meet it. Instead the constraint utilises a lower and higher dwelling target, ensuring spatial plans contain enough dwellings in between these two figures:

$$\textit{Subject to} \quad D_{W_{MIN}} \leq D^{dw} \leq D_{W_{MAX}} \quad (6.1)$$

where $D_{W_{MIN}}$ and $D_{W_{MAX}}$ 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. This allows for the exploration of d within D as significant changes in spatial plans can occur, possibly increasing the number of dwellings, without the development plan being discarded. Once again the constraint handling method whereby spatial plans which don't meet the constraints are discarded from the search is used, for this instance those which don't meet the required number of dwellings.

6.2.3 Changes in Objective Function Parameterisation

Due to significant changes in the representation of the spatial planning problem the calculation of the sustainability objectives were adapted. This made a number of changes from the evaluations presented in Equations 4.2-4.9 in Chapter 4. Previously these were defined on the basis of a set number of $d_{i,j} \in D$ and a consistent number of dwellings, dw_{ij}^+ . As the changes mean the total number of dwellings in a development plan, D^{dw} , can vary and the objective functions (Equations 6.2-6.6) were all formulated to be proportional to the value of D^{dw} .

The new calculation of the objective function f_{heat} is defined as total product of the number of dwellings at a location d_l^{dw} and the corresponding heat hazard h_l :

$$\textit{Minimize} \quad f_{heat} = \sum h_l d_l^{dw} \propto D^{dw} \quad (6.2)$$

As with Equation 4.2, the calculation of heat risk has a number of assumptions. The calculation does not take into account future projected increases in population density and/or changes in

the demographic profile (i.e., > proportion of >75) etc. In addition the calculation does not include any expression of exposure (e.g., no expression of building stock) due to a lack of available data. Overall the computation assumes that the risk is proportional to the population which interacts with the heat hazard. This is a change from using a vulnerability constituency as per Equation 4.3 and 4.4 and was done to reduce the computational complexity. Also as the spatial resolution was increased, population density was found not to be as representative.

The objective function f_{flood} remains characterized by a proportional risk assessment of development within 1 in 100 and 1 in 1000 year flood zones (the former is penalized by an order of magnitude reflecting the lower likelihood of a flood). Once again the use of probability outlines such that you do not have any knowledge of the interval variability on flood depth and hence the ability of undertake a finer-scale inter-zonal flood damage calculation. The calculation assumes that the risk is proportional to the number of dwellings within each zone and is represented as:

$$\text{Minimize} \quad f_{flood} = \left(10^0 \sum z_l^{100} d_l^{dw} + 10^{-1} \sum z_l^{1000} d_l^{dw} \right) \propto D^{dw} \quad (6.3)$$

where z^{100} and z^{1000} are spatial grids representing the 1 in 100 and 1 in 1000 flood zone extents respectively at the locations identified by l . The objective f_{dist} remains characterized by an accessibility measure, however a number of town centers replace the defined CBD in the parameterization to represent the many potential centres for services, amenities and employment within a larger urban environment. The calculation assumes that the location of these CBDs remain consistent in the future. The optimization of the objective function f_{dist} is expressed as:

$$\text{Minimize} \quad f_{dist} = P(d_l, c_l, R) \forall c_l \wedge d_l \in D \propto D^{dw} \quad (6.4)$$

where $P()$, is the shortest path between a d_l and it's closest point designated as a town centre centroid, c_l , over a road network, R . The objective function f_{sprawl} continues to be calculated on the number of development sites which fall outside the defined urban extent:

$$\text{Minimize} \quad f_{sprawl} = \sum d_l \neq u_l \forall d_l \in D \propto D^{dw} \quad (6.5)$$

The availability of the London Brownfield Sites Database presented the opportunity to incorporate an objective to optimise brownfield field development. The utilisation of brownfield land (often referred to as previously developed land) for development is a often cited policy goal internationally (Baing 2010) and also within the UK (DCLG, 2011a). The calculation of this objective function does not include any consideration of the costs of developing on brownfield (i.e. for remediation). This 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 :

$$\text{Minimize} \quad \sum d_l \neq b_l \forall d_l \in D \propto D^{dw} \quad (6.6)$$

Appendix B2 sets out the modified Evaluate module to handle these new calculations. Once again a spatial constraint which prevents the appropriation of development to cells designated as greenspace, g_l is employed:

$$\text{Subject to} \quad d_l \neq g_l \forall d_l \in D \quad (6.7)$$

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

$$\text{Subject to} \quad d_l = 1 \text{ if } d_l \cap a_l \quad (6.8)$$

where a_l represents cells designated as being available for development. The existing and new constraints were enforced in the same manner as in Chapter 5, by excluding greenspace cells and cells not designated as available for development from the lookup and hence ensuring that they could not be assigned development within a spatial plan.

6.3 London Case Study Configuration

6.3.1 The Greater London Authority

To demonstrate the utility of the modified Multi-Objective Spatial Optimisation Framework it was applied to generating spatial development plan of residential development for Greater London. Figure 6.2 demonstrates the spatial extent of the Greater London Authority (GLA), which has a land area 29 times that of Middleborough. London was selected due to its prominence as focal point for sustainable development in the UK and Europe (Walsh et al. 2013). The city is experiencing increasing urbanization with a projected population increase of a million from 2011 to 2031 (GLA, 2011a) and is projected to experience significant climate change induced impacts into the future (Greater London Authority 2007). The GLA Climate Change Action Plan (2007) sets out projections resulting from climate change, including:

1. Annual heat wave events by 2050 (defined as two day time temperatures exceeding 32 °C with intervening night exceeding 18 °C);
2. Increase in mean summer temp of 2.7°C;
3. 15% increase in mean winter rainfall; and,
4. 18% decrease in mean summer rainfall.

This coincides with ambitious energy mitigation targets of a 60% reduction from 1990 levels by 2025 (Greater London Authority 2011b) due to London accounting for 8.4% of total UK GHG emissions (GLA et al. 2011).

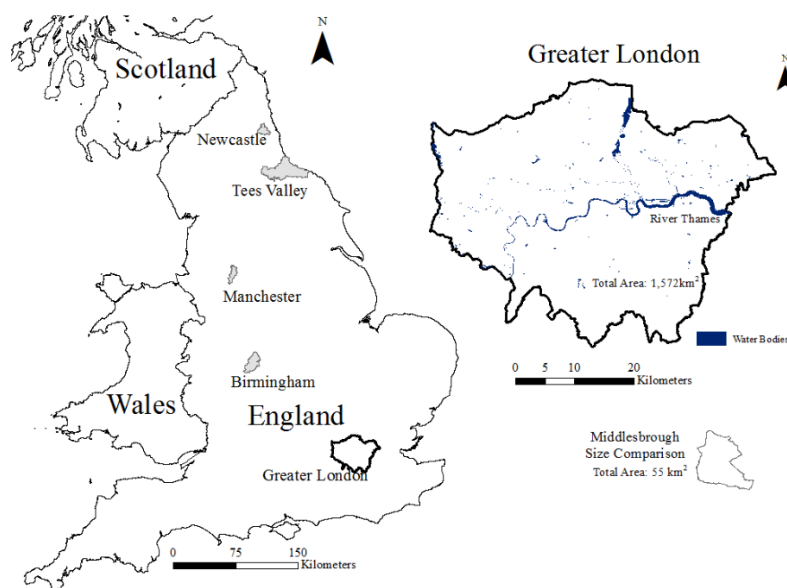


Figure 6.2 Case study area of Greater London.

Table 6.1 taken from the Greater London Authority (2011c) details the sustainability objectives utilized during the London Plans Integrated Impact Assessment (IIA). Objectives and indicators highlighted identify those which are addressed in the application either directly as an objective to optimise, i.e. objective 1 to maximise brownfield development, or through constraints, e.g. objective 3 restricting development on greenspace and objectives 2 and 4, or indirectly assessed, proxies of accessibility and sprawl for objectives 13 and 14. Notably responses to climate change are not considered and instead considered separately.

6.3.2 Problem Formulation

The case study develops spatial plans for the time period 2011-2021 in line with the time period considered by ‘The London Plan: Spatial Development Strategy for Greater London’ (2011). The method of determining a development plan using the methodology outlined in Section 6.2.1 requires an upper and lower limit for the number of dwellings in a development plan. The lower limit is represented by the 32,210 minimum annual net additional homes per year (322,100 over 10 years) outlined by Key Performance Indicator 4 of the Greater London Authority (2011c) (see No. 4 in Table 6.1), whilst the upper limit is represented by the total estimated number of dwellings required to accommodate all future predicted population growth, 340,000 which was taken from Greater London Authority (2011a). These figures are used to represent DW_{MIN} and DW_{MAX} respectively in Equation 6.1. To constrain the variable range a set range of development densities were adapted reflecting the extremes and intermediate values of the residential dwelling density units per hectare in table 3A.2 of GLA (2011b):

$$den = \{35,60,100,150,250,400\} \quad (6.9)$$

After experimentation it was found that a spatial resolution of 200m (4 hectares) was the finest that could be employed for London. Lower resolutions (i.e. 100m) led to long and inefficient searches whilst higher resolutions (i.e. 500m) were found to be too removed from real world planning. Therefore, the number of dwellings that could be assigned to each cell on the basis of the GLA density values corresponded to:

$$dw = \{140,240,400,600,1000,1600\} \quad (6.10)$$

Table 6.1 Indicators for monitoring the sustainability effects of the London Plan (table 1 (Greater London Authority 2011d). Objectives address directly and indirectly by the framework are highlighted.

No.	Key Performance Indicator	Target
1	Maximise the proportion of development taking place on previously developed land	Maintain at least 96% of new residential development to be on previously developed land
2	Optimise the density of residential development	95% of development comply with housing density location and the density matrix (see Table 6.2)
3	Minimise Loss of Greenspace	No net loss of open space designated for protection
4	Increase supply of new homes	Average completion of minimum 32,210 net additional homes per year
5	Increase in supply of affordable house	Completion of 13,2000 net additional affordable homes per year
6	Reducing Health inequalities	Reduction I the difference in life expectancy between those living the most and least deprived areas of London
7	Sustaining economic activity	Increase prop of working age in employment 2011-31
8	Ensure sufficient development capacity in office market	Planning permission to be 3 times as high
9	Ensure there is sufficient employment land available	Release of industrial land (B2/B8 use over 1,000 sqm) to be in line with benchmarks in the Industrial Capacity SPG
10	Employment in Outer London	Growth in total employment in Outer London
11	Increased employment opportunities for those at a disadvantage	
12	Improving the provision of social infrastructure and related services	Reduce average class size
13	Reduced reliance on private cars	Increase per head public transport usage
14	Reduced reliance on private cars	Zero car traffic growth
15	Reduced reliance on private cars	Increase share of bicycle from 2% to 5% by 2026
16	Reduced reliance on private cars	50% increase in Blue ribbon network use
17	Increase in number of jobs created in areas with high public transport accessibility	50% of B1 development in PTAL zones 5-6
18	Protection of biodiversity habitat	No net loss of Sites INC
19	More recycling	45% recycled by 2015, 0% in landfill by 2031
20	Reduce Co2	Zero carbon in residential development by 2016, and in all development by 2019
21	Increase in renewable energies	Just in line with Regional Renewable Energy Assessment 2010
22	Increase Urban Greening	Increase total area of green roofs
23	Improve Blue Ribbon Network	Restore 15km of rivers and streams
24	Protecting London's heritage	Reduce proportion of designated heritage assets at risk as % for total number

6.3.3 Input Datasets

Figure 6.3 presents the input spatial datasets for the case study. Figure 6.3a presents 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 the urban heat island on the basis of surface land cover characteristics. In this particular case, the number of days heat wave events were experienced annually was employed; for London this is defined as two day time temperatures exceeding 32 °C with intervening night exceeding 18 °C (DoH 2010). This particular approach has been utilised for the development of future heat for a number of urban, areas including Tilburg in the Netherlands (Maiheu & Hittekaart voor Tilburg 2011), Antwerp and New York (Lauwaet et al. 2015) as well as London and Bilbao (De Ridder et al. 2014) and is being utilised by the EU RAMSES (Reconciling Adaptation, Mitigation and Sustainable Development for Cities) project (Hooyberghs et al. 2015).

Floodzones in Figure 6.3b were represented by the Environment Agency (EA) flood zones 2 and 3 as was the case in Chapter 5. London's town centre network (c_{ij}) (Figure 6.3c) was represented by OS Mastermap Strategi Settlement Seeds, whilst the road network, R , was extracted from the OS Meridian 2 roads datasets. The urban extent, u_{ij} , in Figure 6.3d was extracted and rasterized from OS Meridian 2 Developed Land Use Areas (DLUA). Locations of brownfield sites were provided by the London Development Agency's (LDA) London Brownfield Sites Database, and was rasterised to a 200 metre spatial resolution. Lastly a greenspace dataset, g_{ij} , (Figure 6.3f) was extracted from OS MasterMap topographic data corresponding to features where the Theme was 'Natural'. In addition UK designated sites; Special Sites of Scientific Interest (SSSI), Ancient Woodland, National and Local Nature Reserves, Special Protection Areas and Special Areas of Conservation, were added to this dataset. These were pre-processed using the ArcGIS package utilising the tools shown in Appendix D.

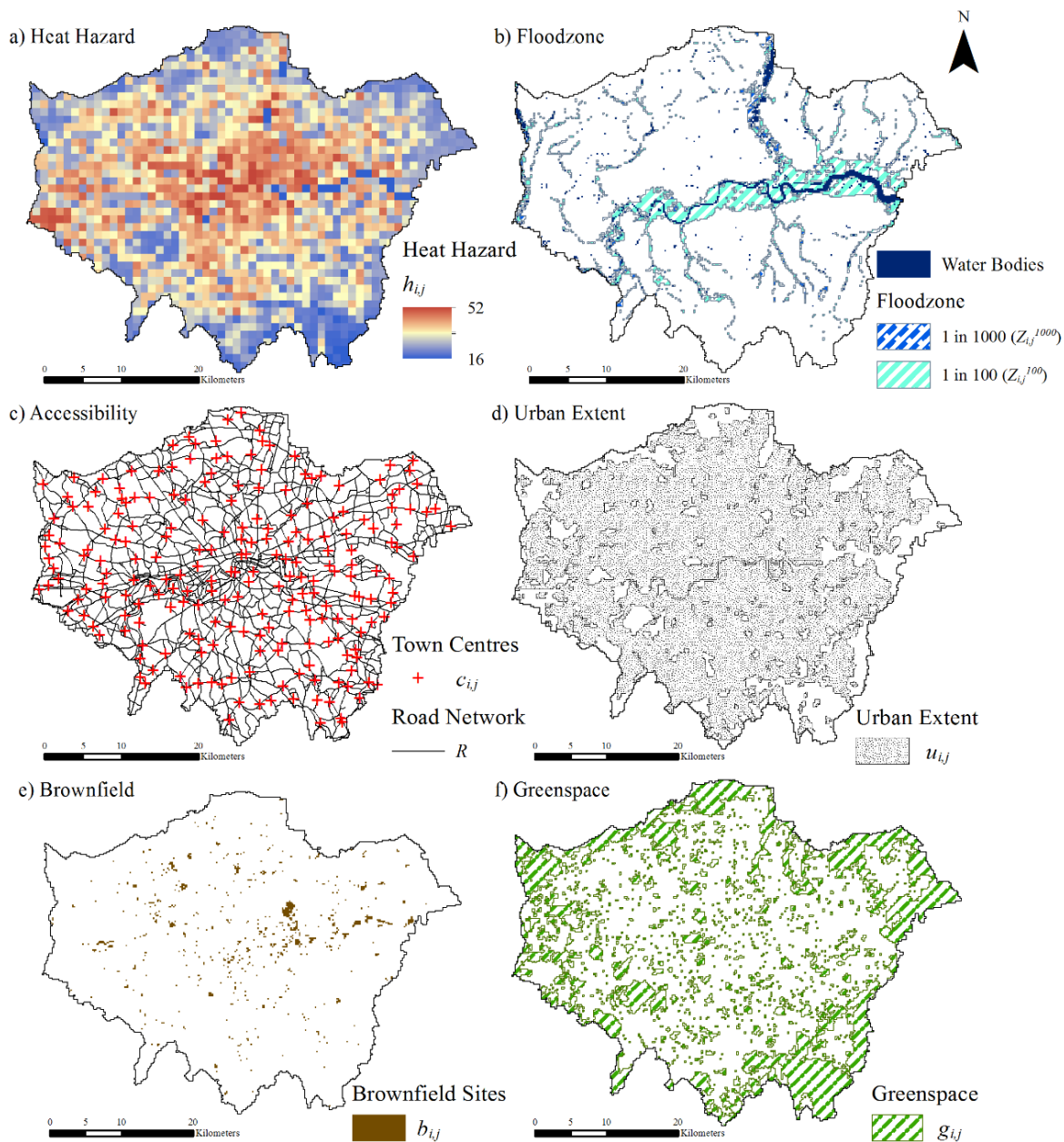


Figure 6.3 Input spatial datasets for London case study.

6.3.4 Identifying Developable Areas

To identify potential areas for future residential development, MasterMap topographic data was utilised. In order to mask out areas that were not suitable for development, a dataset of Current_Water was again generated by selecting all topographic areas where the ‘Theme’ attribute was “Water”. Equally, to mask out currently developed land all features with one of the following MasterMap characteristics were extracted:

1. Theme = 'Land' AND Make = 'Multiple'
2. Descriptiv = 'Building' AND Make = 'Manmade'
3. Descriptiv = 'Rail' AND Make = 'Manmade'
4. Descriptiv = 'Road Or Track' AND Make = 'Manmade'
5. Descriptiv = 'Road Or Track' AND Make = 'Unknown'
6. Descriptive = 'Roadside' AND Make = 'Natural'

The resulting mask vector datasets are shown in Figure 6.4. These were then used to identify areas available for development by subtracting them from the entire space available. Areas designated for brownfield development were added to the land available for development. Figure 6.5 shows the final 3307 cells (13,228 hectares) identified as being available for development, with brownfield sites distinguished.

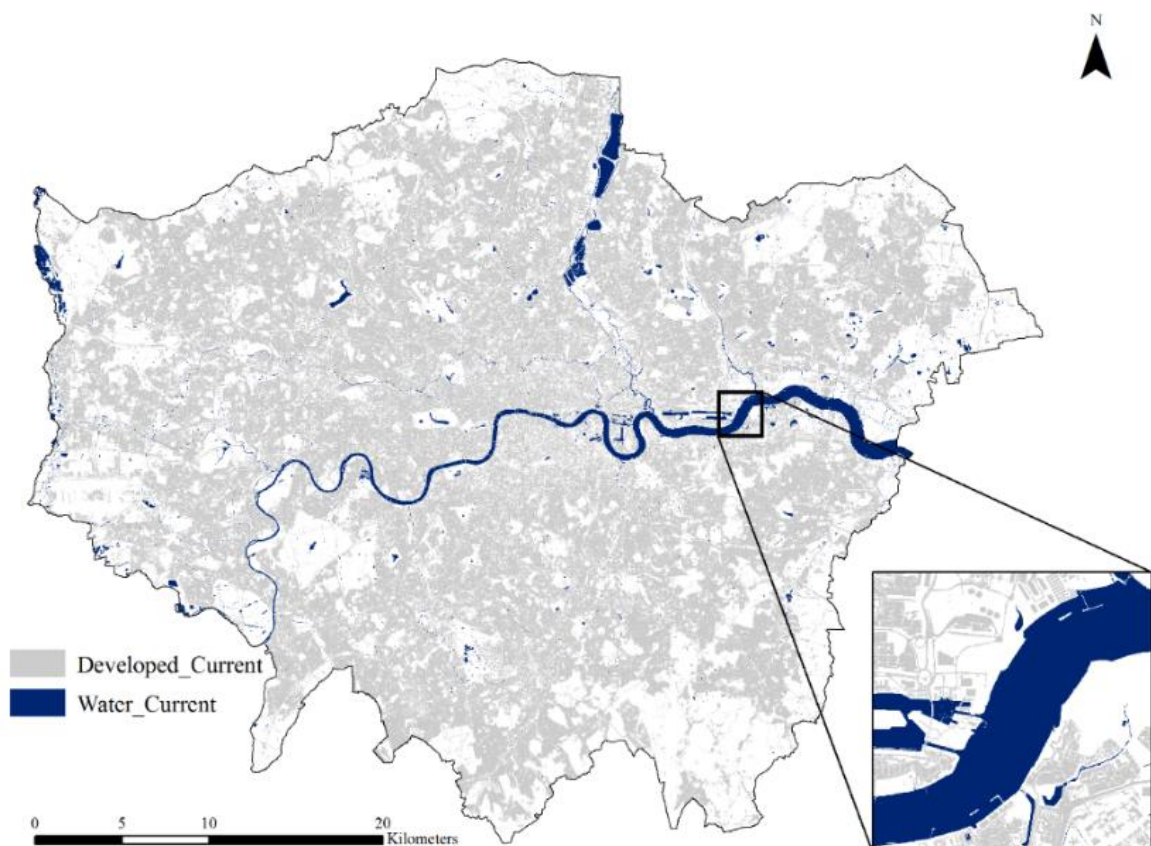


Figure 6.4 Planning constraints for London case study.

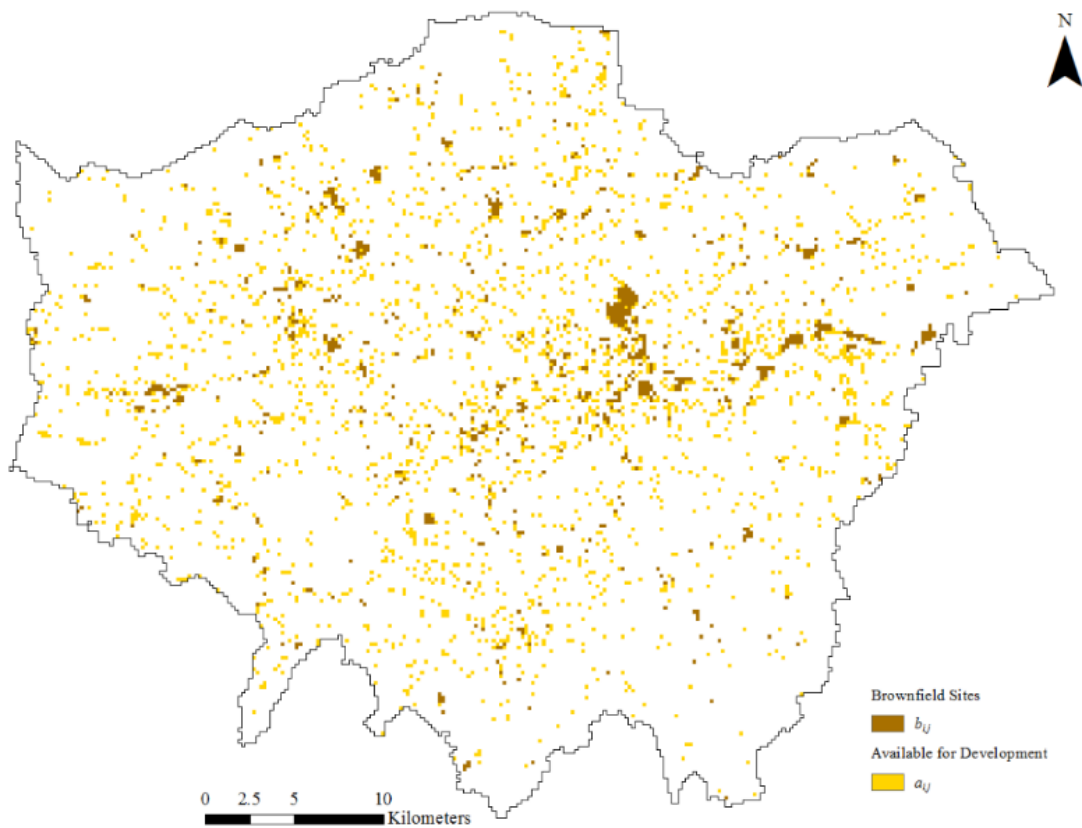


Figure 6.5 Available areas for development at a 200m spatial resolution including designated brownfield sites.

6.3.5 Planning Constraints

To more closely mimic the real world spatial planning process, London’s current planning restrictions on density of housing units per hectare (u/ha) based on accessibility were incorporated into the optimisation framework. Table 6.2 outlines the restrictions on maximum dwelling density based on the accessibility of development adapted from table 3.2 in of the Greater London Authority (2011d). The current accessibility is shown in Figure 6.6a which shows the Transport for London Public Transport Accessibility Layer (PTAL). PTAL classifications are calculated on the basis of accessibility measures to public transport nodes for buses, rail, underground and DLR stations combined with average waiting times⁷. Figure 6.6b simplifies this for the accessibility standards outlined in Tale 6.2. Objective 2 in Table 6.1 sets a target of 95% of new development meeting the PTAL density requirements. To facilitate this a constraint was added to the London application which only considers development sites in a development plan, D , which meet this value.

⁷ <https://files.datapress.com/london/dataset/public-transport-accessibility-levels/PTAL-methodology.pdf>

Table 6.2 PTAL accessibility standard for new development in London (adapted from Table 3A.2 in London’s Spatial Strategy (Greater London Authority 2011e))

PTAL Classification (see Fig. 2f)	1a	1b	2	3	4+
Maximum <i>dw</i> (uha)	60	60	100	100	N/A

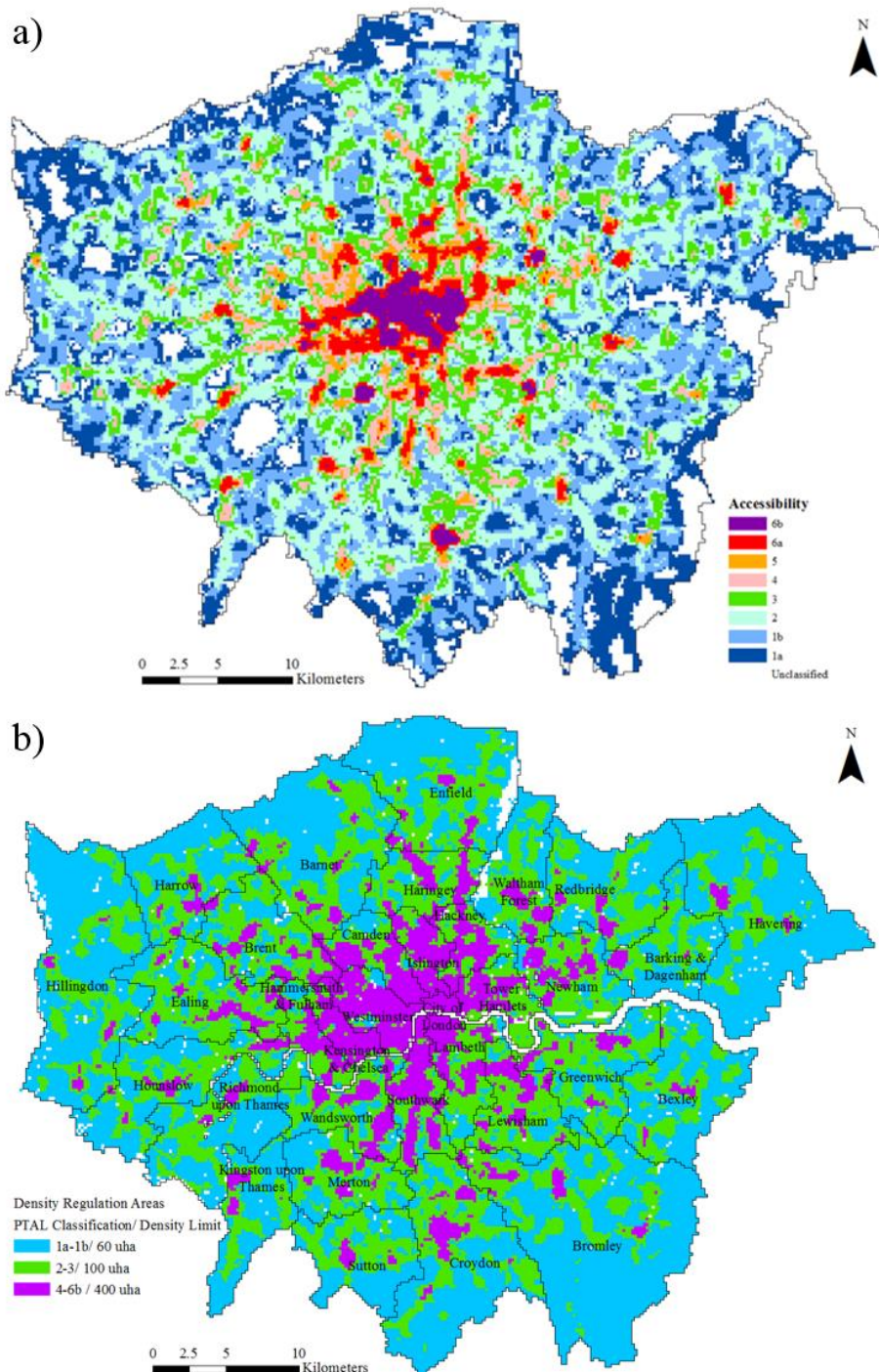


Figure 6.6 a) PTAL Classifications (sourced from the London Datastore⁸) and b) simplified PTAL for planning constraints in Table 6.2.

⁸ <http://data.london.gov.uk/dataset/public-transport-accessibility-levels>

6.4 Further Analysis

6.4.1 Scaled Pairwise Preference Vectors

Sources have suggested the sheer number of Multi-objective Pareto-optimal (MOPO) spatial plans can be overwhelming for planners (Xiao et al. 2007). Although the generation of a Pareto-optimal set greatly aids the understanding of the spatial planning problem the decision-maker still has to choose a single solution from this set. The previous application found over 568 MOPO solutions and it is likely that more complex spatial planning application, such as the London case study of this chapter, with a larger number of variables, will result in larger Pareto-optimal sets being generated. Therefore to address this issue and aid interpretation of the results approaches that helped refine and identify ‘promising’ Pareto-optimal solutions were investigated.

The K-means clustering algorithm is a commonly used method to reduce the size of the MOPO set to a user defined K number of clusters (Taboada & Coit 2005; Jimenez 2007). This is done by randomly locating K centroids in the objective space. At each iteration solutions in the MOPO set are assigned to the closest centroid based on their objective functions. A mean is then taken of all the solutions in each cluster and this becomes the new centroid. The algorithm continues by minimising the squared distances of solutions in each cluster. Once the algorithm terminates the closest solution to each centroid is returned as a local optima for that cluster. The main advantage of the method is that it doesn’t require any subjective judgement on the preferences of the objectives and the set is reduced to a required size, K , defined by the user, to choose from. For this reason K-means methods are the most widely applied non-hierarchical clustering technique (Luke 2009). However its utility as part of an urban planning decision support tool is limited as the nature of the application requires the ability to apply societal and planning preferences.

Alternatively Carrillo & Taboada (2012) describes the use of a non-uniform weight generator to reduce the size of the Pareto set. In this approach objectives are ranked non-numerically based on their importance to the decision-maker. For a set of objective functions, f :

$$\textit{Maximise} \quad f_1 > f_2 > f_3 \quad (6.11)$$

is used to determine a relative weighting system:

$$\textit{Maximise} \quad w_1 > w_2 > w_3 \quad (6.12)$$

Numerous randomly selected weight-sets are generated which fit with these preferences and are applied to the MOPO set as per the weighted sum method (defined in Section 3.3). This is repeated for a pre-selected number of iterations to extract optimal solutions to form a smaller practical set of promising solutions which fit with the preferences. The advantage of this approach is that it can reflect planner's priorities without specifying a specific weighting scheme. However, there is still a significant number of solutions for the decision maker to choose from. Baheranwala (2005)'s study found that the method was able to reduce the MOPO set by 90%. Based on the MOPO set from the previous application of Chapter 5 this would still leave a 50 solutions to consider.

The Analytical Hierarchical Process (AHP) using pairwise comparison matrixes is an established Multiple-criteria decision analysis method and has been utilised in developing weighting systems for multi-criteria applications (Eastman 1999; Yahaya et al. 2010; Musungu et al. 2012). Significantly the approach has been commended for its ability to more accurately quantify priorities within numerical weighting schemes (Rao et al. 1991). The developed weighting systems are often applied using some form of weighted summation to deliver a single optimal spatial plan. For example Deng (1999) employed the approach to produce weights for its weighted sum optimisation approach. A number of applications have used AHP to derive weightings between different land uses for compatibility objectives in their land use allocation applications (Masoomi et al. 2012). However, like with other weighting methods it has the limitation that it takes no appreciation of the trade-offs in the objectives (Eastman 1999). Therefore the work intends to use the knowledge of the relationships between objectives found by the Pareto-optimisation, as suggested by Deb (2001), to ensure the weighting system discovers plans which are more representative of the preferences of planners

In order to undertake the post-optimisation filtering of the result-sets four planning scenarios were identified that would capture the key tensions between different planning scenarios from the literature outlined in Table 6.3. Table 6.4 outlines the determination of unscaled pairwise matrix weighting based on these planning scenarios. In the absence of expert knowledge it was assumed that prioritized objectives were 'extremely more important' than other objectives in

order to deliberately exaggerate particular choices. These weightings aren't final and once the application is carried out they are scaled by the trade-offs found between objectives to ensure they consider these relationships and derive a more representative set of weights. The approach consists of several steps. First each objective is rated in terms of its relative importance compared to the other objectives on a 9 point reciprocal scale as per Figure 6.7 where 9 indicates 'extremely more important', 1/9 indicates 'extremely less important' and 1 denotes no preference between the objectives.

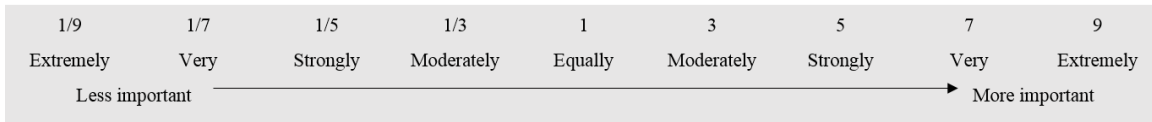


Figure 6.7 Pairwise comparison matrix nine point rating scale

These are then used to formulate a pairwise comparison matrix (Table 6.4a), and Eigenvector analysis used to calculate a corresponding set of weights (Table 6.4c) that sum to 1 as per weighted summation method (Eastman 1999).

Table 6.3 Outline of differing planning priorities

Priority	Justification
1. Low Carbon City	The UK's Climate Change Act (House of Commons, 2008) legally binds the UK government to reduce the UK's greenhouse gas emissions by 80 per cent by 2050. As one of the biggest drivers of emissions, London has targets for a 60 percent reduction in carbon dioxide emissions (below 1990 levels) by 2025 (Greater London Authority 2007). In this context the decarbonisation objectives of f_{dist} and f_{sprawl} are prioritised.
2. Low Risk City	London has a unique threat from extreme heat compared to other UK cities due to its southern latitude and considerable heat island whilst the UK's House of Commons Environmental Audit Committee (2015) reports that flooding is the biggest adaptation challenge facing the UK. In this context this scenario prevention of exposure to climate change induced hazards is prioritized, namely f_{heat} and f_{flood} .
3. Green and Spacious City	Land conservation through development on previously developed land is a popular policy to prevent the need to develop on greenfield sites (Baing 2010). Therefore this scenario prioritizes the objective $f_{brownfield}$.
4. Balanced City	To act as a control and comparison a spatial plan will be derived on the basis of equal priorities for all the objectives.

Table 6.4. Pairwise comparison matrix for the differing planning priorities. Note these are unscaled values and are modified before the weights are applied.

1. Low Carbon City													
a)	f_{heat}	f_{flood}	f_{dist}	f_{sprawl}	$f_{brownfield}$	b)	f_{heat}	f_{flood}	f_{dist}	f_{sprawl}	$f_{brownfield}$	c)	Weightings
f_{heat}	1	1	1/9	1/9	1	f_{heat}	0.05	0.05	0.05	0.05	0.05	f_{heat}	0.05
f_{flood}	1	1	1/9	1/9	1	f_{flood}	0.05	0.05	0.05	0.05	0.05	f_{flood}	0.05
f_{dist}	9	9	1	1	9	f_{dist}	0.43	0.43	0.43	0.43	0.43	f_{dist}	0.43
f_{sprawl}	9	9	1	1	9	f_{sprawl}	0.43	0.43	0.43	0.43	0.43	f_{sprawl}	0.43
$f_{brownfield}$	1	1	1/9	1/9	1	$f_{brownfield}$	0.05	0.05	0.05	0.05	0.05	$f_{brownfield}$	0.05
Sum	21	21	2.33	2.33	21							Sum	1
2. Low Risk City													
	f_{heat}	f_{flood}	f_{dist}	f_{sprawl}	$f_{brownfield}$		f_{heat}	f_{flood}	f_{dist}	f_{sprawl}	$f_{brownfield}$		Weightings
f_{heat}	1	1	9	9	9	f_{heat}	0.43	0.43	0.43	0.43	0.43	f_{heat}	0.43
f_{flood}	1	1	9	9	9	f_{flood}	0.43	0.43	0.43	0.43	0.43	f_{flood}	0.43
f_{dist}	1/9	1/9	1	1	1	f_{dist}	0.05	0.05	0.05	0.05	0.05	f_{dist}	0.05
f_{sprawl}	1/9	1/9	1	1	1	f_{sprawl}	0.05	0.05	0.05	0.05	0.05	f_{sprawl}	0.05
$f_{brownfield}$	1/9	1/9	1	1	1	$f_{brownfield}$	0.05	0.05	0.05	0.05	0.05	$f_{brownfield}$	0.05
Sum	2.33	2.33	21	21	21							Sum	1
3. Green and Spacious City													
	f_{heat}	f_{flood}	f_{dist}	f_{sprawl}	$f_{brownfield}$		f_{heat}	f_{flood}	f_{dist}	f_{sprawl}	$f_{brownfield}$		Weightings
f_{heat}	1	1	1	1	1/9	f_{heat}	0.08	0.08	0.08	0.08	0.08	f_{heat}	0.08
f_{flood}	1	1	1	1	1/9	f_{flood}	0.08	0.08	0.08	0.08	0.08	f_{flood}	0.08
f_{dist}	1	1	1	1	1/9	f_{dist}	0.08	0.08	0.08	0.08	0.08	f_{dist}	0.08
f_{sprawl}	1	1	1	1	1/9	f_{sprawl}	0.08	0.08	0.08	0.08	0.08	f_{sprawl}	0.08
$f_{brownfield}$	9	9	9	9	1	$f_{brownfield}$	0.69	0.69	0.69	0.69	0.69	$f_{brownfield}$	0.69
Sum	13	13	13	1.44	13							Sum	1
4. Balanced City													
	f_{heat}	f_{flood}	f_{dist}	f_{sprawl}	$f_{brownfield}$		f_{heat}	f_{flood}	f_{dist}	f_{sprawl}	$f_{brownfield}$		Weightings
f_{heat}	1	1	1	1	1	f_{heat}	0.2	0.2	0.2	0.2	0.2	f_{heat}	0.2
f_{flood}	1	1	1	1	1	f_{flood}	0.2	0.2	0.2	0.2	0.2	f_{flood}	0.2
f_{dist}	1	1	1	1	1	f_{dist}	0.2	0.2	0.2	0.2	0.2	f_{dist}	0.2
f_{sprawl}	1	1	1	1	1	f_{sprawl}	0.2	0.2	0.2	0.2	0.2	f_{sprawl}	0.2
$f_{brownfield}$	1	1	1	1	1	$f_{brownfield}$	0.2	0.2	0.2	0.2	0.2	$f_{brownfield}$	0.2
Sum	5	5	5	5	5							Sum	1

6.4.2 Regulatory Scenarios

Keirstead's & Shah's (2013) review of the contribution of spatial optimisation to urban planning identifies its potential to elicit baseline/benchmark performances for objectives. This coincides with the debate surrounding the effects of regulation on the ability of urban planners to meet sustainability pressures (Echenique et al. 2012). To this end the analysis was carried out under several different regulatory frameworks to gauge their impact on to meet the sustainability objectives considered. These consisted of:

i. Business as Usual (BAU)

Continuation of current regulatory framework which includes restrictions to ensure high density development within high accessibility areas (see Section 6.3.5). The framework is carried out as per set out in Section 6.3.

ii. Density Deregulation

The restrictions on high density development in low accessibility areas outlined in Section 6.3.5 are relaxed to investigate the impact on meeting the risk prevention objectives.

iii. Exclusively Brownfield

Areas available for development in the case study are restricted to brownfield sites (Figure 6.3e) reflecting its prioritization including UK governments aspiration of 60% brownfield development (DCLG, 2011b) and the Greater London Authorities aim of 98% of brownfield development (GLA, 2011b).

The application of the MOSPOF to the case study was run under these different regulatory frameworks and the results of which are presented in Section 6.6.6.

6.5 Application Parameters

Table 6.5 outlines the run-time parameters for the London case study. The framework was run several times in order to determine the search parameters which allowed for the best search and produced the most optimal results. Due to the size of the problem to solve of the newly defined spatial planning problem, initialisation was even more crucial to the performance of the GA

algorithm. To sufficiently represent the 3,307 cells designated as being available for development a figure of 2,500 initial spatial plans in the parent set was utilised (see Figure 6.8) as testing found it sufficiently represented the spectrum of possible development sites. Ideally each site would be represented with each particular development density so that all possible combinations are represented however it was limited by the computational efficiency and increasing the size of initial set significantly increased the running time.

The NSGA-II algorithm was utilised due to its successful application for the Middlesbrough case study in Chapter 5 and it's wide use in the previous urban planning applications (Cao et al. 2011). The representation as a fixed length list allows for the retention of using the two point crossover operator (described in Section 4.5). Alternative crossover operations were tested but were found to offer little benefit whilst increasing the runtime. The mutation operator utilised was a shuffle-index mutation, where elements selected for mutation are swapped within D . Crucially this retains the original D^{dwells} (total number of dwellings) whilst spatially varying the spatial location, l , of d . The mutation probability, $p_{mutation}$ was purposefully set to a higher value than for the case study of Middlesbrough due the requirement of the GA algorithm to have to work harder to maintain a diverse set for a more complex problem and with the time restrictions on the run.

The use of random initial plans caused poor convergence as the plans were so diffuse. A number of sources have recognised the advantage of seeding GAs with good initial solutions (Harik & Goldberg 2000; Keedwell & Khu 2005) Therefore in order to improve the initial representation of spatial plans the initialisation was modified so that a small percentage of initial spatial plans were biased towards particular parameters ensuring the search begins from an already optimal development plans. For example spatial plans were developed consisting entirely of a single development density to ensure that this eventuality was covered in the initial parent set. Spatial plans were created which also constrained development to brownfield sites and outside of floodzones. This preferential initialisation helps accelerate the convergence of spatial plans towards being optimal across all the sustainability objectives as they start from a superior configuration.

Table 6.5 Run Parameters for case study application of the Spatial Optimization Framework

Parameter	Description	Value
G	Number of generations	400
$N_{oparents}$	Number of parent D selected for each generation (pop size)	2500
$p_{crossover}$	Probability of applying a crossover to two D	0.7
$p_{mutation}$	Probability of mutating a D	0.2
p_m	Probability of mutating an element (d_i) within D .	0.05

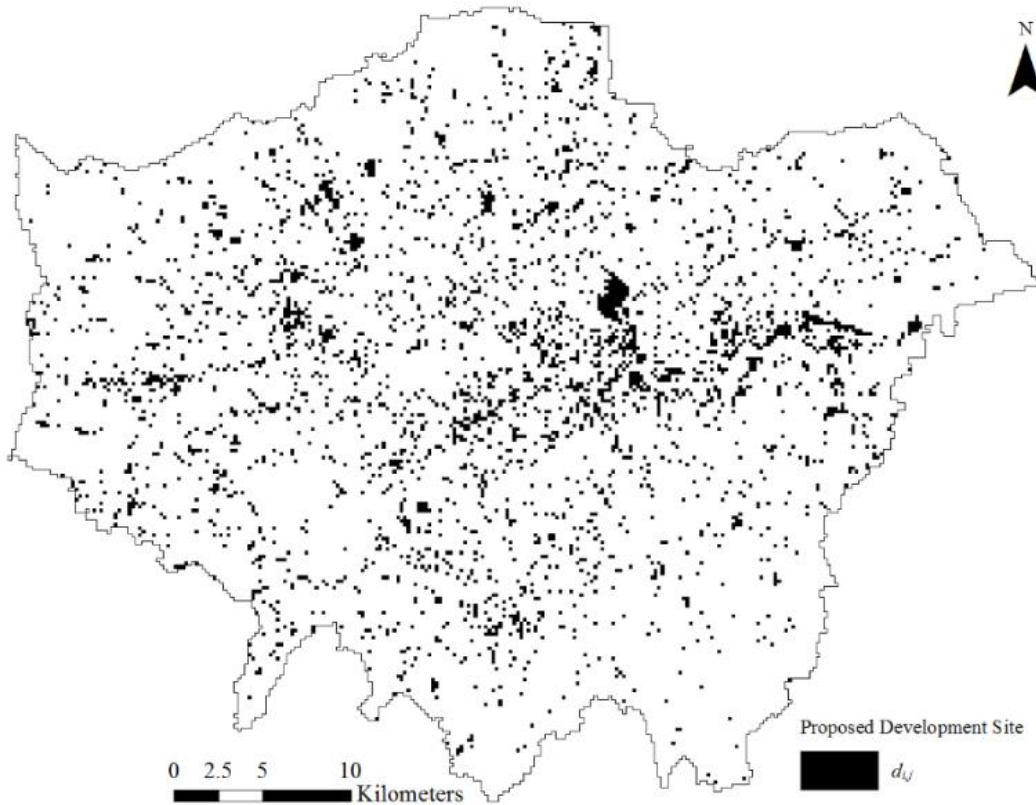


Figure 6.8 Development sites represented in the initial ($g = 0$) parents set.

6.6 Results

Table 6.6 outlines the run statistics of the application to the London case study. One concern of the way the algorithm was formulated above was that it may lead to a high number of solutions being unfeasible as when the GA combined spatial plans many of these may exceed or fall under the minimum and maximum number of dwellings permitted. During the application the average retention rate after the dwelling total constraint is 88.5% meaning that the difference between D_{min} and D_{max} was sufficient to not exclude too many solutions from the search.

Table 6.6 Run statistics

Total Run Time	5d 1hr 14mn
Total Spatial Configurations Assessed	890, 232
Average retention rate after Dwelling Total Restraint	88.5%
Average retention rate after PTAL Restraint is	99.23%
Total MOPO Solutions found	31,716

Moreover the average retention rate after PTAL constraint was 98.2% as the initial development plans met the density constraints.

Despite the use of biasing in the initialisation for the objective $f_{brownfield}$, Figure 6.9 demonstrates that for the spatial plan which is $\min(f_{brownfield})$, the algorithm is able to improve the performance of the plan in correspondence with other objectives, in this case f_{heat} . Table 6.7 quantifies the statistics of the Pareto front throughout the application. The performance of the entire Pareto set, $N_{f_{heat},f_{brownfield}}$, improves consistently throughout the application with a 73% improvement in the average of the solutions demonstrating that this initialisation improves convergence overall. However at two stages there's a significant deterioration in $\min(f_{heat}) \Rightarrow f_{brownfield}$ in order to allow for the most optimal spatial plan for $\min(f_{heat})$.

Table 6.8 and documents the convergence in the Pareto front for $N_{f_{heat},f_{dist}}$ shown in Figure 6.10. Despite both objectives not being subject to biasing in the initialisation, the framework is able to elicit significant improvements in the Pareto front throughout the application. Although the improvement is proportionally smaller between the 200th and final generation there seems to be the potential for further convergence. However we were limited by the amount of time it took.

Table 6.7 Convergence statistics for $N_{f_{heat},f_{brownfield}}$ during the case study application.

	Normalised Performance at Generation and Percentage Improvement								
	1st	50th	%	100th	%	200th	%	Final	%
Average $N_{f_{heat},f_{brownfield}}$	0.63	0.27	58.06	0.23	12.00	0.21	9.63	0.17	18.25
$\min(f_{heat})$	0.60	0.35	40.83	0.23	36.07	0.11	49.15	0.00	100.00
$\min(f_{heat}) \Rightarrow f_{brownfield}$	0.94	0.13	86.16	0.20	-51.92	0.18	9.20	0.20	-12.37
$\min(f_{brownfield}) \Rightarrow f_{heat}$	0.79	0.61	23.29	0.61	-0.78	0.58	4.92	0.54	7.84

Table 6.8 Convergence statistics for $N_{f_{heat}, f_{dist}}$ during the case study application.

	Normalised Performance at Generation and Percentage Improvement								
	1st	50th	%	100th	%	200th	%	Final	%
Average $N_{f_{heat}, f_{dist}}$	0.59	0.36	39.59	0.31	13.05	0.26	16.49	0.19	26.18
$\min(f_{heat})$	0.60	0.35	40.81	0.23	35.86	0.13	43.48	0.00	100.00
$\min(f_{heat}) \Rightarrow f_{dist}$	0.81	0.33	59.00	0.24	28.45	0.26	-7.45	0.39	-52.76
$\min(f_{dist})$	0.27	0.14	46.04	0.08	41.25	0.05	42.13	0.00	100.00

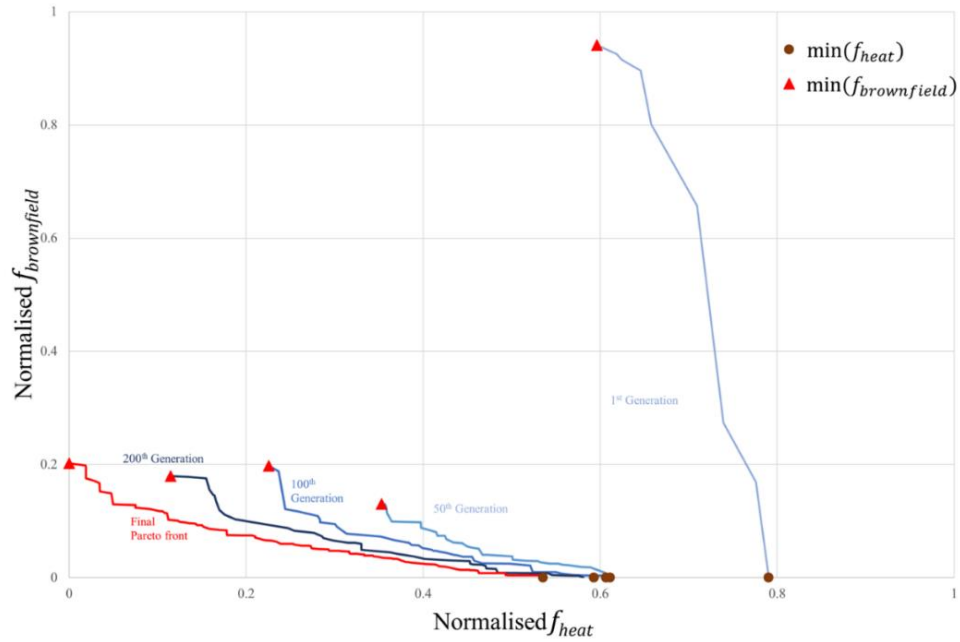


Figure 6.9 Convergence of the Pareto front $N_{f_{heat}, f_{brownfield}}$ during the GA application.

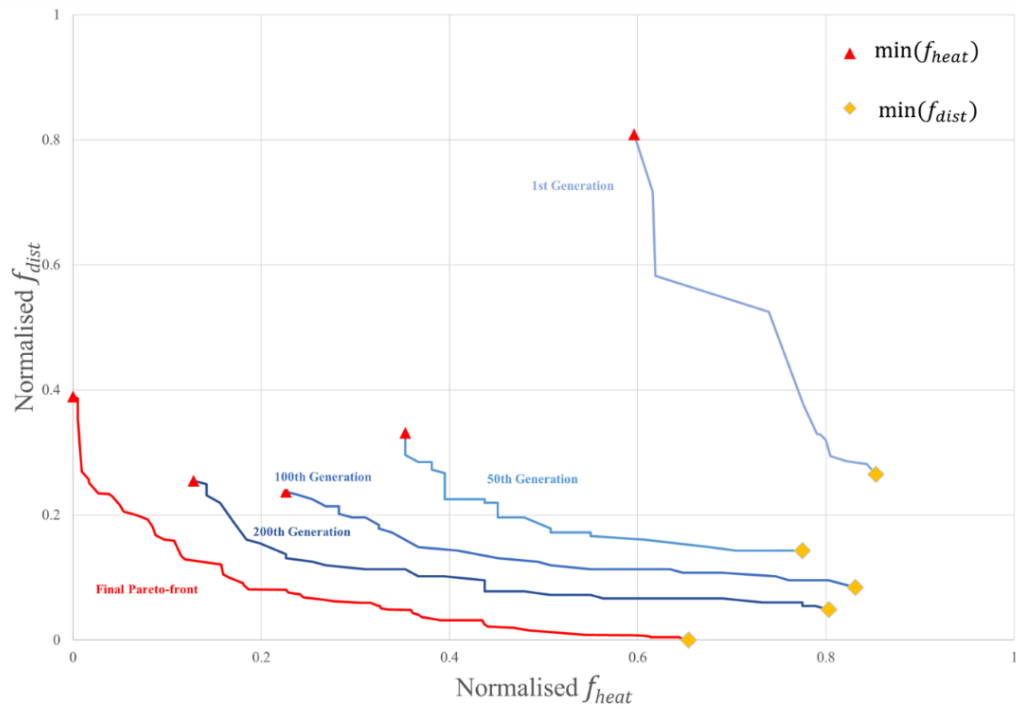


Figure 6.10 Convergence of the Pareto front $N_{f_{heat}, f_{dist}}$ during the GA application.

6.6.1 Resulting Pareto Fronts

Figure 6.11 presents the normalised Pareto fronts for London between pairs of sustainability objectives resulting from the application of the modified Multi-Objective Spatial Optimisation Framework, while Table 6.9 quantifies the best trade-offs between the objectives, and also states the number of solutions which lie on each Pareto front.

The results highlight clear conflicts between optimising f_{heat} simultaneously with the other objectives (Figures 6.11a-d) during the development of spatial plans for London. This is especially true of f_{flood} as the solution $\min(f_{heat}) \Rightarrow f_{flood} \geq 0.16$ whilst, $\min(f_{flood}) \Rightarrow f_{heat} \geq 0.65$ as the floodzones correspond to areas of low heat hazard next to the river. Indeed 113 solutions lie on the Pareto front $N_{f_{heat}, f_{flood}}$ reflecting the magnitude of the conflict as development moves towards and away from floodzones. 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 fact that compact development close to existing urban centres ultimately correlates spatially with areas of high heat hazard primarily due to land use patterns. Meanwhile restricting development to brownfield gives $\min(f_{brownfield}) \Rightarrow f_{heat} \geq 0.54$ indicating insufficient brownfield sites in low heat hazard. It is worth noting, however, that the best f_{heat} performance can be achieved with 85% of development being allocated to brownfield sites (normalised performance of 0.2).

As in the case of Middlesbrough, conflicts between f_{flood} and the other objectives are much less pronounced with $\min(f_{flood}) \Rightarrow f_{dist} \geq 0.08$ and $\min(f_{sprawl}) \Rightarrow f_{flood} \geq 0.12$. The Pareto front between f_{flood} and $f_{brownfield}$ is not shown as the framework is able to optimise both simultaneously, i.e. $\min(f_{flood}, f_{brownfield})$. However, f_{dist} and $f_{brownfield}$ have a noticeable conflict with $\min(f_{dist}) \Rightarrow f_{brownfield} \geq 0.18$ and $\min(f_{brownfield}) \Rightarrow f_{dist} \geq 0.3$, suggesting a lack of brownfield sites in very close proximity to town centres. A less intuitive result of the analysis is the conflict between f_{dist} and f_{sprawl} (Figure 6.11i) with $\min(f_{dist}) \Rightarrow f_{sprawl} \geq 0.29$ and $\min(f_{sprawl}) \Rightarrow f_{dist} \geq 0.11$ due to the proximity of some of London's town centres to the edge of the urban extent of the GLA. Likewise, in the case of $f_{brownfield}$ and f_{sprawl} (Figure 6.11j) to fully maximise one individual objective requires a significant trade-off with the other.

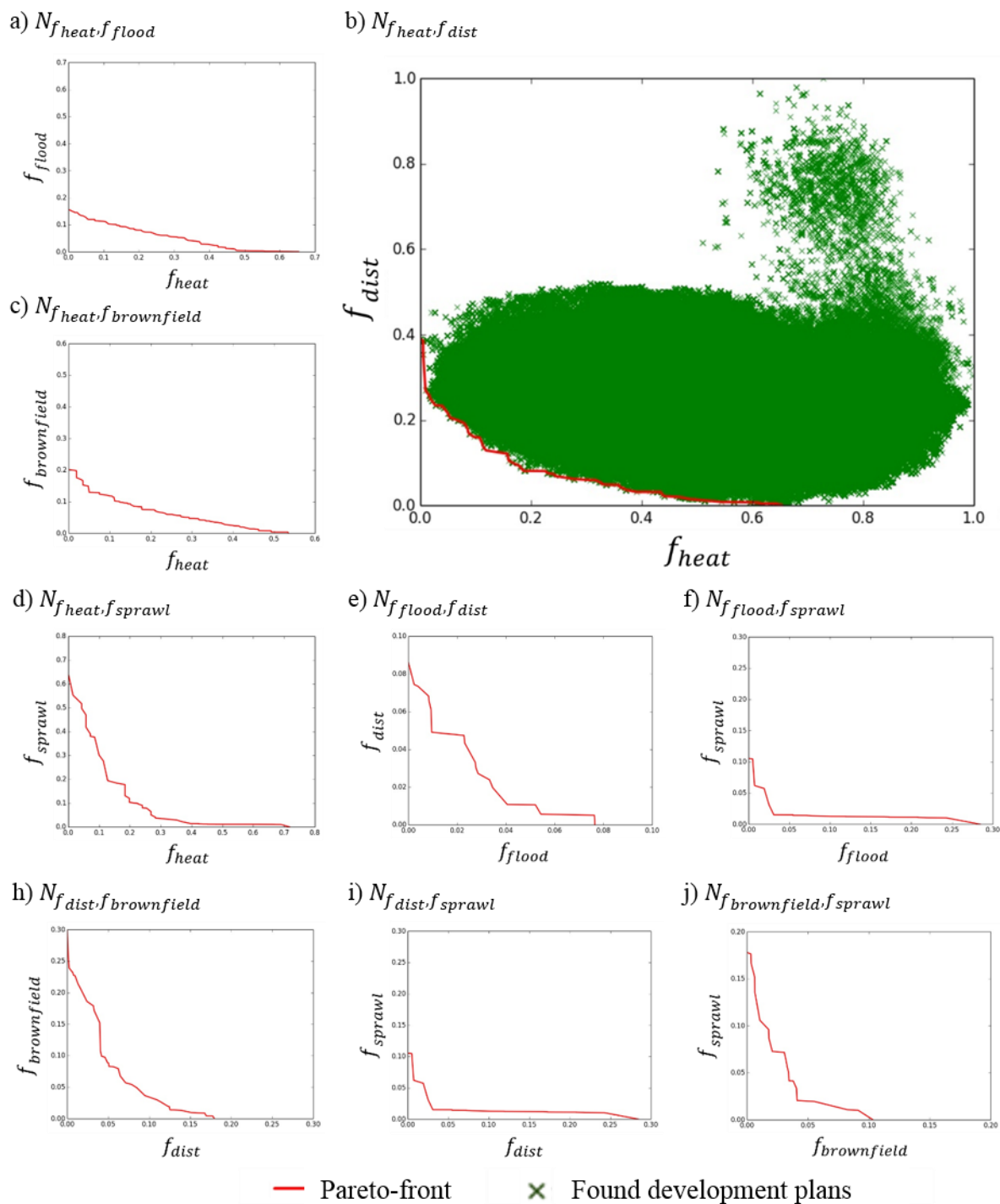


Figure 6.11 Pareto fronts between sustainability objectives for the London case study.

Table 6.9 Pareto front trade-off matrix.

		Best Trade-off in corresponding objective.				
		f_{heat}	f_{flood}	f_{dist}	f_{sprawl}	$f_{brownfield}$
Optimised objective: $\min(\cdot)$.	f_{heat}	NA	0.16 (113)	0.39 (64)	0.64 (55)	0.2 (115)
	f_{flood}	0.65	NA	0.09 (20)	0.03 (11)	0 (1)
	f_{dist}	0.65	0.08	NA	0.11 (27)	0.3 (44)
	f_{sprawl}	0.72	0.12	0.29	NA	0.1 (21)
	$f_{brownfield}$	0.54	0	0.18	0.18	NA

(Number of Solutions in Pareto front)

6.6.2 Pareto-optimal Spatial Configurations

Figures 6.12 – 15 present a series of best spatial plans to meet the sustainability objectives outlined in this case study whilst their objective performances normalised throughout the MOPO solutions is mapped in Figure 6.16. Note the densities of development are ignored for visualisation. Figure 6.12 presents the best spatial development strategies $\min(f_{heat})$ and a comparison with the best spatial development strategy for $\min(f_{flood})$ to demonstrate the cause for the significant conflict demonstrated in Figure 6.11a. In order to achieve the best performance in f_{heat} development is strategically located in lower heat hazard areas in the south, south east, north and north east of London. The spatial plan performs relatively well at optimizing $f_{brownfield}$ with a normalized performance of 0.4 compared to a range of Pareto-optimal spatial plans (see Figure 6.16). This can be seen in Figure 6.12b as development is located in brownfield sites which correspond with lower heat hazard. However these commonly lie within close proximity of the river, and therefore within flood zones causing the poor performance in f_{flood} (normalized performance of 0.58 compared to the range of Pareto-optimal spatial plans). This is especially true of the areas on the neighbouring the Thames in the east of the study area and in the north next to the rivers tributaries (windows ii and iii in Figure 6-12b).

Likewise the spatial plan for $\min(f_{flood})$ utilizes the abundance of brownfield sites on the banks of the river Thames (Figure 6.12c) and is able to keep all development on brownfield sites whilst completely avoiding floodzone, $\min(f_{flood}, f_{brownfield})$. This is significant as it demonstrates the ability to couple risk reduction with the desirable brownfield development planning policy. However, to avoid developing within the floodzone the spatial plan is forced to develop in higher heat hazard areas as can be seen in Figure 6.12b(i). The reduced emphasis on avoiding high heat hazard areas allows development to be more spatially focused on brownfield sites in the west of the study area away from central and eastern floodzones.

Both spatial plans share strategic development trends in outer London indicating that these areas are spatially optimal for a number of the objectives outlined, but both are still is forced to locate some development in central locations (Figure 6.12b and c) to fulfil the required quota of dwellings (Equation 6.1), as the density regulations prevent high-density development in outer London (refer to Figure 6.6). Both spatial plans develop alongside the river in the east of the study area (Figure 6.12b (iii) and 6.12c (iii)). However $\min(f_{heat})$ develops south of the river

whilst $\min(f_{flood})$ develops the north. Development in this area contributes to the poor performances in f_{sprawl} and f_{dist} of both spatial plans as it is an undeveloped area outside the urban extent with insufficient infrastructure. Indeed due to the scale of the conflict the framework finds 113 solutions for $N_{f_{heat},f_{flood}}$.

Figures 6.13 and 6.14 demonstrate the best spatial plans for optimizing accessibility, $\min(f_{dist})$, with respect to brownfield development and heat hazard respectively. Figure 6.13 demonstrates how the spatial plan strategically develops brownfield areas close to town centres to achieve a trade-off with $f_{brownfield}$. For example, the large brownfield site in Newham, central London, is heavily developed due to its proximity to the town centres of Stratford, Bow and Leyton. Meanwhile, Figure 6.14 conveys how development can be located in areas with good accessibility to employment and services as well as corresponding low heat risk; in particular around the town centres of Greenhill and Ealing in east London and Wood Green and Tottenham in north London. Figure 6.15 demonstrates the spatial plan for $\min(f_{brownfield})$ for the Pareto-set $N_{f_{heat},f_{brownfield}}$ as there are several spatial plans which are $\min(f_{brownfield})$. The figure shows how the spatial plan attempts to reconcile the optimal plan for brownfield against f_{heat} by locating on brownfield sites in low risk areas such as the brownfield sites north of the river in the east of the study area. However this negatively effects f_{dist} and f_{sprawl} as these areas are located towards the edge or outside the current urban extent (see Figure 6.3d)

Figure 6.16 provides a visual overview of the best spatial strategies relative to their performance across the all of objectives. As stated, the spatial configurations $\min(f_{heat})$ and $\min(f_{flood})$ perform poorly in terms of minimising f_{sprawl} as they develop brownfield sites outside the currently developed areas along the east of the river. This leads to 16 % and 17% of proposed development occurring outside of the current developed extent. The spatial configuration for $\min(f_{heat})$ performs poorly in f_{flood} and $f_{brownfield}$ as low heat hazard areas correspond with floodzones. This is reciprocated as the solution $\min(f_{brownfield}) \in N_{f_{heat},f_{brownfield}}$, achieves a normalised performance of 0.54 in f_{heat} , whilst achieving a good performance in f_{flood} (0.09). Lastly, $\min(f_{brownfield})$ performs particularly poorly in f_{dist} suggesting there is a lack of ideally situated brownfield sites in close proximity town centres.

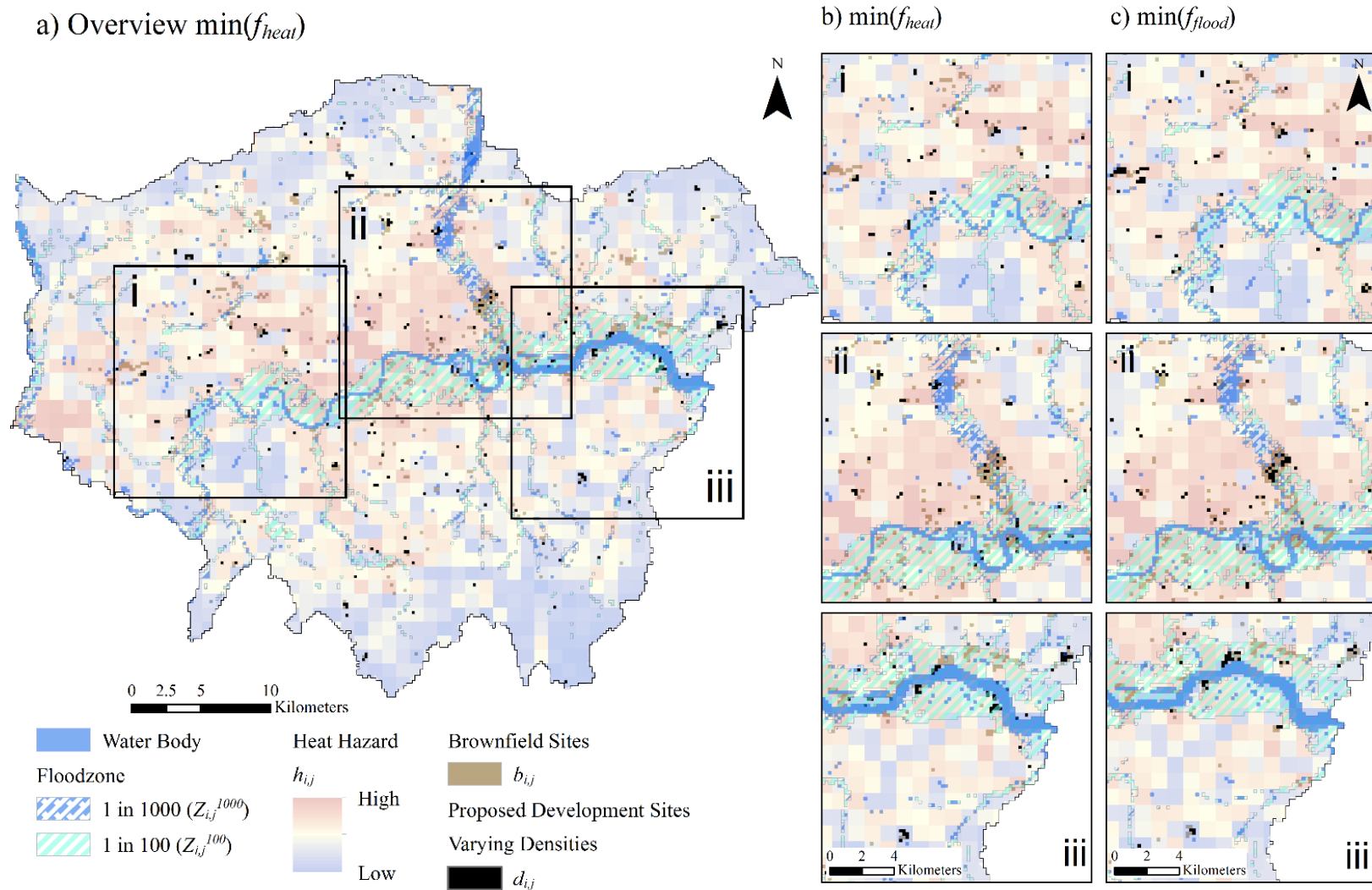


Figure 6.12 a) Overview of spatial configuration for $\min(f_{heat})$, b) viewing windows i, ii and iii, and c) comparison with the spatial plan for $\min(f_{flood}, f_{brownfield})$. For clarity of visualisation varied densities of development are not shown.

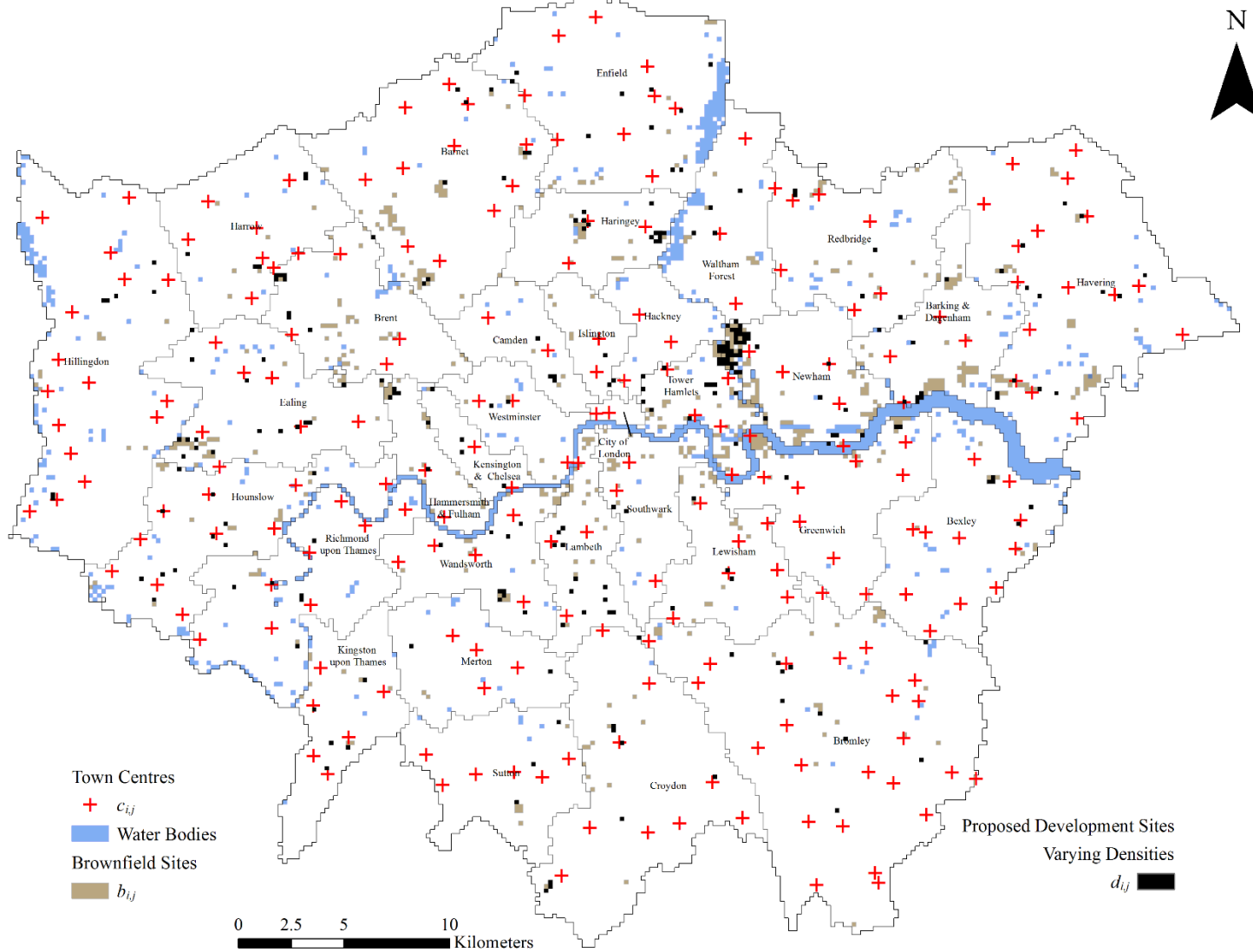


Figure 6.13 The spatial plan for $\min(f_{dist})$ shown against brownfield sites.

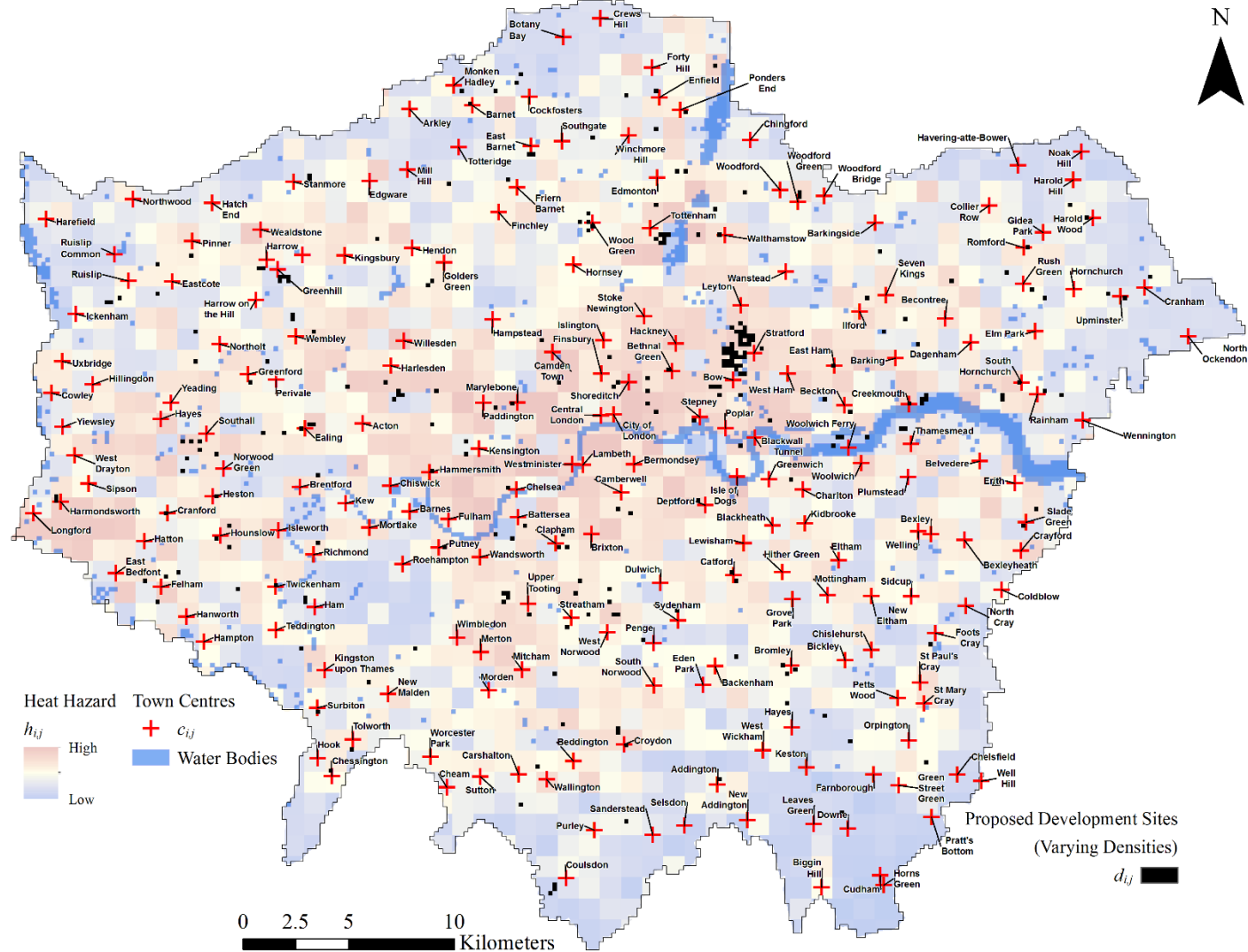


Figure 6.14 The spatial plan for the solution which is $\min(f_{dist})$ against heat hazard.

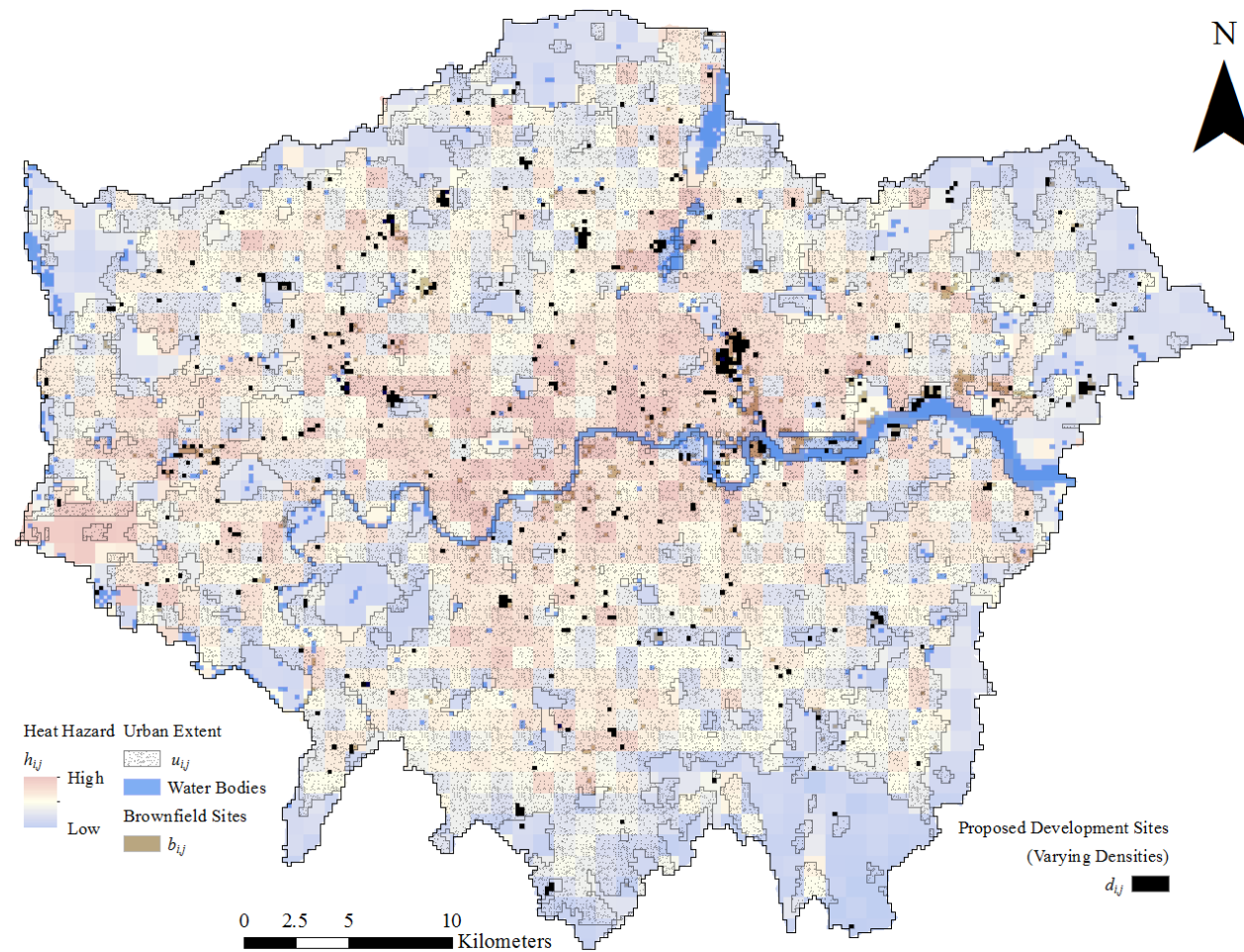


Figure 6.15 The spatial plan for the solution which is $\min(f_{brownfield})$ in the Pareto-set $N_{f_{heat}, f_{brownfield}}$.

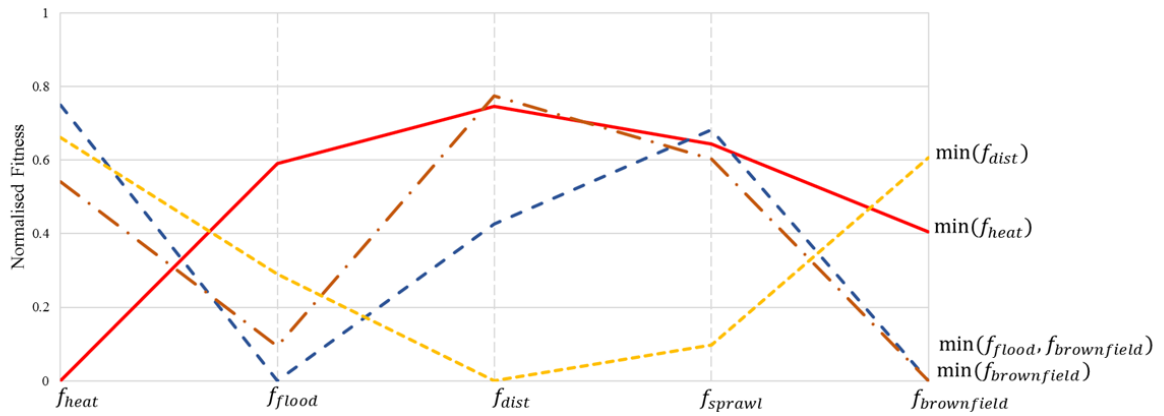


Figure 6.16 Parallel line plot showing the performance of the best Pareto-optimal spatial plans across the range of objectives.

6.6.3 Comparison with London's Current Development Plan

Figure 6.17 presents a borough (local authority) level comparison of Pareto-optimal spatial strategies compared to the Greater London Authority's (GLA) spatial development plan. Of the 33 boroughs investigated 50% have more development assigned in the Pareto-optimal spatial plans compared to the current development plan; showing that the current development plan is underutilising suitable locations at least with regards to the objectives investigated in this work. Equally, the comparison identifies boroughs which the current London development plan has earmarked for high development but which the analysis finds unsuitable with regards to the risk and sustainability objectives. For example the GLA assigns 11,600 dwellings to borough of Hackney (central London), while Pareto-optimal spatial strategies assigns at most 1,600 dwellings. This is consistent across all spatial plans due to the spatial correspondence of high heat hazard, flood risk and poor transport accessibility to town centres in the borough.

Interestingly, around 25% of boroughs have broadly similar numbers of assigned dwellings (within +/- 15%) in the London plan and the Pareto-optimal spatial plans indicating that the current plan in these areas would be able to meet the risk and sustainability objectives investigated in this study. Depending on the objective being prioritised a number of London's boroughs are identified as being particular suitable to be developed. For example a number of boroughs in the West of the study area are highly developed by the spatial plan for $\min(f_{dist})$. Meanwhile the spatial plan for $\min(f_{heat})$ assigns nearly 6 times the number of dwellings proposed by the GLA to the borough of Bexley in the east of the study area, south of the river, due to the corresponding low heat hazard values along the river. Conversely a number of

boroughs in close proximity to the river are developed less by the spatial plan $\min(f_{flood})$ compared to the GLA plan.

Figure 6.18 presents a sub-borough comparison over the borough of Newham between the council's spatial plan and the Pareto-optimal spatial plans as the total number of dwellings assigned are consistent (see Figure 6.17). However due to Newham's spatial properties (numerous brownfield sites, low heat hazard areas and the occurrence of floodzones (Figure 6.18a)) this varies spatially within the borough. Figure 6.18b demonstrates the noticeable differences in the spatial allocation of development at the level of community forums. While $\min(f_{flood}, f_{brownfield})$ and $\min(f_{dist})$ concentrate development in the north west of Newham, $\min(f_{heat})$ instead develops the east and south east. Due to the presence of a floodzone and unsuitability of brownfield sites both $\min(f_{flood}, f_{brownfield})$ and $\min(f_{brownfield})$ avoid the sub-borough zone of Royal Docks and while Newham Council plan development in Canning Town & Custom House, the Pareto-optimal spatial plan avoids these areas due to the presence of a floodzone and high heat hazard. The plan $\min(f_{flood})$ discourages development in Royal Docks as it is predominantly floodzone, whilst the plan $\min(f_{heat})$ assigns more dwellings than Newham council's plan to this area. Due to the proximity to of a town centre in Stratford and West Ham the plan $\min(f_{dist})$ encourages development at these locations, although the heat hazard is relatively high in this community forum area, which in the plan $\min(f_{heat})$ discourages development and instead allocates development to East Ham and Beckton.

It should be noted that different costs of development aren't considered in this analysis (e.g. the cost of developing in outer London v central London). If cost was considered it may affect the results and partially explain the discrepancies with the currently planned situation. Further discussion on this can be found in Section 7.2.3.

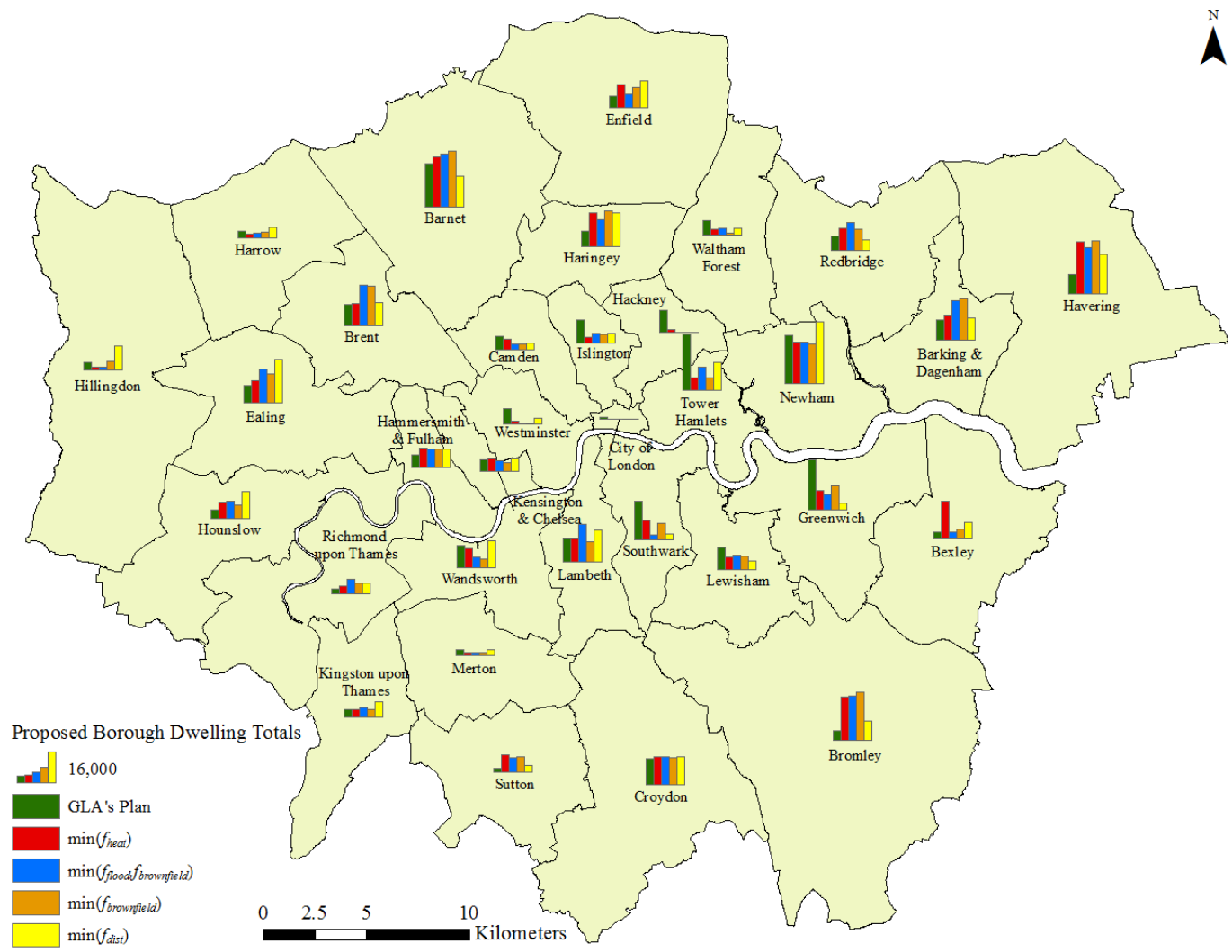
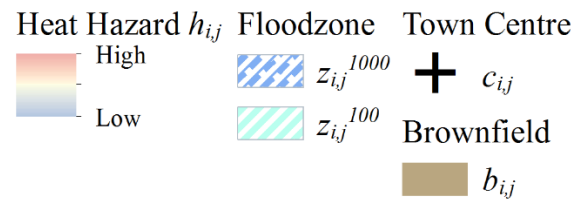
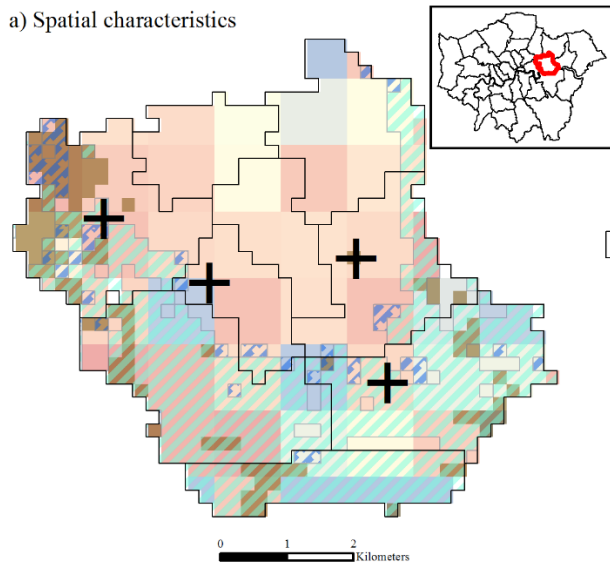
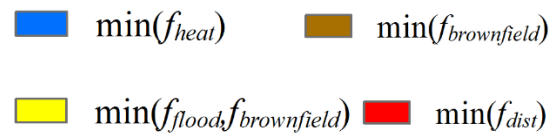
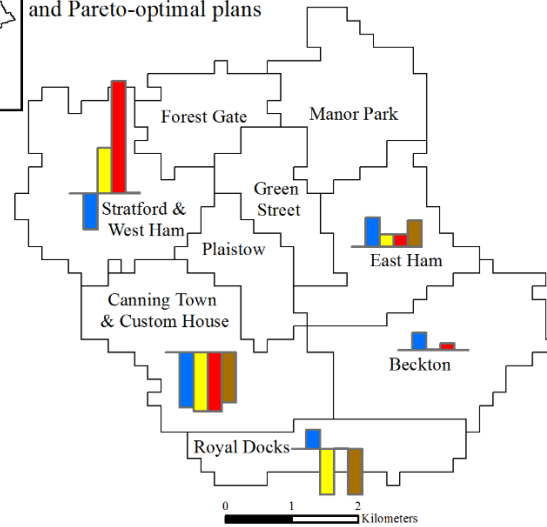


Figure 6.17 Borough level comparison between GLA plan and Pareto-optimal spatial plans.

a) Spatial characteristics



b) Difference in proposed dwellings between GLA's and Pareto-optimal plans



c) Total proposed dwellings of GLA plan and Pareto-optimal plans

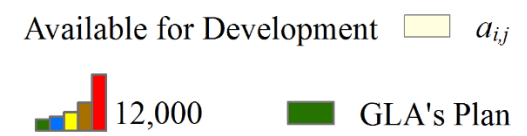
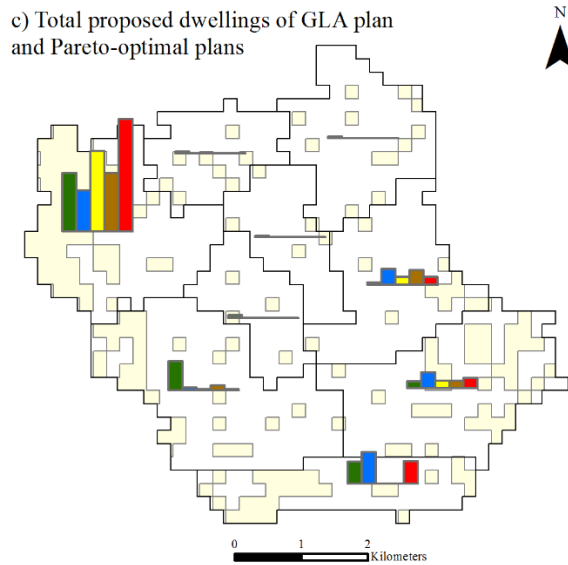


Figure 6.18 Sub-Borough level (community forum areas) comparison between GLA plan and optimal spatial plans.

6.6.4 Multi-Objective Pareto-Optimal Development Sites

Overall 31,716 MOPO spatial plans were found for London by the modified MOSPOF (i.e. within N for $F = \{f_{risk}, f_{flood}, f_{sprawl}, f_{dist}\}$). Figure 6.19 presents a density matrix of the Pareto-optimal spatial development sites. Of the 3307 cells identified as being available for development, 831 (<25%) are developed by at least of one the 31,716 MOPO spatial plans while 207 and 104 are assigned to by more than 50% and 75% of the Pareto-optimal spatial plans respectively. Interestingly 27 of the development sites are assigned in all of the Pareto-optimal spatial plans generated; cells that all correspond to available brownfield land. The figure shows that there is a tendency for spatial clusters of sites to develop with regards to their magnitude of assignment across the entire set of MOPO spatial plans.

Figure 6.20 presents a parallel line plot of MOPO solutions found by the framework (a representative sample of 250 is demonstrated due to high numbers) as well as a representation of the average. These remain normalised throughout all the solutions found and demonstrates how well the MOPOs perform compared to all the possible spatial plans found. It also highlights the wide range of best trade-off spatial plans that were generated. All the MOPO spatial plans found keep f_{flood} below a normalized performance of 0.27 compared to all the spatial plans. This demonstrates that this objective is easy to reconcile with the other objectives. Indeed 420 MOPO spatial plans found which completely avoid any floodplain development. Likewise all the MOPO spatial plans keep brownfield development to below a normalized performance of 0.5 which corresponds with 38% brownfield development. With regards to the GLA's target of 96% brownfield development, the framework is able to elicit 9,691 MOPO spatial plans which meet the target whilst also being found to be best trade-offs across the other objectives. On the other hand MOPO solutions range up to 0.98 normalized value for f_{heat} in order to facilitate good performances for the other objectives (for example $\Rightarrow f_{brownfield}, f_{flood} \geq 0.05$ and $\Rightarrow f_{dist}, f_{sprawl} \geq 0.3$). The average of the MOPO solutions performs most poorly for $\Rightarrow f_{heat} = 0.46$ whilst the next poorest performance is $f_{sprawl} = 0.32$.

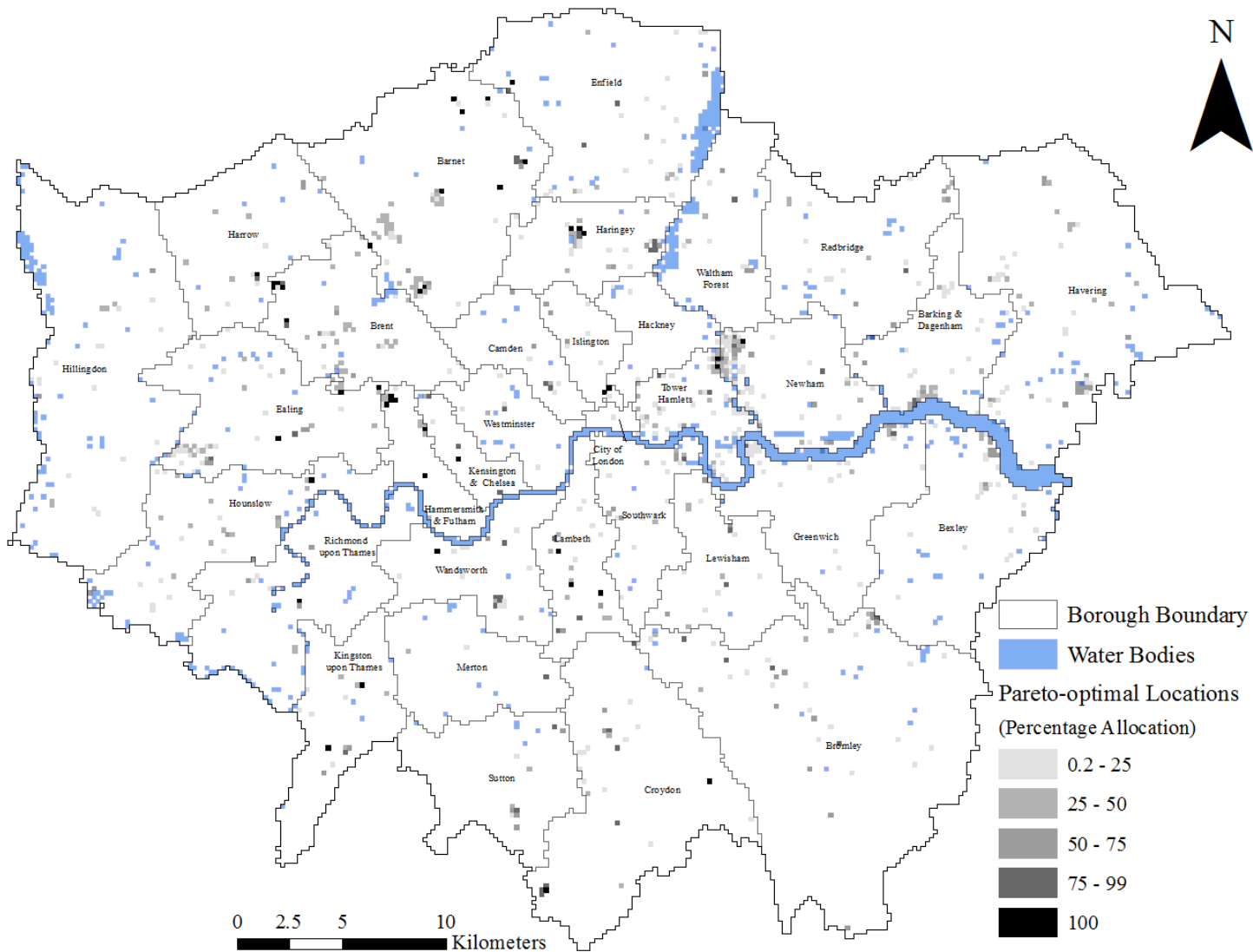


Figure 6.19 Ranked Pareto-optimal Development sites

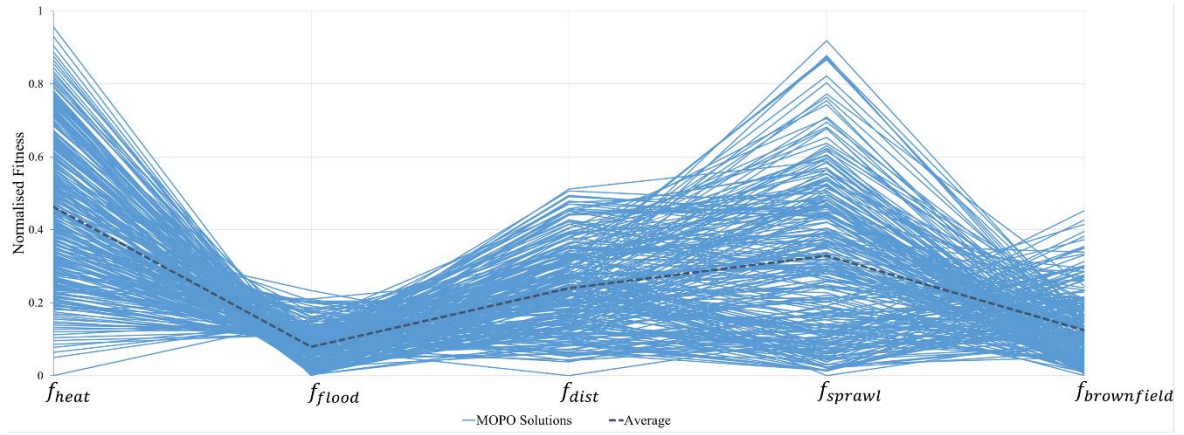


Figure 6.20 Parallel line plot of sample of MOPO solutions.

6.6.5 Prioritised Spatial Plans

Table 6.10 outlines the final derived preference vectors for the different prioritised plans outlined in Section 6.4.1 with the pre-scaled value in brackets (see Table 6.4 for their calculation). Notably the scaling causes the values for w_{heat} to increase reflecting its conflict with the other objectives. This is most pronounced for the equal priorities and hazard risk mitigation plans whilst $w_{brownfield}$ is scaled down to accommodate an increase in w_{heat} . These were then used to extract spatial strategies which are $\min(F^W) \in N$ based on the weighting system:

$$F^W = w_{heat}f_{heat} + w_{flood}f_{flood} + w_{dist}f_{dist} + w_{sprawl}f_{sprawl} + w_{brownfield}f_{brownfield} \quad (6.13)$$

Figure 6.21 plots the resulting spatial plans performances, demonstrating how the process identifies spatial plans which are far more representative of the priorities (in comparison to Figure 5.23). These are normalised and shown against the spatial plans which are $\min()$ for individual objectives for comparison. The process elicits a low risk city spatial plan which reconciles both f_{heat} and f_{flood} to performances below 0.26; this compares to $\min(f_{heat}) \Rightarrow f_{flood} \geq 0.6$ and $\min(f_{flood}) \Rightarrow f_{heat} \geq 0.75$ showing a significant reconciliation which might not otherwise have been found. Moreover the scaled weightings are able to find a balanced city plan is found which keeps the performance in all the objectives under 0.52. Although the green and spacious spatial plan isn't as optimal in f_{flood} and $f_{brownfield}$ as $\min(f_{flood}, f_{brownfield})$ this does achieve a better trade-off in the remaining three objectives.

Overall these plans provide much better balances than plans which are optimal in specific objectives and reveal that good trade-offs can be found to meet a set of priorities.

Figure 6.22 demonstrates the spatial configurations of the prioritised spatial plans while Figure 6.23 presents a borough comparison between the prioritised spatial plans and the GLAs plan. Several of the spatial plans share development strategies in the north and south of London due to the all-round optimality of such sites. Both the Low Carbon City and Green and Spacious spatial plans develop the large brownfield in the centre of London, while the Balanced City utilises spatial development strategies from all the other spatial plans, with development in the central brownfield site (although to a lesser degree) and the west of the study area from the Low Carbon and Green and Spacious plans and development on the north of the river in the east of the study area from the Low Risk city spatial plan. The comparison with the GLA plan (Figure 6.23) reiterates the unsuitability of boroughs currently allocated a high amount development which is important as it demonstrates these are not just sub-optimal for specific objectives but also in terms of prioritised combinations of them.

Table 6.10 Derived preference vectors for prioritized spatial plans.

Planning Prioritizes	Preference Vectors (pre-scaled)									
	w_{heat}		w_{flood}		w_{dist}		w_{sprawl}		$w_{brownfield}$	
Low Carbon City	0.11	(0.05)	0.08	(0.36)	0.05	(0.05)	0.05	(0.05)	0.36	(0.43)
Low Risk City	0.68	(0.43)	0.18	(0.43)	0.05	(0.05)	0.04	(0.05)	0.05	(0.05)
Green and Spacious City	0.21	(0.08)	0.13	(0.15)	0.45	(0.45)	0.45	(0.69)	0.15	(0.08)
Balanced City	0.34	(0.2)	0.14	(0.18)	0.16	(0.16)	0.16	(0.2)	0.18	(0.2)

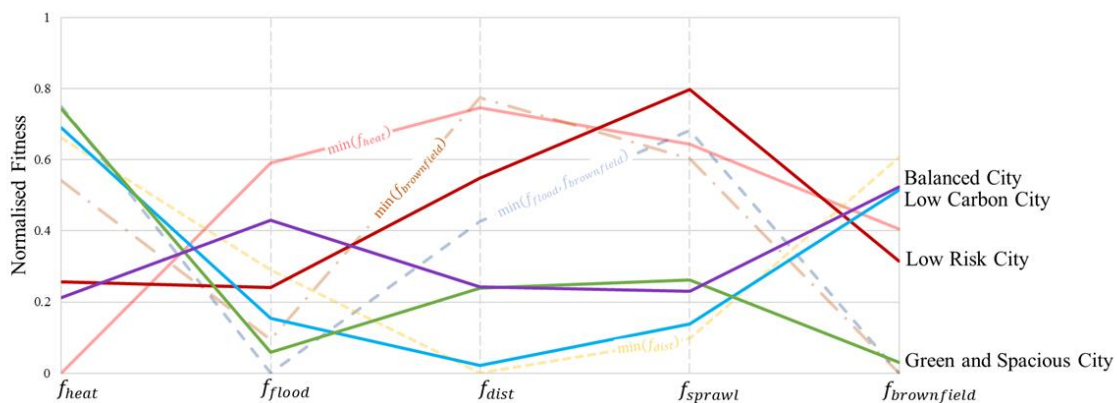


Figure 6.21 Parallel line plot of the prioritized Pareto-optimal spatial plans.

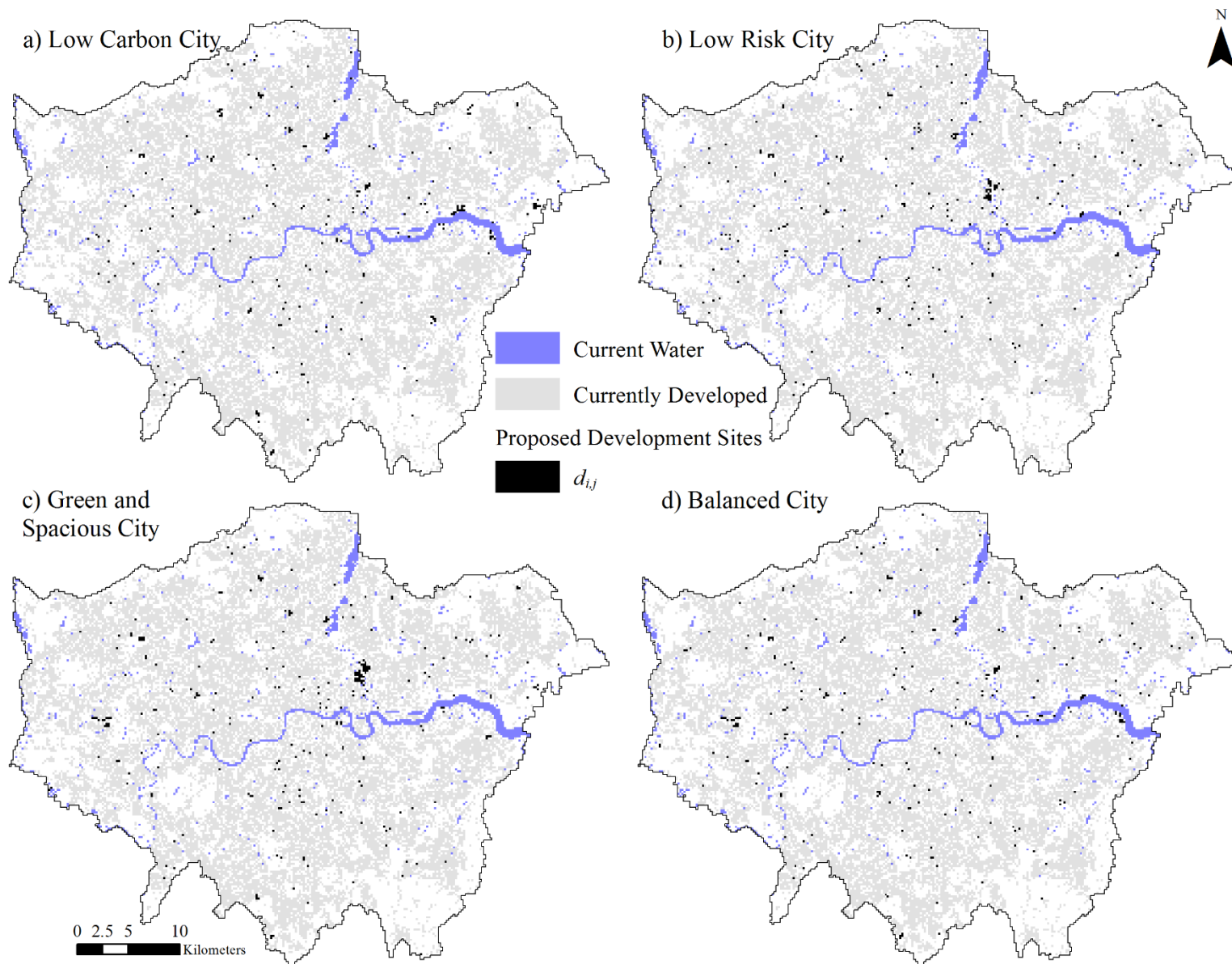


Figure 6.22 Prioritized Pareto-optimal spatial plans.

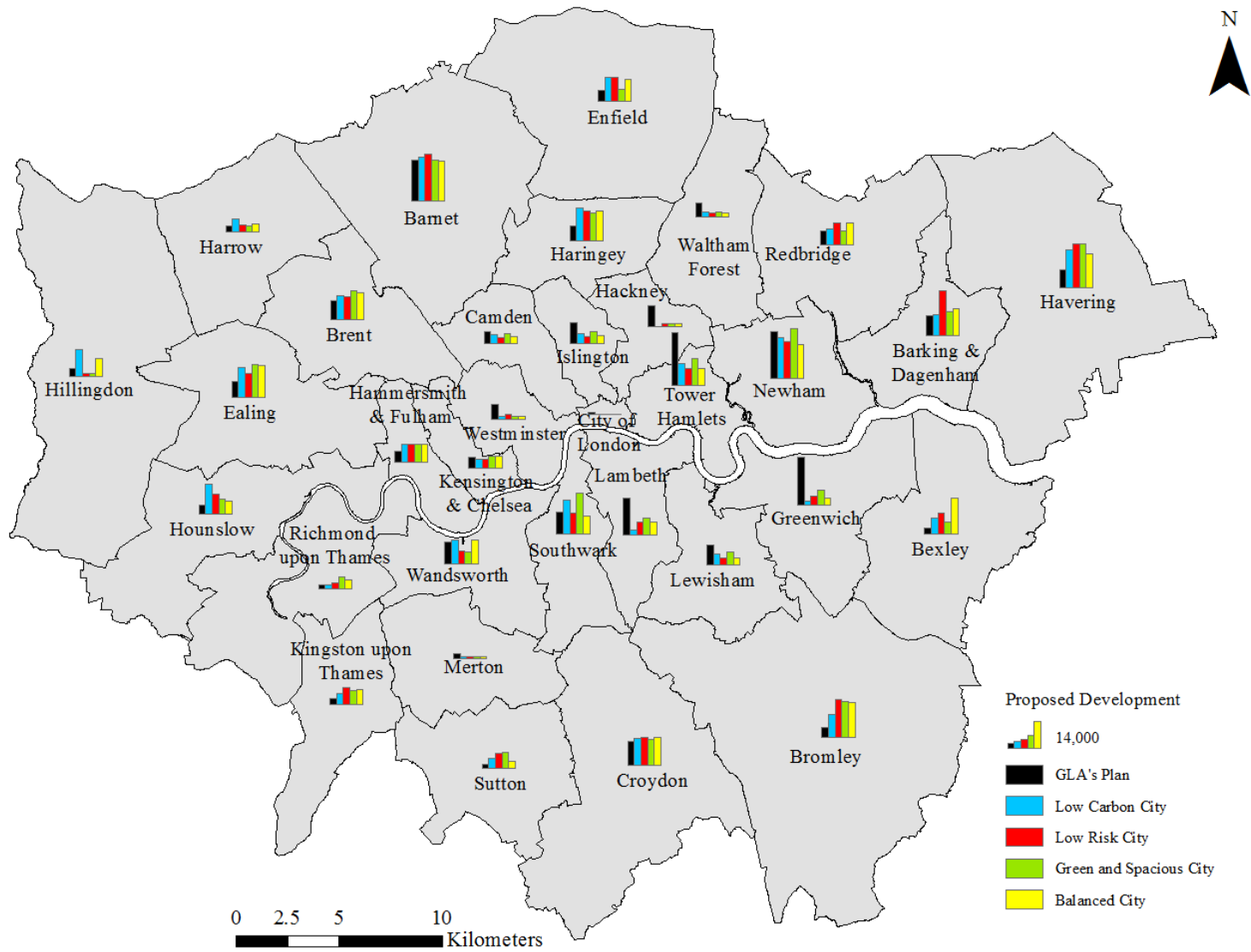


Figure 6.23 Borough comparison of prioritized Pareto-optimal spatial plans.

6.6.6 Regulatory Scenarios

Figures 6.24 and 6.25 outline the key ramifications of the regulatory frameworks on the results of the analysis. Figure 6.24 demonstrates the convergence of f_{heat} against f_{dist} and f_{sprawl} under the differing regulatory scenarios revealing that the relaxation of density regulation allows for significantly better convergence in f_{heat} . The spatial plan $\min(f_{heat})$ found during the ‘Business as Usual’ run achieved a normalized performance of 0.22 compared to the corresponding spatial plan for the density deregulation scenario ($f_{heat} = 0$). Moreover the performance in f_{heat} for the plan $\min(f_{sprawl})$ is improved by 42% (Figure 6.24b). Despite these improvements the regulatory scenario is unable to improve the performance in f_{dist} for $\min(f_{dist})$ or improve $\min(f_{dist}) \Rightarrow f_{heat}$ suggesting that density deregulation has little potential to improve overall accessibility, although the Pareto front $N_{f_{heat},f_{dist}}$ has an average improvement of 20%. Conversely Figure 6.24a also demonstrates that restricting development to brownfield sites has an adverse effect on reducing future heat risk with a 140% worse performance in f_{heat} for the spatial plan $\min(f_{heat})$ compared to the BAU scenario. Meanwhile exclusively developing brownfield sites prevents the optimisation of f_{sprawl} as the previous results show they can’t be simultaneously reconciled. In addition under this regulatory framework the number of MOPO solutions was reduced to 8513 due to the restriction in the search area and one less objective to consider.

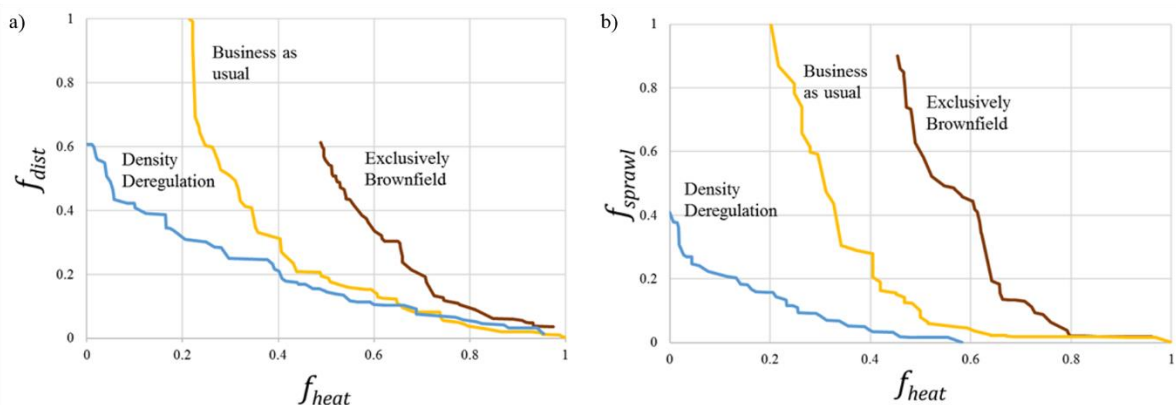


Figure 6.24 Convergence of the Pareto fronts a) $N_{f_{heat},f_{dist}}$ and b) $N_{f_{heat},f_{sprawl}}$ under differing regulatory frameworks.

Figure 6.25 demonstrates the regulatory effect on the distribution of proposed development densities, in this instance for the spatial plan which is optimal for minimizing f_{heat} . Whilst the majority of proposed developed is at 400 u/ha to take advantage of optimal locations, the relaxation of density restrictions has a noticeable effect of lowering development density, with

the re-emergence of 35 u/ha densities in order to dissipate the exposure to the heat hazard. This can be seen in Figure 6.26 where the majority of boroughs see a reduction in the average density for the spatial plan $\min(f_{heat})$ for the density deregulation run compared to business as usual.

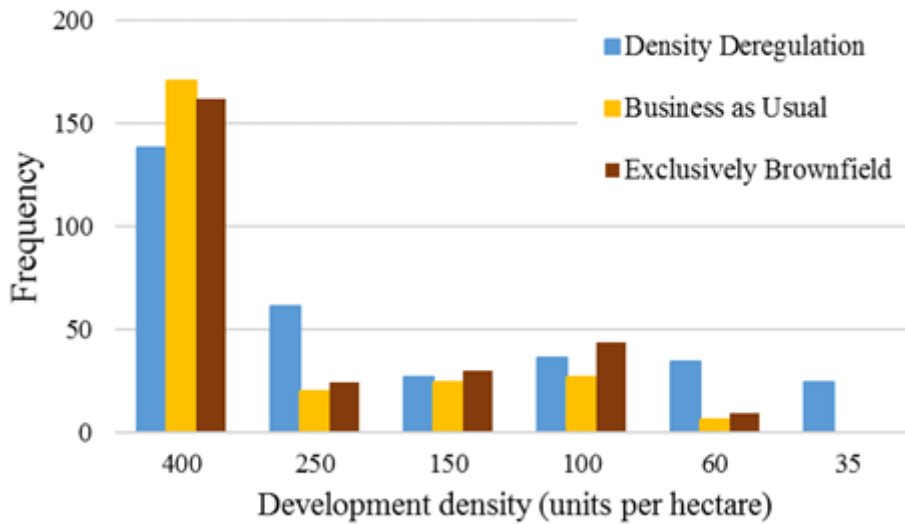


Figure 6.25 The effect on development densities of the spatial plan $\min(f_{heat})$ under differing regulatory frameworks.

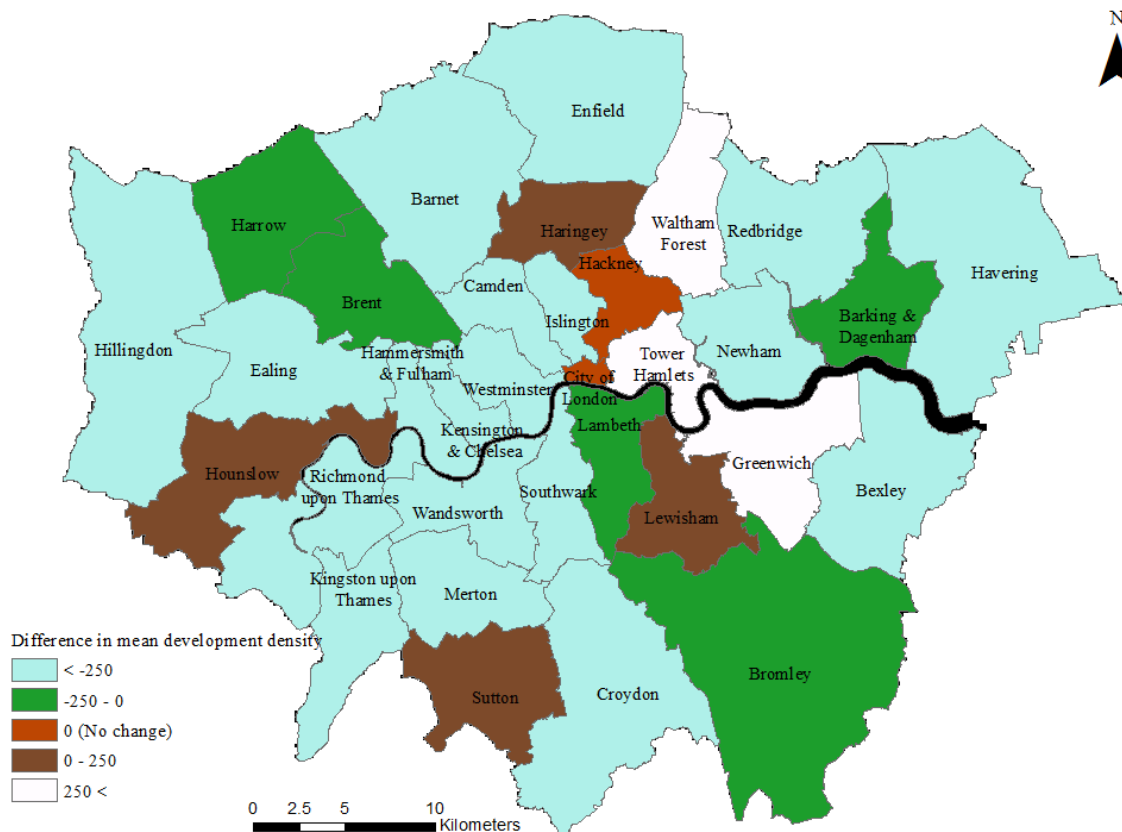


Figure 6.26 Borough development densities of the spatial plan $\min(f_{heat})$ under density deregulation compared to business as usual.

6.7 Summary

This chapter has presented a modified Multi-Objective Spatial Optimisation Framework based on the findings and recommendations of the application to Middlesbrough presented in the previous chapter. A new and unique method for representing spatial plans during the search is outlined which allows for increased complexity whilst maintaining the advantages of retaining a fixed length list representation. The new framework is demonstrated for a case study in London (UK), a larger urban area covering an area of 1,572km², developing optimal future residential development plans against six risk and sustainability objectives whilst also adhering to planning policies and land use constraints.

The results found conflicts between minimising heat risk and the other objectives. Whilst spatial plans are found which optimally meet the objectives the different spatial structure of the flood and heat hazards limits the potential to optimality meet these future hazards. In addition less pronounced conflicts are found which are specific to London, such as an absence of sufficient brownfield sites in close proximity to existing town centres to reduce increased commuting that will occur from increasing the number of dwellings. Significantly spatial development strategies are found which simultaneously avoid developing flood zones and keep all development within brownfield sites. However, the location of brownfield sites makes it impossible to exclusively develop these whilst optimising exposure to heat hazard.

A comparison of the spatial distribution of development with the optimised spatial plans reveals that the currently planned situation is failing to realise the potential to meet the sustainability pressures investigated with its spatial plan. In addition, the framework is used to compare performances against different regulation scenarios which show that improvements can be made in minimising heat risk through the relaxation of density regulations. Despite an overwhelming number of MOPO spatial plans being discovered, the chapter presents an innovative method of combining a well-known MCE approach with the diagnostic information from the Pareto-optimisation to elicit specific spatial plans which best meet a series of potential development scenarios. The success of this is demonstrated in the eliciting of a low risk spatial plan which maintains the normalised performances of minimising heat risk and flood risk to under 0.26, whilst a balanced spatial plan is found which restricts normalised performances across the objectives to under 0.5.

Chapter 7 Discussion

7.1 Introduction

Increasing urbanisation, climate change and resource scarcity are necessitate a move towards more sustainable urban forms. The review of literature in Chapter 2 identified the challenges planners face if they are to achieve urban forms which balance a number of sustainability objectives such as resource efficiency and adaptation to climate change impact. In particular, planners must ensure the transition to sustainable urban form via development which best meets local priorities for risk management and sustainability objectives which may potentially conflict with each other (Williams et al. 2000; Mcevoy et al. 2006; Barnett & O'Neill 2010; Dawson 2011); for example, concentrating development within brownfield sites whilst minimising heat risk (Kazmierczak 2012). Unfortunately current planning practices fail to sufficiently appreciate these conflicts, thereby failing to ensure planning decisions are made which lead to win-win situations and maximise the sustainability of new development (Gibson 2006). Chapter 3 identifies the utility of spatial optimisation as a possible means by which multiple objectives may be considered as part of the urban planning process. However, as Section 3.5.6 outlines, previous optimisation applications to urban planning have been limited to exercises in land use allocation with little or no explicit treatment of real world sustainability aims, especially those concerned with climate related risks.

In response, Chapter 4 details the development of a Multi-Objective Spatial Optimisation Framework for planning future urban development with respect to a series of real world and highly prioritised sustainability objectives. Specifically, the framework optimises the location of a discrete number of future residential development sites that meet future demand whilst minimising the risk faced from natural hazards and also satisfy planning constraints. The framework is demonstrated for two real world urban case studies in Chapters 5 and 6. This chapter presents a discussion of the findings of the work, in the context of the aims and objectives set out in Chapter 1. Section 7.2 discusses and draws out the main findings of the application of the framework to the case studies presented and also highlights the implications of these findings. Thereafter, Section 7.3 evaluates the overall success of the developed framework in meeting the challenges identified in the literature critique in Chapter 2 and how the uniqueness of the approach improves upon the weaknesses of the previous applications identified in Chapter 3.

7.2 Case Studies Findings

The results of the application of the developed framework to Middlesbrough and London are presented in Chapters 5 and 6 respectively. The urban areas were chosen specifically to demonstrate and test the ability of the framework to handle both a medium and large urban spatial planning problem. This section discusses the main findings of these case studies.

7.2.1 Sustainable Planning Conflicts

As found in the review of the literature (see Section 2.3) the results of the case studies identify and corroborate a number of instances of conflicting sustainability objectives during the spatial planning process (Hamin & Gurran 2009), as well as identifying a number of additional conflicts which have not been reported to date in the literature.

The applications to both Middlesbrough and London identified significant conflicts between minimising heat risk, f_{heat} , whilst simultaneously optimising other planning objectives. For the smaller case study of Middlesbrough the derived spatial plans which maximise accessibility, $\min(f_{dist})$, and prevent urban sprawl, $\min(f_{sprawl})$, focus development in the centre of the study area in close proximity to the CBD. However, in order to optimally minimise heat risk, $\min(f_{heat})$, development is predominantly located in the south east of Middlesbrough leading to worse performances in $\min(f_{heat}) \Rightarrow f_{dist} = 1$ and $\Rightarrow f_{sprawl} = 1$. This reiterates the literatures that the greatest heat risk is to be found in the centre of cities (Graves & Philipson 2000; Wong et al. 2011; Hunt & Watkiss 2011). Therefore if planners wish to optimise accessibility and sprawl a higher heat risk has to be accepted. Otherwise, if future heat risk is the main concern planners need to implement development plans with lower accessibility and on the urban eprophery leading to urban sprawl.

This trend is continued in the case study for London. However the relationship isn't as clearly defined due to the presence of multiple centres of employment and services (represented by town centres). As a result $\min(f_{heat}) \Rightarrow f_{dist} = 0.39$ meaning that whilst a conflict exists, there is the allowance for more of a trade-off with lower heat risk whilst having suitable access to employment areas. Specifically, London has a number of smaller satellite centres of employment and services in addition to the large employment centre of the City of London. As such, spatial development plans that mitigate to some degree heat risk whilst still maintaining a

high spatial accessibility and low urban sprawl can be achieved by strategically targeting specific town centres; e.g. Bow, Stratford, Greenhill, Wood Green (see Figure 6.14 for more examples). As these centres of services and employment vary in their capacity and importance, an interesting inquiry would be whether if this was taken into account it would affect the results. However, in order to fully minimise heat risk development has to take place outside the urban centres of London along the river Thames in the East of London leading to undesirable levels of sprawl ($\min(f_{heat}) \Rightarrow f_{sprawl} = 0.64$) whilst to ensure all development takes place within the urban extent it increases exposure to heat risk; $\min(f_{sprawl}) \Rightarrow f_{heat} = 0.72$.

A key finding of the case studies are the conflicts between adapting to flood risk and heat hazard. In the case of Middlesbrough this conflict is relatively small with the development strategy for $\min(f_{heat})$ only placing two development sites in flood zones in the far south and north of the study area. However, for London this conflict is much more significant with the best spatial strategy $\min(f_{flood}) \Rightarrow f_{heat} = 0.65$. This is reciprocated to some degree with the spatial development strategy $\min(f_{heat}) \Rightarrow f_{flood} = 0.16$, equating to 19% of dwellings being placed within flood zone areas to ensure the best minimised heat risk. In London the conflict is a result of low heat risk areas corresponding to flood zone areas on the side of the Thames (see Figure 6.12), which are likely a result of the cooling effect of the ‘blue infrastructure’ (Voskamp & Van de Ven 2015). Acknowledgement of such a conflict has not been widely recognised in the literature. However, a significant number of the world’s largest urban conurbations have developed around major rivers (Huq et al. 2007). As such, this finding if replicated in other such cities casts doubt on the ability to fully combat and address heat and flood risk adaptation simultaneously for future urban development.

As identified in Section 6.6.1 an unintuitive result of the application to London is the conflict between minimising sprawl and maximising accessibility. The prevalence of a number of town centres in London means that the most accessible employment and service areas aren’t necessarily within the currently built up area. This can be seen in the trends for the development strategy $\min(f_{dist})$ in Figure 6.17, with development focused towards boroughs in the extreme west of London. It also suggests that there is a lack of available development areas within the existing urban fabric of London that have high accessibility. The consequence of this is that limiting urban sprawl isn’t synonymous with maximising accessibility, and therefore transport emissions, as has been asserted in the literature (Bertaud & Richardson 2004; Newman 2014).

Development plans for both case studies are found which reconcile limiting urban sprawl with adapting to flood risk; a relationship that has rarely been found in other studies (Sanders & Phillipson 2003). However, in both case studies there are conflicts with the simultaneous pursuit of flood risk adaptation and accessibility, a feature that has been found in other studies such as Hamlin & Gurran (2009). This conflict is, however, relatively small for London and Middlesbrough ($\min(f_{dist}) \Rightarrow f_{flood} = 0.08$ and $= 0.16$ respectively) Thus, it suggest that in the case of flood risk, which has been recognised as one of the biggest adaption challenges for the future (House of Commons Environmental Audit Committee 2015), that development can be designed alongside other sustainability objectives; certainly more so that avoiding exposure to heat risk which was found to be harder to implement simultaneously with the other objectives. However, whilst the risk from fluvial (river) flooding is addressed in this study, potential increased risk associated with pluvial (surface water) flooding and flood from sewers still needs to be investigated.

The inclusion of maximising brownfield development (represented by $f_{brownfield}$) for the London case study provided a number of interesting outcomes regarding the ability to implement a widely perceived efficient land use planning policy (Baing 2010). The framework was able to derive development plans that developed all available brownfield sites whilst avoiding flood risk; a positive finding given the significant concern in London regarding future flood risk (Greater London Authority 2011c). Unlike flood risk, maximising brownfield development was found to conflict with adapting to heat risk due to brownfield sites being concentrated in urban centres that are the foci of heat (Kazmierczak 2012). Interestingly the development strategy $\min(f_{brownfield}) \in N_{f_{heat}, f_{brownfield}}$ attempts to mitigate this by developing brownfield sites in close proximity to blue infrastructure such as the main rivers. However, not only does this lead to increased flood risk ($f_{flood} = 0.10$ (see Figure 6.16)) but it still results in a poorly adapted plan for heat risk ($f_{heat} = 0.65$). The utility of brownfield development is dependent on the spatial location of brownfield sites. However the analysis finds that for London there is sufficient capacity of brownfield outside of flood risk zones.

Maximising brownfield development was found to conflict with the objective of accessibility to employment ($\min(f_{brownfield}) \Rightarrow f_{dist} = 0.18$). This implies, as has been reported in the literature, that many brownfield sites on old disused industrial areas, are often significant distances from current employment hubs (Syms et al. 2003; Kazmierczak 2012); suggesting that if developed major investment may be needed to provide suitable transport infrastructure

for access to employment. The importance of where brownfield sites are located with regards to the spatial form of a city is also highlighted by the finding that brownfield development conflicted with preventing urban sprawl ($f_{sprawl} = 0.18$). This is surprising as a number of sources identify brownfield development as a method to limit expansion and external growth of cities (American Planning Association 2000), so much so that brownfield development is a mainstream policy for many cities in a number of countries as a means of limiting sprawl (Baing 2010). Indeed, the Greater London Authority (GLA) spatial strategy (GLA 2011) sets a target of 96% brownfield development for London, while the UK government has reiterated its importance more broadly with regards to planning development within UK urban areas (Department for Communities and Local Government 2011a). However, the findings for London cast doubt as to whether meeting such targets will result in less urban sprawl and a retention of compact urban form while the population of urban conurbations grow into the future.

Section 6.4.6 analysed the implications of different regulatory frameworks for development. As noted in Section 2.3 regulation of development can play a crucial role in ensuring sustainable development. A number of sources advocate that high density development is necessary to ensuring high accessibility in urban areas (Newman 2014). However the results of the case study demonstrate that relaxing density constraints in London, whilst leading to lower average development density (Figure 6.25 and 6.26), have little impact on accessibility (see Figure 6.24a). These findings add to a growing body of work which show that high density development doesn't necessarily increase accessibility and reduce travel distances (Melia et al. 2011; Echenique et al. 2012).

The analysis also demonstrate reductions to heat risk that can be made by reducing development density; an average 30% improvement in f_{heat} for the spatial plans in $N_{f_{heat},f_{dist}}$. This also supports the finding that high density development increases population heat exposure (Tomlinson et al. 2011), as well as lower development densities can reduce exposure to heat risk (Buxton, 2000). Most significantly the results demonstrate that the improvements in managing heat risk can be achieved simultaneously with achieving a high level of accessibility; with the Pareto front $N_{f_{heat},f_{dist}}$ having an average improvement of 20% in the density deregulation scenario compared to the business as usual scenario (Figure 6.24a). In the London case study this is facilitated by strategically locating development in areas further from the heat island which were previously protected from development. This presents a potential solution

for planners to better alleviate heat risk which the analysis found to be hard to reconcile with the other objectives.

Overall the magnitude of these conflicts justifies the effort invested in the application of such a framework to Middlesbrough and London and highlights the need to consider objectives simultaneously in an analytical framework during the spatial planning process. This is especially true of heat risk which Section 2.5.5 and 4.2.3 found to be under-considered in sustainability appraisals despite the analysis finding it to be heavily conflicted with the other objectives. Overall the evidence of how these conflicts interact spatially provides useful information to planners and aid them prepare spatial plans with them in mind.

7.2.2 Optimal Spatial Development Strategies for Sustainable Development

The application of the framework to the Middlesbrough case study identified 568 Multi-objective Pareto-optimal (MOPO) solutions, defined as outperforming all other found solutions in at least one of the objectives considered, whilst 31,716 MOPO solutions were found for the London case study. Planners can choose these plans in the knowledge that there are no other plans that perform better across the range of sustainability objectives. These MOPO solutions (shown in Figures 5.18 and 6.20) provide planners with a variety of possible development solutions which best meet their priorities, including those found on the Pareto fronts between sustainability objectives. For example when considering heat risk and accessibility, the Pareto set $N_{f_{heat}, f_{dist}}$ for London identifies 65 different plans to best balance their achievement; plans which maximise either are found alongside plans which balance the two to f_{heat} and $f_{dist} < 0.14$.

During the application for London 18,500 spatial plans were found which entirely avoid flood zones, 420 of which were also best trade-off development plans in the other objectives. In the case of Middlesbrough 115 development plans, from a total of 570, were found that avoided any development in a flood risk zone and which were also best trade-offs for the remaining objectives. The fact that such numbers of MOPO plans could be generated that avoided entirely any flood risk is a significant finding as it indicates that it is potentially possible to completely eliminate the risk of flooding which is considered the biggest challenge climate adaption challenge to the UK (House of Commons Environmental Audit Committee 2015).

However the main strength of the discovery of these Pareto-optimal plans are the development strategies and trends which are identified to alleviate a number of planning conflicts. The plotting of these MOPO spatial plans as density matrixes (see Figure 5.17 and Figure 6.19) highlights a number of areas which are optimal development locations to meet a number of objectives. For Middlesbrough the north of the study area is identified as an optimal location for development which performs well for all four of the objectives considered (Figure 5.17) providing planners with the ability to balance of minimising heat risk whilst not extending the urban sprawl or distances to centres of local services and employment. In particular the MOPO density matrix resulting from the GA run finds twenty one potential development sites which are developed by $\geq 75\%$ of the MOPO spatial plans.

The trend for optimal development areas is less clearly defined in London. Instead the density matrix (see Figure 6.19) identifies a number of spatially variable optimal development clusters. For example, a number of clusters are found within the large brownfield area in the centre of London (see Figure 6.3 to identify the brownfield site) which balances low heat and flood risk which is close to a town centre. There are also a number of optimal development areas in the outer boroughs of London, such as in North Hammersmith and Fulham. In total 104 cells (408 hectares) of available land for development are assigned to by 75% of the MOPO spatial plans (see Figure 6.20). For both Middlesbrough and London, these Pareto-optimal sites consist of a third of the average total development area requirement for a development plan.

Overall, despite the existence of conflicts between the climate related and sustainability objectives evaluated, the framework is able to identify a number of plausible spatial development plans when considering them simultaneously. Specifically the framework is able identify a number Pareto-optimal spatial development clusters within each study area from which planners can construct spatial planning plans which are optimal against multiple criteria and objectives. The spatial strategies found to balance these varied between the two case studies assessed reiterating the need found in Section 2.3 for contextualised strategies rather than one size fits all models of sustainable development. Moreover the assessment of development against a number of sustainability concepts (the objectives used cover half the aims identified in Section 2.2) ensures a more inclusive aim of sustainability is pursued.

7.2.3 Comparison to Current Development Strategies

In both case studies the ‘best’ optimised spatial development plans were considerably different from those proposed by the planning authorities of Middlesbrough and London. For Middlesbrough 100% of the optimal spatial configurations found by the Genetic Algorithm approach outperformed the current spatial development strategy with respect f_{heat} , while the optimal un-weighted Pareto-optimal spatial plan found by the framework lead to a 59% improvement in f_{dist} and 100% in f_{flood} .

In London there is a noteworthy difference in the spatial allocation of residential development between the ‘best’ Pareto-optimal spatial plans and the GLA’s plan (Section 6.6.3). Whilst the performance of the GLA’s plan wasn’t quantifiable (as the spatial disaggregation of GLA development plan was not available) the higher development in central London boroughs, such as Tower Hamlets, Southwark and Greenwich (see Figure 6.17), indicates it insufficiently maximizes the ability to meet the sustainable objectives investigated. Instead the Pareto-optimal spatial plans indicate that a general trend away from centrally focused development to development in the outer boroughs of London is needed to meet these sustainability pressures.

Both of these case studies indicate that planning in these two urban areas is failing to maximise the sustainability of their plans. This maybe be a result of, and collaborates, the problems associated with current practice in the sustainability appraisal process identified in Section 2.5.5, such as failing to sufficiently identify the conflicts which exist between the objectives and failing to consider a range of different planning options to ensure the best solutions are chosen. Alternatively the difference in performance may be as a result of ‘satisficing’ whereby planners select plans on the basis of meeting a baseline criteria rather than looking to optimize their performance (Simon 1996) (see Section 2.5.2). An example of this can be seen in Section 2.5.4 where development in Manchester was assessed by a criteria of being within 30 minutes of local services rather than looking to maximise accessibility.

7.2.4 Limitations of the Case Studies

The results of the case studies identify a plethora of knowledge about conflicts in sustainable spatial planning and best methods to placate them. However, there a number of limitations with regards to their contribution to the spatial planning field. Whilst the Pareto-optimal spatial plans

found are more sustainable (with regards to the sustainability objectives assessed) than the current spatial planning strategies, it should be noted that planning decisions are not taken solely on the basis of sustainability. In particular, a number of other considerations need to be taken into account which the framework at present doesn't address including the cost of development, the cost of new infrastructure to facilitate new development and, particularly in the case of London, the cost of remediation of contaminated land needed for brownfield development (Lange & McNeil 2004). Therefore, if the framework was to simultaneously consider cost as an objective alongside the sustainability objectives it may identify significant conflicts, with financially cost effective strategies performing more poorly for the other sustainability objectives investigated. Indeed, it is acknowledged that ensuring sustainability will require significant investment (Conroy & Berke 2004) and therefore this factor is likely to be a major factor in choosing where to develop.

Furthermore, qualitative factors often also have a major role to play on deciding the spatial location of development (Gobster & Ryan 2011). The work fails to consider half the sustainability aims found in Section 2.2 to define sustainability, including the consideration of the health and quality of life of the cities' occupants. Indeed a number of these were identified in the review of sustainability appraisals (discussed in Section 4.2.3 and summarised in Table A in Appendix A) but rejected as being inappropriate to be considered spatially and analytically by the framework developed in this research. These include particular objectives related to the impact of development on crime, the health and wellbeing of residents and education of residents. These factors combined might go some way to explain why the plans as proposed by the local authorities differ significantly from the Pareto-optimal spatial plans. Thus, while the results of the framework provide a multitude of benefits to sustainable urban planning, the optimal spatial strategies identified require further quantitative and qualitative assessment before they are totally relevant to the spatial planning process.

Currently the results of the framework are limited in scope to the appreciation of residential land use. Interestingly, the analysis of Middlesbrough found optimal development sites corresponding with those designated for economic development by the council (Figure 5.22). This raises the question of whether if these economic and residential development were considered simultaneously would these areas be found to be more suitable for either. This is potentially significant as the review of literature identified the placement of residential and economic development constitutes a significant development conflict (see Figure 2.8).

Moreover Section 2.2 identifies economic sustainability as a key constituent of urban sustainability.

Despite the utility of the results of the spatial optimization framework, it should be noted that humans are not rational actors. It has long been recognized (e.g., Tinbergen, 1956) that there are both political and analytical aspects to decision making. The political aspect of planning and sustainable development has been widely discussed in the literature (Richardson 1997; Stirling 1999; Harriet Bulkeley & Betsill 2005; Sager 2011). This work intends to contribute to the analytical aspect and whilst useful cannot be considered in isolation. Rather the outputs from the application should act as an evidence base upon which further qualitative and quantitative analysis can be applied to develop a final development plan. Indeed a number of sources have indicated positive reactions from planners to the use of such modelling tools (Xiao et al. 2007; Keirstead & Shah 2013). Therefore the methods developed in this work but should be integrated within the wider planning decision making process.

7.3 Discussion of the Multi-objective Spatial Optimisation Framework

From a review of the literature in Chapter 2 a number of considerations for effective sustainable spatial development were identified that could be addressed by an improved decision support methodology that had the ability to simultaneously consider a number of sustainability objectives. Based on this, Chapter 3 identified a number of spatial optimisation approaches which could be potentially employed to satisfy this including the use of Pareto-optimisation. It also identified a number of weaknesses of previous optimisation applications such as the failure to consider risk alongside other sustainability objectives.

In response Chapter 4 presented the development of a Multi-Objective Spatial Optimisation Framework which consider evolutionary planning of future residential development. Specifically the Chapter outlines a methodology around using Pareto-optimisation and both Genetic Algorithm and Simulated Annealing approaches. In addition Section 6.2 outlines a series of modifications made to the framework to consider and adapt it to the more complex London application, including investigating variable housing densities during the spatial allocation of residential development. In this section the strengths and weakness of the developed approach are considered. In particular the utility to the spatial planning process and the performance of the optimisation approaches adopted are considered.

7.3.1 Utility of the Approach

Chapters 5 and 6 demonstrate the ability of the framework to handle both a medium sized planning problem for Middlesbrough (covering 55 km²) and a larger more spatially complex planning problem for London (1,572km²). This is a significant improvement over a number of previous urban applications which were restricted to smaller and/ or synthetic areas; Ligmann-Zielinska et al. (2005) uses a 20x20 synthetic grid, Masoomi et al., (2012) studied a district in region 7 of Tehran, Iran, with an area less than 15.4 km² whilst Cao et al (2011), (2012) and Cao & Ye (2013) considered Tongzhou New Town, China, with an area of 906 km² at lower spatial resolution (400m). In addition a major strength of the approach developed in this work is the coupling with the sustainability appraisal process. By incorporating real world sustainability objectives as objective functions to assess during the planning of future residential development the framework more closely how sustainability is ensured by the planning process. Indeed the use of widely used and prioritised urban sustainability objectives (identified from a review of planning literature (see Section 4.2.3)) correspond with a number of the sustainability objectives currently considered by both Middlesbrough Council and the GLA during the preparation of their own spatial development plans (with explicit heat risk objectives being the exception).

This is in contrast with previous applications which focus on a more abstract ideas of sustainability (see Section 3.5.6) and define sustainability objectives exclusively around compact city principles through assessing the contiguity of development and compatibility of land uses to act as an accessibility measure. The former objective is further discredited, alongside a number of compact city principles, as the results of this work found that optimising urban sprawl (compaction) and accessibility (characterised as distance to employment and services) are not necessarily compatible (see discussion of conflict in Section 7.2.1). Indeed the calculation of shortest path distances over existing road networks from new development to centres of employment and services using network analysis allows for a more realistic assessment of accessibility compared to proximity and basic Euclidean distances previously utilised as a proxy (Ligmann-Zielinska et al. 2005; Cao et al. 2012). Moreover the unique approach to simultaneously consider a number of sustainability objectives, including risk based objectives not considered in previous applications, is justified by the significant conflicts identified between them. As previous applications fail to consider risks in their assessment of

sustainability they exclude a major urban sustainability consideration in relation to climate change.

The ability to directly compare and evaluate the results in relation to current spatial development is a further major advantage of the approach developed in this research. Such comparison has allowed the work presented here to show that current development plans are sub-optimal from a multi-objective sustainability perspective. In this regard, the evolutionary approach adopted to planning in this research meets the requirements of a successful planning decision support tool as identified in Section 3.5.7 and is in-line with the sustainability appraisal method demonstrated in Section 2.5.4.

The use of raster grids to simulate the urban landscape successfully allows for the assessment of derived development plans against spatial properties such as flood zones and greenspaces across the study area. Whilst representing urban parcels as homogenous cells loses some urban detail, the spatial resolutions employed (1 ha spatial resolution for Middlesbrough and 4 ha for London) allows for a balance between realistically representing urban form while providing a computationally tractable spatial representation from which the optimisation can identify optimal development patterns. Indeed as Section 7.2.4 discusses, the general spatial pattern of the Pareto-optimal development locations is arguably the most valuable output of the framework as opposed to specific development plans.

7.3.2 Appropriateness of the Optimisation Approach

Chapter 4 outlines the methodology for both a Simulated Annealing (SA) and Genetic Algorithmic (GA) approach to the spatial optimisation application. Both approaches were chosen as the review of their applications found that they had both been successfully employed to large urban areas and, as the variables aren't directly used in the search mechanism, could be flexibly employed to a number of applications. A SA approach centred on the Thermopolis equation (Equation 3.16) was developed and complimented by the recommendations of Nam & Park (2000) to allow for Pareto-optimisation. Meanwhile a GA approach was adapted from the Non-dominated Sorting Genetic Algorithm II (NSGA-II) developed by Deb et al. (2002) which facilitates Pareto-optimisation into the selection procedure.

Because of the simplicity of the SA approach, and despite the existence of a number of existing packages, this was developed in-house and tailored around the requirements of the framework. The ability to control how the location of new development is systematically changed at each iteration proved a great advantage as it ensured it was placed within discrete areas available for development. Alternatively the GA approach utilised a bespoke Python module to handle the evolutionary operators of crossover, mutation and selection. A major weakness of the GA was problems related to handling the constraints, which collaborates the experience in the literature (Coello 1999; Deb 2000; Prasad et al. 2004; Konak et al. 2006). This was solved by redesigning the problem so that constraint violations didn't occur and ejecting a small number of solutions from the population. This is fortunate as the use of penalty functions, which most GA applications have to use (Deb 2000), would have been problematic. As discussed in Section 3.4.7 serious consideration needs to be paid to any penalty function approach with too large a penalty preventing that area of the variable space being assessed; too small a penalty allows too many unfeasible solutions to be generated, reducing computational efficiency (Michalewicz 1992; Yeniyay 2005).

Crucially both the SA and GA (after a redesign of the problem to handle constraints) offered the flexibility to handle discrete variables which were necessary to ensure the application was evolutionary (i.e. limited development to areas not currently developed). The case study in Chapter 5 found that both approaches were capable of identifying a number of spatial plans which greatly improved upon the current development plans (see Section 5.5.6). However, despite the difficulties of adapting the problem to be handled by the GA the comparison of the results of the framework demonstrated the GA as being superior for this application (see Section 5.5). The GA has a much quicker run time than the SA (collaborating previous work (Sidiropoulos & Fotakis 2009)) as a result of its dynamic search compared to the systematic local search method of the SA (10 hours compared to 15 hours respectively), making the latter unsuitable for larger applications, whilst outperforming it in identifying best development plans to optimise heat risk and accessibility. In addition, whilst Nam & Park (2000) modifications to the SA approach allowed for the convergence to and discovery of a number Pareto fronts (see Figure 5.11), it is significantly outperformed by the Pareto fronts of the GA (see Figure 5.13) with, for example, an average 29% improvement in performance for $N_{f_{heat}, f_{dist}}$. Whilst Nam & Park (2000) found that its Pareto-optimisation approach for SA performed nearly as well compared as a GA, the considerable conflict between f_{heat} and f_{dist} in this application likely prevented the full examination and convergence of the Pareto front.

The use of a Genetic Algorithm (GA) optimisation (using the NSGA-II methodology (Deb et al. 2002)) for the more complex London case study enabled the derivation of a wide range of potential development plans to be assessed (890,233 in total), and allowed the discovery of a number of spatial plans which were optimal throughout the five objectives being considered (31,716 MOPO solutions, representing 3.5% of the total solutions analysed). The effectiveness of the evolutionary operators, crossover, mutation and selection allowed for the dynamic search of development plans leading to convergence on the sustainability objectives considered. For example, the framework achieved a 73% improvement on average in the Pareto front of $N_{f_{heat},f_{dist}}$ despite the inherent conflict and increase of the number of solutions in $N_{f_{heat},f_{dist}}$ from 10 at initialisation to 115 in the final set. However this was facilitated by the use of biasing in the initial parameterising where a number of initial development plans were provided alongside random initial plans to improve the initialisation and speed up the convergence. This was necessary as during testing the use of completely random solutions was found to have very poor convergence. Whilst good initial solutions are often cited as a pre-requisite for successful optimisation application (Cao et al. 2011) it potentially presents a limitation on the utility of the approach as effort must be taken to inform the initialisation. Despite this, the NSGA-II algorithm used improved the performance of spatial plan $\min(f_{brownfield})$ (which was initially biased to brownfield land) in f_{heat} by 32% during the application demonstrating its effectiveness. Whilst this was used for flood zone, sprawl and brownfield, the framework was still able to significantly improve the convergence of $N_{f_{heat},f_{dist}}$, two objectives unaffected by the biasing, with an average 68% improvement throughout the application.

The initial parameters, determined by testing, and the mutation operator prevented the optimisation approach prematurely converging and improvements in the Pareto front continued up until the final generations. Indeed, a weakness was that the approach terminated after a pre-determined number of iterations (due to time limitations). Table 6.7 demonstrates that in the final 50 generations there is still a significant improvement in the Pareto front $N_{f_{heat},f_{brownfield}}$ (18% on average) suggesting that if the application had been allowed to continue further convergence may have taken place. With the limitations on time removed, the termination of the application would ideally be decided by lack of improvement in the Pareto front for several consecutive iterations. It is accepted that complex problems like this there are a huge number of potential solutions and in fact heuristics are premised on the basis that it is inefficient to examine every

possibility (Rothlauf 2011). With this in mind the approach presented here presents a good estimation of the Pareto front.

A major weakness of the developed framework was the speed of the application. This limits its potential to provide swift results based on differing inputs. Whilst the GA is demonstrably quicker than the SA, the run time of over 5 days for the London application is significant. Other reasons for this are discussed in later sections. However, the construction of the GA approach is one likely source of the long run time. Section 6.2.1 presents modifications to the GA to incorporate the investigation of different development densities within the development plan, but as a result the size of the development plan under consideration increases from a required number of development sites (a list of 54 discrete locations for the Middlesbrough case study) to considering the entire area available for development (an array of 3307 elements each related to a discrete location for the London case study). This likely contributed to a degree of redundancy as an average of 270 development sites were required to be considered to fulfil the required number of dwellings. However as a method by which to incorporate differing development densities the approach is superior to variable length representations requiring considerable constraint handling and has less redundancy than a grid based representation.

7.3.3 Assessment of the Pareto-Optimisation Approach

Section 3.3 reviewed methods of handling multi-objective optimisation problems and found Pareto-optimisation (PO) to be the most suitable approach over methods which combine a number of objectives into a single objective to optimise (weighted sum (WS)). Figures 5.11, 5.12 and 6.11 demonstrate the spatial Pareto-optimal development solutions found for the combination of the objectives under consideration, while Figures 5.18 and 6.19 demonstrate the performance of the solutions which are Pareto-optimal throughout the objectives considered (i.e. Multi-objective Pareto-optimal (MOPO)).

In many ways the use of a non-dominated sorting procedure to generate the optimal development plans provides an unbiased appreciation of the objectives as no initial preferences are necessary. Thus, in the context of developing a set of tools to aid decision support within multi-objective spatial optimisation this approach has the advantage that it does not need prior expert consultation to generate feasible development plans. Instead the approach developed in this research allows for the determination of a wide range of mathematically determined optimal

plans in the absence of expert knowledge, from which the derivation and visualisation of the Pareto-optimal fronts provides a refined sub-set of spatial development plans for decision makers to investigate further in terms of their relative trade-offs.

The ability to recognise intermediary best trade-off solutions whilst not restricting itself to a single final solution at each iteration means that the approach in this work is more likely to converge on robust Pareto front. This is best illustrated in Figure 5.19 where for Middlesbrough a development plan $D \in N_{f_{heat}, f_{dist}}$ is found which $\Rightarrow f_{heat} = 0.43$ and $\Rightarrow f_{dist} = 0.41$ despite significant conflict between the two objectives, while for London a $D \in N_{f_{dist}, f_{sprawl}}$ is found which $\Rightarrow f_{dist} = 0.03$ and $\Rightarrow f_{sprawl} = 0.01$ despite the conflict between the minimisation of both objectives. In such circumstances, it is unlikely that a weighted sum approach to approximate the Pareto front (described in Section 3.3) would find these, as it is highly dependent on the initial weighting scheme..

The most significant advantage of using PO for this application is the knowledge it provides of the interactions between objectives. This was crucial in not only identifying and collaborating the known conflicts between urban sprawl and heat risk but also the discovery of conflicts between adaptation to heat and flood risk, as well as between maximising accessibility simultaneously with brownfield development (Section 7.2.1). The ability of PO to identify these conflicts meets the requirement set in Section 2.3 to consider potential conflicts between sustainability efforts whilst the best trade-off information can help ensure decisions are taken which are win-win in the sense that they maximise the possible performance of chosen plans in the objectives considered. Moreover the vast quantity of diagnostic information can contribute to the evidence base on which to make these decisions, aiding the requirement of sustainable development decisions to be based on localised evidence (see Section 2.3).

As identified in the literature (Sayers et al. 2014) this level of information comes at a large computational price. The need to assess such a wide variety of development plans to identify a good distribution of solutions on the Pareto front and within the MOPO set make it necessary to assess a very wide range of potential intermediary solutions. Indeed for London it was necessary to assess a total of 890,233 potential development plans in order to ascertain 31,716 MOPO solutions, whilst for Middlesbrough 251,232 potential developments plans were required to determine 568 MOPO solutions. For this work, the value of the information identified by this approach far outweighs the problems associated with the long running time.

A often cited criticism of PO which was identified in the literature review in Section 3.3 and discussed in Section 6.4.1 is the volume of MOPO solutions found provides a burden on decision makers to identify final solutions. With the number of MOPO identified this is true of the both the Middlesbrough and London applications. To address this issue, this work has employed the analytical hierarchical process (Saaty 2008) to derive a set of weights for hypothetical planning decisions which are scaled by the trade-offs found by the Pareto-optimisation, a method suggested in the literature (Deb 2001). These weights are then used to filter the MOPO sets to determine a single solution for each hypothetical planning decision. Using this approach, the ‘Low Risk City’ development plan which managed to achieve f_{flood} and f_{heat} values of 0.23 and 0.25 respectively. In the case of the ‘Balanced City’ development plan all the objectives were < 0.52 .

These results are in contrast to an example in Section in 5.5.7 where the assigning a set of preference vectors (weights) (Table 5.11) in the absence of considering the conflicts between objectives leads to highly unrepresentative resulting plans. Because of the conflict with heat risk in Middlesbrough unscaled weighting of the Pareto-optimal solutions produces plans which fail to balance their performance in f_{heat} , i.e. equal priorities $\Rightarrow f_{heat} = 0.76$ (see Figure 5.24). This supports the literature that the effective choice of weighting is hampered by a lack of knowledge of how objectives interact (Deb 2001; Prasad et al. 2004). Indeed, it is unlikely without prior knowledge of the conflicts that a weighted sum approach would have been able to find the spatial plans extracted in Section 6.6.5.

7.3.4 Choice of Software Platform

The use of the Python programming language allows for a powerful and flexible platform for the framework outlined in Figure 4.1 with the development of a number modules to handle specific tasks. In particular modules were developed to evaluate the development plans investigated and to ensure constraints on the search. Meanwhile the interoperability of the Geospatial Data Abstraction Library (GDAL) with Python makes the platform highly suitable for handling spatial problems compared to other platforms such as Matlab (Venkataraman 2009), which limit the potential input formats and have limited operability. In particular the ability to handle and import spatial data allowed development plans to be compared to spatial fields such as the heat and flood hazards.

The flexibility of the python language allowed the development of a number of bespoke functions for the SA approach, whilst the availability of the existing module Distributed Evolutionary Algorithms for Python (DEAP) (Fortin et al. 2012) provided a number of key evolutionary operators for the Genetic Algorithm optimisation. The presence of this and several other bespoke optimisation modules makes Python particularly suitable for optimisation applications. The interoperability with the Matplotlib module was essential in visualising the outputs of the framework. Although a user interface wasn't developed in the course of the work of this thesis, the PyQt module offers significant potential to develop a bespoke graphical user interface within python (Harwani 2013). Finally, while python is often reported to have better run times than other interpreted languages (Matott et al. 2011), the issue of computational efficiency may be addressed by developing the complex numerical functions (e.g., the non-dominated sorting) within an language such as C++ and then developing a wrapper for this within Python in order to speed up execution times (Josuttis 2012).

7.4 Conclusion

In conclusion, the results of the case studies collaborates a number of the sustainability conflicts which exist in the literature. In addition the results of this research identify a number of conflicts which planners should consider, including increased flood risk from using blue infrastructure to alleviate heat stress and the potential of brownfield development to actually increase urban sprawl. With this in mind, the spatial optimisation approach developed in this work can derive spatial development patterns which best meet and dissipate conflicts across a range of objectives whilst identifying plans which best meet specific priorities. Indeed the work finds that a number of sustainability objectives can be optimally met simultaneously and there exists a number of development trends which are universally optimal across the objectives.

The utility of the framework to the issue of sustainable urban spatial planning is enabled by the novel approach of assessing climate related risk objectives alongside planning objectives providing crucial information in how they relate spatially. Moreover the methodology mimics that of the sustainability appraisals, allowing for a more realistic interpretation of results in relation to the process of sustainable urban planning.

Lastly, with regards to the methodology, the work finds that genetic algorithms are well suited to handle the large multi-objective problem that sustainable spatial planning presents. Moreover the use Pareto-optimisation to identify a number of Pareto-optimal solutions provides a multitude of benefits including, but not limited to, an un-biased range optimal potential development plans from which planners can select, including a number of best trade-off spatial plans, as well as a plethora of diagnostic information on planning conflicts.

Chapter 8 Summary, Conclusions and Future Work Recommendations

8.1 Introduction

The aim of this research is to generate an optimisation based methodology for decision support to assist urban planners enable the transition of cities to be more climatically sensitive and sustainable by accounting for a range of different, and often competing, policy objectives. To achieve these the following objectives were to be addressed:

1. Review the field of sustainable urban planning in order to recognise the conflicts and barriers that can occur during the transition to more sustainable cities and the best methods to overcome these;
2. Recognise the major spatial planning objectives and aims of sustainable urban planning to be addressed by this work;
3. Review the field of algorithmic optimisation, in particular their application to urban spatial planning and infrastructure assessment, to identify a series of suitable optimisation approaches for addressing the sustainable spatial planning of cities;
4. Develop a spatial optimisation framework, consisting of the approaches identified by objective 3, to enable and act as a decision support tool for planners to meet the objectives identified in objective 2;
5. Apply the optimisation suite developed to several real sustainable urban planning problems to demonstrate the utility of the spatial optimisation approach developed.

The following section describes how these objectives have been met whilst Section 8.3 outlines the implications and main finding resulting from the thesis. Lastly Section 8.4 chapter outlines a number of key future research themes associated with the work.

8.2 Summary

The first objective was achieved by performing an extensive review of literature concerning urban sustainability. The review found that whilst urban sustainability is typically characterised around economic, societal and environmental sustainability the increasing likelihood of climate change, and their impact on urban areas, is necessitating a wider definition which also considers climate change adaptation and mitigation. In addition the review of sustainable urban forms it was found that models of fail to address sustainability as a whole as sustainability initiatives

often conflict and negatively affect one another. Instead cities should instead incorporate a wide range of effective development strategies to address their specific sustainability concerns which should be determined on the basis of localised evidence. This was found to be best achieved through the methodology of sustainability appraisals whereby a number of sustainable options for urban areas are investigated. However, the review identified a number of issues with the current methodology such as lack of joint assessment of the relationship between objectives. In conclusion the review found planners require sophisticated decision support tools which support complex multi-objective decision making in terms of assessing a wide range of alternatives to ensure the best solutions are found to maximise future sustainability.

To meet objective 2 an extensive review was performed of sustainability appraisals in relation to the spatial planning of urban areas. Section 4.2.3 summarises this review with the full review presented in Table A in Appendix A. Special care was taken to; (i) recognise the key urban sustainability objectives considered during sustainable urban planning, (ii) recognising in this list those that are important within a spatial planning context, (iii) recognising in this set the subset that can be addressed within a spatial optimisation framework. The final set consisted of: (i) minimizing risk from future heat waves; (ii) minimizing risks from future flood events; (iii) minimizing travel to reduce transport emissions; (iv) minimizing urban sprawl; and, (v) preventing the development of greenspace. By considering both traditional sustainable planning objectives (iv and v) alongside with those related to risk (i and ii) and emission mitigation (iii) the sustainability objectives investigated met the broader definition of sustainability identified in objective 1. The objectives are formally defined by Equations 4.2-9.

Chapter 3 presents a review of the field of algorithm optimisation with particular emphasis on their contributions to spatial and urban planning applications. The review found that the optimisation of multiple objectives is best supported by Pareto-optimisation where a wide range of best trade-off solutions are returned without the need to pre-determine a set of preferences. A review of spatial optimisation search mechanisms identified two promising optimisation approaches. Simulated Annealing iteratively assesses a wide range of solutions with a search mechanism which mimics the cooling of a metal to decrease the probability of accepting inferior solutions and converge on optimal solutions. Genetic Algorithms evolve a number of solutions by combining the attributes of those find most optimal to produce a new set of solutions with the intention of deriving optimal solutions. These were chosen as potential approaches as they've been proven to be efficient for large urban applications and are suitable for Pareto-

optimisation. The review concluded that there is a research gap for the use of spatial optimisation to address multiple real world sustainability objectives (particularly climate risk adaptation) for sustainable development of urban areas that resembles the planning decisions faced in the future.

To meet objective 4, Chapter 4 presents the methodology for a Multi-Objective Spatial Optimisation Framework. The framework was developed using the Python programming platform and consisted of a number of modules (outlined in Figure 4.1). These included a Spatial Optimisation module to drive the search for optimal spatial set ups of future residential development using both a Genetic Algorithm and Simulated Annealing (identified by objective 3) approaches. An Evaluation module was developed which assess the performance of derived development plans against the real world sustainability objectives (i-iv). The Python extension *PyRaster* in conjunction with the Geospatial Data Abstraction Library enabled the handling of spatial data to calculate the performance of future development plans against the chosen sustainability objectives from objective 2 with respect to their local spatial properties. Lastly an Output module is developed to handle the Pareto-optimisation through a non-dominated sorting algorithm and the identification of Pareto fronts between the objectives considered.

Lastly to meet objective 5, Chapters 5 and 6 present applications of the framework to preparing future spatial plans for Middlesbrough and London respectively, representing medium and large sized urban areas (54.55 km² and 1,572 km² respectively). Current planning documents were examined to formulate the planning problem to be incorporated into the framework to optimise. Spatial datasets were collated for both urban areas, including the identification of areas available for development and grids to represent climate risks.

The framework was applied to the planning problem for Middlesbrough using the two optimisation approaches developed in Chapter 4. Development strategies were found which optimally address a number of sustainability pressures such as flood risk and preventing urban sprawl. However, major conflicts were found for heat risk adaptation against other objectives and preventing urban sprawl and maximising accessibility. Despite this the analysis found that development strategies focused in the North of the study area are able to balance these and provide best trade-offs. Both optimisation approaches were able to identify Pareto fronts between the sustainability objectives being considered and develop a number of these best trade-off plans. Although Simulated Annealing was found to be applicable to the spatial planning

problem its long run time rules out its use for larger applications. However, the Genetic Algorithm was found to have a much better search performance and was used for the London application.

The common planning goal of developing brownfield sites was included into the analysis due to the availability of a dataset for London. During the analysis, conflicts between adapting to heat risk and preventing urban sprawl were found. However, the presence of multiple town centres within London's urban extent allows for strategic placement of development to limit its conflict with accessibility. The presence of the River Thames provides a conflict between developing in low heat areas on its banks and avoiding flood zone development. However a best strategy to adapt to heat risk is found by the framework with 81% of development outside of flood zone areas. Lastly the analysis is unable to reconcile this planning goal with preventing urban sprawl or maximising accessibility and the analysis found that brownfield development exposes residents to the urban heat island effects. Recognising these conflicts the framework presents best strategies to mitigate their impact based on the preferences of the planner. The analysis identifies a number of optimal development areas which are optimal throughout the objectives. Unfortunately these are not sufficient to fully meet housing requirements, therefore planners must make a decision with respect to preferences.

8.3 Implications and Key Findings

In the transition to sustainable urban areas it is crucial to simultaneously aim for and consider a broad spectrum of sustainability. However the complexity and high dimensionality of such a requirement necessitates the use of support tools for urban planners whilst the ability to handle large datasets and computing power provide huge potential for improving the decision making process. Overall the results presented in Chapters 5 and 6 and discussed in Chapter 7 have demonstrated the utility of spatial optimisation to the field of sustainable urban spatial planning. The discovery of a number of planning conflicts justifies the need for such a decision support tool, whilst the ability of the developed framework to prepare optimal development strategies in the presence of conflicting sustainability objectives justifies the approaches employed. The work is novel in that it assess development against a number of real world objectives and focuses on areas available for development, mirroring the sustainability appraisal process to support the spatial planning process. This allows for the derivation of future development plans which are climatically sensitive as well and sustainable in terms of efficient land use and travel.

The research presented in this thesis contributes a number of important findings for urban planners and other stakeholders. Firstly it corroborates a number of sustainability conflicts that are identified in the literature, for example limiting urban sprawl and maximising accessibility while adapting to heat risk. In addition the research identifies less acknowledged conflicts between ‘blue infrastructure’ to combat heat risk and minimising exposure to flooding.

Whilst the tradeoffs and impacts vary according to city, the optimisation framework is shown to be transferable and scalable. Data permitting it could be applied to a range of city types, regions and perhaps even national scales. Moreover optimal spatial plans are mathematically determined, providing an unbiased assessment for stakeholders to fully consider a range of alternatives. Lastly the resulting diagnostic information provides a significant evidence base so planners can make their decisions in full knowledge of the tensions between objectives and best trade-offs.

The results of the application to London question the ability to pursue efficient land use through brownfield development whilst effectively meeting other planning objectives such as accessibility and adapting to heat risk. The results also contribute to the body of evidence which casts doubt on the ability of compact city principles to constitute a sustainable city. The analysis finds that containing urban sprawl isn’t synonymous with maximising urban sprawl for London with several centres of services and employment whilst analysis under differing regulations found high residential density wasn’t necessary to maximise accessibility. Instead, the results found that strategic extensions of the urban extent can increase accessibility whilst the relaxation of density restrictions allows for better heat risk adaption alongside equal levels of accessibility.

The discovery of these findings are a direct result of the novelty of the approach to consider a number of objectives from a spectrum of sustainability challenges. From the author’s knowledge no previous research has sought to optimise traditional planning objectives with risk-based objectives. The analysis also highlights the importance of considering the spatial structure for modulating risk and sustainability objectives during the planning of future development. The mimicking of the spatial planning process allows for direct comparisons with current development strategies and finds that existing plans for Middlesbrough and London fail to meet a number of sustainability pressures.

Overall, the thesis provides a number of key contributions to the field of sustainable urban spatial planning. Specifically it provides; the development of a spatial optimisation decision support methodology which considers a range of real world sustainability objectives; applications of the methodology to two real world urban areas, including London an epicentre of sustainability concerns; analysis from the application collaborates a number of sustainability conflicts as well as identifying a number not currently identified; and, the basis for a optimisation based decision support tool to aid the spatial planning process.

8.4 Further Research

Despite the utility of the Multi-Objective Spatial Optimisation Framework developed in this research, the work could be improved and extended in a number of ways, both in terms of the methodological approach employed and in terms of the applications it can address. In particular there are a number of limitations identified in Section 7.2.4 and 7.3.5. In this section a number of research directions are discussed and evaluated.

8.4.1 Inclusion of Further Infrastructure

An intuitive next step in the work would be the inclusion of spatial allocation of economic development into the framework. The reason for this would acknowledged the conflict between of economic and residential development (as set out in the planner’s conflict (see Figure 2.8)). Furthermore as Section 2.2 sets out sustainable economic activity is a critical element of overall sustainability. The framework is currently designed in such a way that this can be facilitated by incorporating a designated economic allocation, e , within D :

$$D_n = [d^{dens}, e, 0, d^{dens}, \dots, e, 0, d^{dens}, d^{dens},]$$

d = Residential development e = Economic development

Constraints would need to be defined for $e \in D$ based on maximum and minimum required amounts of economic development land. The designation of economic development within the development plan can then be assessed against a number of economic sustainability objectives. For example, the Greater London Authority (2011) sets out objectives to ensure the location of economic activity is in highly accessible areas and sets a target of 50% of economic sites within

outer London to ensure it is more closely located to residential areas. Crucially by this simultaneous consideration both residential and employment development the framework can more effectively reduce travel times by locating them in proximity to one another.

Furthermore to enhance the planning of transport infrastructure alongside new residential development, decisions on transport planning (i.e. bus routes, planned roads and light rail stations) could be simultaneously incorporated by the framework. This could potentially take the form of two simultaneous optimisation applications, where residential and economic development is allocated whilst transport decisions are optimised at each iteration to meet these new spatial requirements. Section 3.5.3 outlines a number of optimisation applications to urban transit/ transport networks (Kepaptsoglou & Karlaftis (2009) provides an extensive overview) which could be incorporated into the framework with the nodes within the network storing the attributes of the land parcel/cell it spatially correlates with (to identify increased passengers from proposed development). This would allow for the simultaneous assessment of development plans alongside transport planning, ensuring it is located where most needed, leading to further joined up development strategies which Section 2.4 found to be crucial to ensure the transition to sustainable cities.

8.4.2 Further Qualitative and Quantitative Assessment

Although the objectives used in this research represent a broad range of risk, mitigation and current planning objectives, in practice the sustainability credentials of future development are assessed against up to 15 objectives (Atkins 2009; Essex County Council 2010; Middlesbrough Council 2013b). The review of planning sustainability appraisals described in Section 4.2.3 found a significant number of these are qualitative (see Appendix A), including quality of life indicators and objectives to improve health. Whilst Section 4.2.3 disregarded their use for the scope of this work, it is worth considering a proxy for these such as a generalised quality of life objective based on distance to amenities such as greenspace and education, while the highly prioritised health based sustainability objectives could be represented by an accessibility measure to existing general practitioners and hospitals.

As Section 7.2.3 discusses, there are considerable variations between the two local authority's current plans investigated and the Pareto-optimal spatial plans found by the framework which may be as result of other considerations outside of those investigated, such as the cost of land.

As a reflection that decisions aren't solely made on the basis of sustainability it would be worthwhile incorporating a number of further objectives outside the realm of sustainability into such an optimisation framework, including the effect on the landscape as well as health and education outcomes. Indeed a number of previous optimisation applications consider cost as one of their objectives (Woodward et al. 2013; Sidiropoulos & Fotakis 2011). However, it is worth considering that the inclusion of further objectives to evaluate development plans will lead to further computational intensity so these should be as simple as possible.

A number of improvements could also be made with regards to the parametrisation and implementation of several of the sustainability objectives employed in this research. Accessibility measures could be improved through the use of a Generalised costs to represent more realistic travel times (which incorporates the cost of public transport) (Ford et al. 2015). In addition the framework could utilise more advanced assessment of climate risks of proposed development. For example Willems et al. (2012) identifies a number of advanced methods for assessing the impact of extreme rainfall events which could be used to plug the gap, identified in section 7.2.1, in the frameworks risk assessment methodology to incorporate an assessment of the impact of proposed development on pluvial (surface water) flooding. Moreover Weitzman (2009) describes a series of methods to intelligently gauge the economic impact of climate change events which could be used for the assessment of economic development within the framework. However there needs to be trade-off between with the complexity of sustainability evaluation to ensure the application can be carried out in a realistic time framework and that optimisation can search through a wide enough alternative to be effective and return globally optimal solutions.

Although a number of sustainability considerations can be considered through the spatial distribution of development a several interventions aren't exclusively spatial, for example the use of retro-fitting to make buildings more energy efficient (Kazmierczak 2012) and the raising of flood defences to reduce flood risk (Woodward et al. 2013). These considerations could be incorporated into the framework as decision variables to provide a more holistic choice of sustainability interventions alongside the spatial layout of the urban area. For example this could test the dissipating of heat risk from urban densification by coupling it with dwelling retro-fitting (Krebs et al. 2010; Carter et al. 2014) or utilise development sites close to blue infrastructure to alleviate heat risk and then use flood defences to minimise the subsequent flood risk. As the framework can currently handle discrete variables encoded decision variables can

be facilitated into the variable set. For the two sustainable interventions given, decision variables could relate to specific heights of defences for discrete potential locations and investment levels for retro-fitting for wards.

8.4.3 Temporal Optimisation and Handling Uncertainty

A worthwhile addition to the research would be the inclusion of a temporal aspect to the optimisation as a reflection that a number of sustainability interventions are time dependant, i.e. may negatively affect sustainability in the short term but allow for positives in the long term (Keirstead & Shah 2013). For example a traffic bypass which increases emissions initially but allows for lower overall emissions over time by reducing congestion (Wood et al. 2007). Proposed development plans could be assessed over a period of time with the optimisation function redeveloping plans based on the performance throughout the time frame. This mirrors the approach taken by Woodward et al. (2013) which tests a portfolio of decisions over time. The impact of development on accessibility and car emissions over time could be handled by Agent Based Modelling (see Section 3.5.5) to model how the movement of pedestrians and auto-mobile traffic react based on the location of development and increased population.

With the incorporation of a temporal aspect to the optimisation, it provides an opportunity to handle uncertainty which is a major issue for decision support tools associated with sustainability (Dorini et al. 2011). There is a significant degree of uncertainty with regards to any future climate projections (Jones et al. 2009) including those used to represent climate hazard data for the evaluation of both heat and flood risk. Whilst the hazards investigated are spatially consistent (see Jenkins et al. (2014) for heat hazard data for Middlesbrough and Lauwaet et al. (2015) for London), the magnitude of the event can vary significantly influencing how planners prioritise these the objectives. Therefore it would be worthwhile testing the adaptation of the derived development plans for their impact over a range of magnitudes to test its performance for a number of potential future climate change induced events. This would provide information on whether the proposed adaptation methods perform well across a number of potential scenarios. In addition there is uncertainty in the modelling of accessibility and transport related emissions which could be handled by testing a number of future population and traffic projections.

It should be noted that this would greatly increase the computational requirements. A possible solution would be the use of parallel computing which involves breaking down large problems

into multiple problems which are processed simultaneously and has been used extensively to handle highly complex computational problems (Navarroa et al. 2014). The approach outlined in this work lends itself well to this with solutions sets tested under a set of future projections on separate processors.

8.4.4 Further Decision Support

Suitable visualisation to aid the interpretation of results is a critical part of a decision support tool (Kapelan et al. 2005a), and are particularly important in high dimensionality Multi-objective Pareto-optimal applications where understanding results present a significant challenge (Xiao et al. 2007). Although Chapters 5 and 6 utilise a number of methods to visualise the results of framework, including the plotting of Pareto fronts and parallel line plots, the incorporation of further objectives would likely compound efforts to compare and contrast the performance of spatial plans across all of the objectives. A number of further visualisation tools exist in the literature which could aid interpretation. Figure 8.2 demonstrate a selection of visualisation tools to convey the results of higher dimensionality problems. Figure 8.2a shows the use of radar graphs by Kumar et al. (2013) to convey the performance of different development strategies over a wide number (15) of sustainability objectives. Meanwhile Figure 8.2b demonstrates a intuitive method used by Fu et al. (2013) using colour scales, graduated symbols and orientation to increase the dimensionality of 3D Pareto front plots to represent 6 objective dimensions. As discussed in Section 7.3.4 the Python platform provides a number of visualisation packages and a user interface could be easily developed in conjunction with the framework which incorporated and extended the visualisation methods considered above.

As already mentioned, the utility of the framework to planners would be greatly improved by the development of a user interface allowing for better exploration of plans. Xiao et al. (2007) details a suitable blueprint for a generalised user interface for spatial optimisation applications as shown in Figure 8.3. They idealise that planners can pick specific plans based on their performance on a range of Pareto fronts then compare their performance across a range objectives with other selected plans using a parallel line plot. In particular Xiao et al. (2007) identifies the ability to identify spatial plans which display close performances but vary substantially as an informative comparison tool (Bennett et al. 2004). This provides an effect platform to compare and contrast the results of the framework. Ideally in a more formal

planning support tool it would incorporate the full set of data necessary to develop spatial plans geared towards helping the decision maker make the best decision.

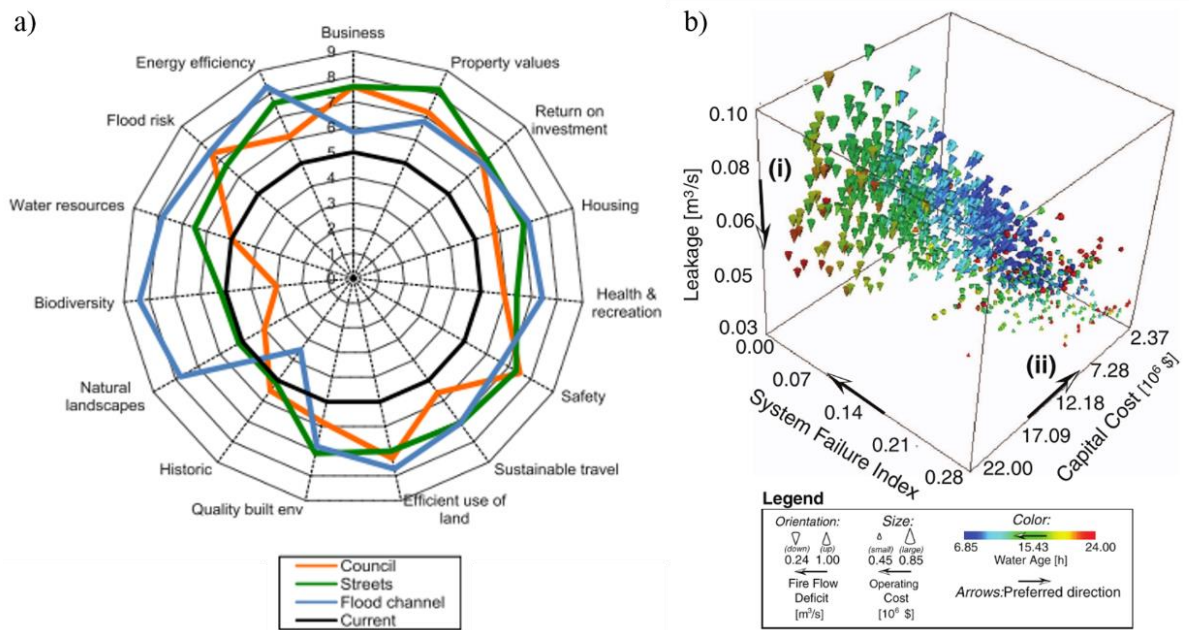


Figure 8.1 Visualisation tools to convey the performance of solutions over multiple objectives from a) Kumar et al. (2013) and b) Fu et al., (2013).

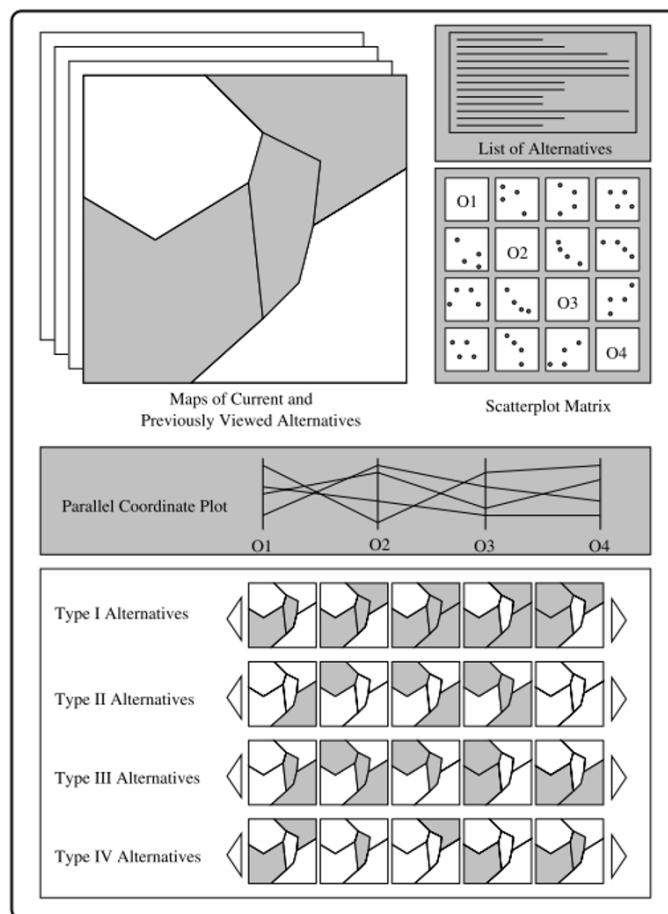


Figure 8.2 Idealised visual support system for multi-objective spatial optimisation from Xiao et al. (2007).

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Appendix A Review of Sustainability Appraisals

Table A 1 List of sustainability objectives outlined from a review of spatial planning documents.

Field	Sustainability	Sources (see below)
Environmental	Minimise the loss of open space, increase urban greening and improve green infrastructure	1,2
	Mitigate environmental costs of new development through sustainable development materials	1-4
	Increase energy generated from renewable sources	1-6
	Protection of biodiversity habitat	1,3,4,6-8
	Improve blue network	1,3
	Improve/ ensure good air quality	3-10
	Protect and enhance geodiversity and biodiversity of soil.	1,6,9
	Reduce flood risk/ prevent development in flood plains	2,3,5,8,9
	Adapting to and mitigating against climate change	3,4,6-10
	Living within environmental limits	4
	Avoid new development in those areas likely to be vulnerable to the impacts of climate change	3
	Increased resilience of infrastructure (transport, water, drainage)	3
	Maximising opportunities from positive impacts of climate change in the Region.	3
	Promote passive solar use and energy	5
	Conservation management of bush land	5
	Wildlife corridor enhancement	5
	Reduce and manage contaminated sites	5
	Protection of coastal & marine systems	5
Combat cause of Climate change/ decrease GHG emissions	4-7,9	
Protect water quality	4,6-9	
Minimise noise pollution levels	6,10	
Transport	Achieve a reduced reliance on the private car and a more sustainable model split for journeys	1,3,5,9
	Improve accessibility to jobs, facilities, goods and services	3,10
	Sustainable transport provision	2,4,6,7,10
	Minimise emissions from transport	2,8,10
	Affordable transport provision	2
	Encourage cycling and walking potentially by designing streets to deter cars	2,5
	Reduce traffic	3,7
	Reduce the need for people to travel	9
Land use and Planning	Efficient use of land through development taking place on previously developed land (brownfield)	1,6,7,9
	Compact and high density development	1-3
	Make more productive use of land	2,3
	Increased provision of sustainable transport modes	3,7
	Decentralised energy supply systems	3
	Land uses which help capture carbon	3
Community and Health	An increased supply of housing including affordable homes	1,3,6,7,9
	Improve health and reduce health inequalities	1,3-9
	Reduce economic exclusion	1,7
	Improve provision of social infrastructure and related services	1
	Protect and enhance heritage, historic environment and landscape.	1,3,4,6-10

	Improve educational achievement and the skills/ qualifications of the population/ workforce	3,4,7,8
	Improve the quality of housing	3,8
	Reduce crime and the fear of crime	3-8
	Increased public involvement in decision making and civic activity	2,3,5
	Sustainable communities	4
	Minimise social exclusion/ poverty and increase social cohesive communities	2,5-8
	Provide equal and adequate education opportunities and access to services	2,6-8
	Enhance a sense of community ownership/ involvement	5-7,9
	Promote area as a fun place to live	5
	Community access to information and responsibility on sustainability issues	5,6
	Development of triple bottom line accountability	5
	Sense of place and satisfaction	6
	Promote healthy and active lifestyles	6,8
Economic	Strengthening and sustaining economic activity	1,4,7-10
	Ensure that there is sufficient development capacity in the stock market	1
	Increase in the number of jobs located in high accessibility areas	1
	Developing a more sustainable employment market	4
	Sustainable economy	6,8-10
	Promote investment in skills and learning	6
	Rewarding and satisfy employment	8
	Efficient patters of economic growth	8
Resources	Increase in waste recycled or composted and	1-3,5,7
	Elimination of waste to landfill	1
	Reduce amount of waste produced	2,3,5-8
	Better use of resources	3,7
	Increase household recycling	1
	Minimise demand for water consumption through efficiency and conservation methods	1,6,8
	Energy efficiency of new developments through planning and design;	3,6

Table A1 References

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Appendix B Evaluation Modules

B.1 Middlesbrough Framework Evaluation Module

The evaluation module receives spatial plans of development and determines the performance against a series of objectives. Before calling the module, development plans, D , in the form $[(i,j), (i,j), (i,j) \dots]$ are spatial located onto a gridded spatial plan $[[0,0,0 \dots], [0,1,0\dots], [0,1,1\dots]]$ to be directly assessed against the inputted spatial grids for floodzone etc.

```
1. # -*- coding: utf-8 -*-
2. """
3. Evaluate 25/05/15
4. Author: Daniel Caparros-Midwood
5.
6. This module forms the evaluation portion of the spatial optimisation framework
7. for the Middlesbrough Cases Study. It takes development plans plotted against the
8. stuy area and returns their performance in the following objectives:
9. 1. fheat
10. 2. fflood
11. 3. fdist
12. 4. fsprawl
13. 5. fgreenspace
14.
15. """
16.
17. import numpy as np # Module to handle mathematical calculations
18. import rasterIO # Module to handle spatial datasets
19.
20.
21. def Calc_fheat(Spatial_Plan, PopDens, Data_Folder):
22.     """ Calculcates a heat risk value for the spatial plan. The vulnerability raster
23.     is updated with the increased population resulting from the proposed spatial
24.     plans. A comparison is then taken between the original and future heat risk
25.     by multiplying heat hazard by the current and updated vulnerability dataset.
26.
27.     """
28.     Heat_Hazard = rasterIO.readrasterband(rasterIO.opengdalraster(Data_Folder+'Heat_Hazard_100m.tif'),1)
29.     Vulnerability = rasterIO.readrasterband(rasterIO.opengdalraster(Data_Folder+'Vulnerability_100m.tif'),1)
30.
31.     # Combining the increase in population spatially to current population
32.     Spatial_Plan_Pop = np.multiply(Spatial_Plan,PopDens)
33.     Future_Vulnerability = np.add(Spatial_Plan_Pop, Vulnerability)
34.
35.     # Calculate the current heat risk to calculate the increase associated
36.     # with this spatial plan
37.     Current_Risk = np.multiply(Heat_Hazard, Vulnerability)
38.     Current_Risk_Sum = np.sum(Current_Risk)
39.     # Calculate future heat risk based on the spatial appropriation of increased
40.     # population
41.     Future_Risk = np.multiply(Heat_Hazard, Future_Vulnerability)
42.     Future_Risk_Sum = np.sum(Future_Risk)
43.     # Objective function is the difference between the risks
44.     fheat = Future_Risk_Sum - Current_Risk_Sum
45.
```

```

46.     return fheat
47.
48. def Calc_fflood(Spatial_Plan, Dwellings, Data_Folder):
49.     """ Calculates the aggregate flood risk to dwellings
50.     """
51.
52.     Flood_Hazard = rasterIO.readrasterband(rasterIO.openGDALraster(Data_Folder+'Floodzone_100m.tif') ,1)
53.
54.     Vulnerability = np.multiply(Spatial_Plan, Dwellings) # Assing the number of dwellings to each cell
55.     fflood = float(np.sum(np.multiply(Vulnerability, Flood_Hazard)))
56.
57.     return fflood
58.
59. def Calc_fdist(Dev_Plan, Data_Folder):
60.     """ Calculates the average distance of proposed development to a CBD.
61.     A pre-
62.     processing module calculates the shortest path distance from all possible
63.     development sites which is stored as a fdist lookup. Based on a proposed development
64.     the function lookups the shortest paths for proposed development sites
65.     and returns an average
66.     """
67.     import fdist_lookup
68.     fdist_values = fdist_lookup.fdist_lookup
69.
70.     # Creating an aggregate of the shortest paths
71.     agg_dist=0
72.     for dev_site in Dev_Plan:
73.         # Find its corresponding feature in the fdist lookup list
74.         for site in fdist_values:
75.             if dev_site==site[0]:
76.                 # Add the shortest path to this site to an aggregate variable
77.                 agg_dist+= site[1]
78.     fdist = agg_dist/len(Dev_Plan)
79.     return fdist
80.
81. def Calc_fsprawl(Spatial_Plan, Data_Folder):
82.     """ Calculates the numbers of proposed developed sites which fall within
83.     the defined urban extent. This is compared to the total number to calculate
84.     a percentage outside the urban extent
85.     """
86.
87.     Urban_Extent = rasterIO.readrasterband(rasterIO.openGDALraster(Data_Folder+'Urban_Extent_100m.tif') ,1)
88.
89.     # Calculates total numberof development sites
90.     No_Sites = float(np.sum(Spatial_Plan))
91.
92.     # Calculate the number of sites which remain once its multiplied by the urban extent measure
93.     # Urban areas are 1 and others are 0 so dev sites outside it are lost in the calculation
94.     No_Sites_WithinUrban = float(np.sum(np.multiply(Spatial_Plan, Urban_Extent))/100)
95.
96.     # We then use the difference between the number of development sites and
97.     # those which correspond with the urban extent to calculate a %
98.     fsprawl = (1 - (No_Sites_WithinUrban/No_Sites))*100
99.
100.     return fsprawl

```

B.2 London Framework Evaluation Module

The evaluation module to evaluate the performance of spatial plans developed by the optimisation framework for London is shown below. There are a number of changes from the original evaluation module. The calculation of the objective $f_{brownfield}$ is now coded

```
1. # -*- coding: utf-8 -*-
2. """
3. Evaluate - 25/05/15
4. Author: Daniel Caparros-Midwood
5.
6. Evaluate module for use with the Spatial Optimisation Framework. Used for the London
7. Case study. Takes a development plan outputted by the Optimisation module and
8. assesses them against the series of objectives:
9. 1. fheat
10. 2. fflood
11. 3. fdist
12. 4. fsprawl
13. 5. fbrownfield
14. """
15.
16. import numpy as np
17.
18.
19. def Calc_fheat(London_Dwell_Plan, Data_Folder):
20.     """ Calculates the average exposure each dwelling is subject to. This is done
21.     by multiplying the heat hazard array and dwell plan to calculate the aggregate
22.     heat hazard exposure.
23.     """
24.
25.     Heat = (np.loadtxt(Data_Folder+"Heat_Hazard.txt",delimiter=",")).tolist()
26.     Heat = [float(i) for i in Heat]
27.
28.     #Calculate the total heat hazard experience by the total dwellings
29.     HeatRisk = np.multiply(London_Dwell_Plan, Heat)
30.
31.     # Then divide this by the total number of dwellings in the spatial plan
32.     HeatRisk_per_Capita = np.sum(HeatRisk)/np.sum(London_Dwell_Plan)
33.
34.     # Returns the per dwelling heat hazard exposure
35.     return HeatRisk_per_Capita
36.
37. def Calc_fflood(London_Dwell_Plan, Data_Folder):
38.     """ Calculates the average flood risk experienced per dwelling. Multiplies
39.     the dwell plan by the floodzone array to determine aggregate flood risk then
40.     divide it by the number of dwellings to
41.
42.     NOTE: Floodzone 1 in 100 and 1 in 1000 represented by 1 and 0.1 respectively
43.     """
44.
45.     Floodzone = (np.loadtxt(Data_Folder+"Floodzone.txt",delimiter=",")).tolist()
46.
47.     Floodzone = [float(i) for i in Floodzone]
48.
49.     # Values are 10 and 1 in raster so reducing them
50.     Floodzone = np.multiply(Floodzone,0.1)
51.
52.     FloodRisk = np.multiply(London_Dwell_Plan, Floodzone)
53.
54.     # Calculating a per capita metric as per heat in order to
55.     FloodRisk_per_Capita = np.sum(FloodRisk)/np.sum(London_Dwell_Plan)
56.
57.     return FloodRisk_per_Capita
```

```

57.
58. def Calc_fbrownfield(London_DwellPlan, Data_Folder):
59.     """ Calculate the number of proposed development sites which don't fall on
60.     brownfield sites
61.     Target in London Plan is 96%, not enforcing this, will just use it as a
62.     comparison.
63.     """
64.
65.     Brownfield = (np.loadtxt(Data_Folder+"Brownfield.txt",delimiter=",")).tolist()
66.     Brownfield = [float(i) for i in Brownfield]
67.
68.     # Calculate the number of proposed sites
69.     Total_Dev_Sites = np.count_nonzero(London_DwellPlan)
70.
71.     # Calculate the number of sites which occur on brownfield
72.     Brownfield_Sites = np.count_nonzero(np.multiply(Brownfield, London_DwellPlan))
73.
74.     # Calculating this percentage based on the number of dwellings
75.     Per_Not_Brownfield = (1-
(float(Brownfield_Sites)/float(Total_Dev_Sites)))* 100
76.
77.
78.
79.     return Per_Not_Brownfield
80.
81. def Calc_fsprawl(London_Dwell_Plan, Data_Folder):
82.     """ Calculates the number of development sites which fall within the current
83.     urban area. The number of proposed development sites is calculated by counting
84.     number of elements in the dwell plan which aren't zeros. We then
85.     multiply the two arrays. Development corresponding with falling within urban
86.     areas are retain in urban sites whilst those outside are lost. In this example
87.     we go from two proposed development sites in Dwell Plan to 1 in Urban Sites
88.     giving us a fsprawl value of 50%.
89.
90.     Urban   Dwell Plann   Urban Sites
91.     [0,     [60,         [0,
92.     1, x    0,           == 0
93.     1,     100,         100,
94.     0]     0]           0]
95.
96.     """
97.
98.     Urban_Extent = (np.loadtxt(Data_Folder+"Urban.txt",delimiter=",")).tolist()
99.     Urban_Extent = [float(i) for i in Urban_Extent]
100.
101.     Total_Dev_Sites = np.count_nonzero(London_Dwell_Plan)
102.     # Calculate the number of sites within the urban extent
103.     Urban_Sites     = np.count_nonzero(np.multiply(Urban_Extent, London_Dwell
_Plan))
104.
105.     Per_Not_Urban   = (1-
(float(Urban_Sites)/float(Total_Dev_Sites)))*100
106.
107.     return Per_Not_Urban
108.
109.     def Calc_fdist(Proposed_Sites, Greenspace_Development):
110.         """ Function to calculate the average distance between proposed developme
nt
111.         sites. Import a site lookup based on whether greenspace development is
112.         allowed and lookup their shortest path distance to their closest CBD.
113.         This value is added to a aggregate score and divided by the number of sit
es
114.         Requires the 'Proposed Sites to be in ij format.'"""
115.
116.         import Dist_Lookup as Dist_Lookup
117.
118.         #fdist_values =np.loadtxt('Dist_Lookup.txt', delimiter = ',')

```



```

119.
120.         fdist_values = Dist_Lookup.fdist_lookup
121.
122.         # Creating an aggregate of the shortest paths
123.         agg_dist=0
124.         for dev_site in Proposed_Sites:
125.
126.             for site in fdist_values:
127.                 if dev_site==site[0]:
128.                     # Add the shortest path to this site to an aggregate variable
129.
130.                     # Dividing by 1000 to convert to kilometres
131.                     agg_dist+= site[1]/1000
132.                 fdist = agg_dist/len(Proposed_Sites)
133.         return fdist

```

B.3 Calculate Accessibility Module

To calculate the performance of a spatial plan for f_{dist} the Calculate Accessibility module shown below is run prior to the operation to calculate the shortest path distance between the defined CBD/ town centre and the possible development sites. The shortest path from each possible development site is then recorded to be referenced by the Evaluate module.

```

1. # -*- coding: utf-8 -*-
2. """
3. Calculate_Accessibility 25/05/15
4. Author: Daniel Caparros-Midwood
5.
6. Intended for incorporation with the Spatial Optimisation Framework
7.
8. Module calculates shortest path distance of a road network from cells
9. available for development to identified CBDs Module is preprocessed to produce
10. a lookup table to calculate fdist
11. """
12.
13. import networkx as nx # Network Analysis module to calculate shortest path
14. import rasterIO # To handles spatial data
15. import numpy as np # Mathematical processing
16.
17. def Generate_Development_Sites(Available_Sites, X,Y):
18.     """ Extract the available sites from which to calculate an accessibility measure
19.     .
20.     """
21.     Available_DevSites = []
22.     for x in range(0,X):
23.         for y in range(0,Y):
24.             site_yx = (y,x)
25.             if Available_Sites[site_yx] == 1:
26.                 Available_DevSites.append(site_yx)
27.
28.     return Available_DevSites
29.
30. def Conv_2_Coords(list_of_sites, geo_t_params):
31.     """ Using the GDAL library to calculate the centroid of a coordinate
32.     """
33.     site_nodes = []

```

```

34.     for site in list_of_sites:
35.         y = site[0]
36.         x = site[1]
37.         # coord = coord of raster corner + (cell_coord * cell_size) + (cell_size/2)
38.
39.         x_coord = geo_t_params[0] + (x*geo_t_params[1]) + (geo_t_params[1]/2)
40.         y_coord = geo_t_params[3] - (y*geo_t_params[1]) + (geo_t_params[5]/2)
41.
42.         node_coord=(x_coord, y_coord)
43.         site_nodes.append(node_coord)
44.     return site_nodes
45.
46. def calc_closest(new_node, node_list):
47.     """ Identify closest road node to connect to network
48.     """
49.     # Set initial distance to infinity
50.     best_gdist = float("inf")
51.     closest_node=[0,0]
52.     for comp_node in node_list.nodes():
53.
54.         gdist = (abs(comp_node[0]-new_node[0])+abs(comp_node[1]-new_node[1]))
55.         if abs(gdist) < best_gdist:
56.             best_gdist = gdist
57.             # replaces the previous closest node
58.             closest_node = comp_node
59.
60.     return closest_node
61.
62. def Add_Edges(g, node, closest_node):
63.     """ Add node to the network then add an edge to connect it up to
64.     it's closest node
65.     """
66.     g.add_node(node)
67.     g.add_edge(node, closest_node)
68.     return g
69. def Add_Nodes_To_Network(node_list,network):
70.     """ Handles incorporating new nodes to the network
71.     Adds an edge between the node and the node calculated to be closest
72.     """
73.     for node in node_list:
74.         # Calculate the closest road node
75.         closest_node= calc_closest(node, network)
76.         network.add_node(node) #adds node to network
77.         network.add_edge(node,closest_node) #adds edge between nodes
78.
79. def Calculate_Fitness(Development_Sites, CBD_Nodes, Road_Network, geo_t_params):
80.     """ Calculates the shortest path for each available cell. The network is pre
81.     processed with the available dev sites converted to XY and added to the road
82.     network. The road network needs to be undirected.
83.     """
84.     # Convert sites to geographic centroid
85.     Dev_Nodes = Conv_2_Coords(Development_Sites, geo_t_params)
86.
87.     Road_Network=Road_Network.to_undirected() #remove direction restrictions
88.     #Add CBD and development sites to the road network
89.     Add_Nodes_To_Network(CBD_Nodes, Road_Network)
90.     Add_Nodes_To_Network(Dev_Nodes, Road_Network)
91.
92.     # Calculate the shortest distance from each site to a CBD then return average
93.
94.     fdist_list = []
95.     for Dev_Site in Dev_Nodes:
96.         # Initial shortest difference to infinity
97.         shrtst_dist=float("inf")
98.         for CBD in CBD_Nodes:
99.             # Calculate the shortest path to each CBD

```

```

99.         dist = nx.shortest_path_length(Road_Network,Dev_Site,CBD, weight='Dist')
100.             if dist<shrtst_dist:
101.                 shrtst_dist=dist
102.
103.                 fdist_list.append( shrtst_dist)
104.
105.         return fdist_list
106.
107.
108.     def Calc_fdist(Data_Folder):
109.         """ Function sets in motion the calculating of a series of shortest path
110.         distances
111.         from the centroids of the available sites (in this case Available.tif) to
112.         their
113.         closest town centre. We upload the town centres and Road Network before
114.         extract the available development sites from which to calculate an access
115.         ibility
116.         measure. Returns a list of smallest paths. Then the calc_fdist can collec
117.         t
118.         the smallest paths for their proposed development sites.
119.         """
120.         # Road network which forms the path
121.         Road_Network = nx.read_shp(Data_Folder+'Road_Network.shp')
122.         # The CBD point file which we are calculating the shortest path distance
123.         to
124.         CBD_Nodes = nx.read_shp(Data_Folder+'Town_Centres.shp')
125.
126.         # Extracting the dataset for potential sites to calculate fdist from each
127.         one
128.         file_pointer = rasterIO.openGDALraster(Data_Folder+'Available.tif')
129.         Available = rasterIO.readrasterband(file_pointer,1)
130.
131.         # Extracting the geotrans which is necessary for caluclating the centroid
132.         s
133.         # of potential development sites
134.         d,X,Y,p,geotrans= rasterIO.readrastermeta(file_pointer)
135.
136.         # Extract the cells which are available for development
137.         Sites_to_Calculate = Generate_Development_Sites(Available,X,Y)
138.         # geotrans used to calculate their XY value
139.         fdist_values = Calculate_Fitness(Sites_to_Calculate, CBD_Nodes, Ro
140.         ad_Network, geotrans)
141.
142.         np.savetxt(Data_Folder+'fdist_lookup.txt', fdist_values, delimiter = ',',
143.         )

```


Appendix C Non-dominated Sorting Module

The non-dominated sorting module shown below takes the solutions found by the optimisation module and determines those which are non-dominated. The algorithm is based on Mishra & Harit's (2010) algorithm. Moreover the module can determine non-dominated sets between specified objectives using the 'ObjFunc' variable.

```
1. # -*- coding: utf-8 -*-
2. """
3. NonDom_Sort Module 26/05/15
4. Author: Daniel Caparros-Midoowd
5.
6. Non dominated sorting algorithm to extract Pareto-optimal solutions.
7. The algorithm is based on Mishra & Harit's (2010) algorithm, first sort the solution
8. s
9. by the first objective before iteratively comparing thier performances. By sorting t
10. hem
11. we put solutions which are most likely to dominate at the start leading to less comp
12. utations.
13. Throughout a non-dominated list of solutions is maintained and returned.
14.
15. Requirements:
16. + Objecives,f, requiring maximisation need to be multiplied by -1 prior
17. + Solutions need to be in form [Solution number, Spatial Plan, Fitnesses]
18. + Fitnesses need to be in the form [f1,f2,f3...]
19. + Obj_Func need to be a list of fitness indexes
20. """
21. SolNo, D, Obj_Col = 0,1,2 #specifies that obj funcs are stored in 3rd column
22.
23. from copy import copy
24.
25. def Sort(Solutions, ObjFunc):
26.     # ObjFunc is the set of objectives from which to conduct the non-dominated
27.     # sorting, for example ObjFunc = [f1,f3] or ObjFunc = [f2,f3]
28.
29.     NonDom_list = [] # list of non-dominated solutions
30.     Solution_list = copy(Solutions)
31.
32.     # Sort the solution list by the first objective considered
33.     Solution_list.sort(key=lambda x: x[Obj_Col][ObjFunc[0]], reverse = False)
34.
35.     # Pop the first ranked solution for that objective into the non dom list
36.     NonDom_list.append(Solution_list[0]) #
37.     Solution_list.pop(0)
38.
39.     # Iteratively investigate solutions in the solution list against the non dom lis
40.     t
41.     for Sol in Solution_list: #Check each solution in the solution list
42.
43.         row_count = -
44.         1 #keep a track of which row of the non_dom_list incase it needs to be popped
45.
46.         # Iteratively compare the solution to solutions in the non dom list
47.         for NonDom_Sol in NonDom_list:
48.             row_count += 1
```

```

46.         # Assess the fitness of the
47.         Dominated, Dominates= Domination_Check(Sol[Obj_Col],NonDom_Sol[Obj_Col],
ObjFunc)
48.
49.         if Dominated == True:
50.             # If solution is found to be dominated we stop considering to save
51.             # computational time
52.             break
53.         elif Dominates == True:
54.             # if the solution in the nondom list is found to be dominated we pop
it"
55.             NonDom_list.pop(row_count)
56.             break
57.
58.         if Dominated == False:
59.             # If the solution is found to be undominated by all the solution in non
dom list
60.             # it is added to it
61.             NonDom_list.append(Sol)
62.
63.     # return the list of non dominated solutions
64.     return NonDom_list
65.
66. def Domination_Check(Solution, NonDom_Solution,ObjFunc):
67.     # Assume both solutions are dominated untills there one instance where they outpe
rform the other solution.
68.     Dominates = True # Stores if the solution dominates any solutions in the non dom
list
69.     Dominated = True # Stores if the solution is dominated by a solution in the non
dom list
70.
71.     for Objective in (ObjFunc):
72.         # For each objective function under consideration
73.         if Solution[Objective] < NonDom_Solution[Objective]:
74.             # if the solution is found to outperform (be less than) in any of the obj
ectives
75.             # it is non dominated
76.             Dominated = False
77.         elif Solution[Objective] > NonDom_Solution[Objective]:
78.             # if the non dom solution is found to outperform (be less than) in any
79.             # of the objectives it remains in the non-dom list
80.             Dominates = False
81.
82.     # returns whether sol or nondom_sol is dominated
83.     return Dominated, Dominates

```

Appendix D Pre-processing Models

To reconcile a number of spatial datasets to inputted raster grids for the framework a number of pre-processing models were created using ModelBuilder in ArcGIS 10.1. During development it was realised that it was essential the coordinates of the input raster datasets conformed. Figures D1-3 demonstrate models to achieve this. Based on a user selected cell size, the models use a ‘boundary’ file of the study area to generate template raster grid then sample the input datasets to this template. Moreover Figure D2 demonstrates how 1 in 100 and 1 in 1000 floodzone datasets are combined to form a single flood risk assessment raster.

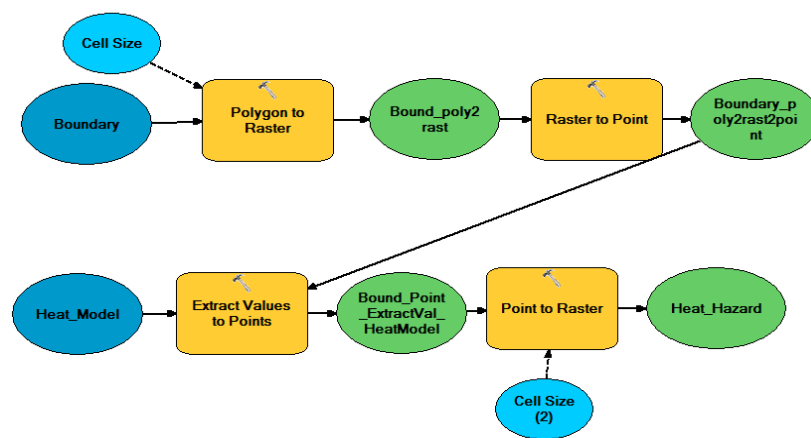


Figure D.1 Pre-processing model for heat hazard input raster

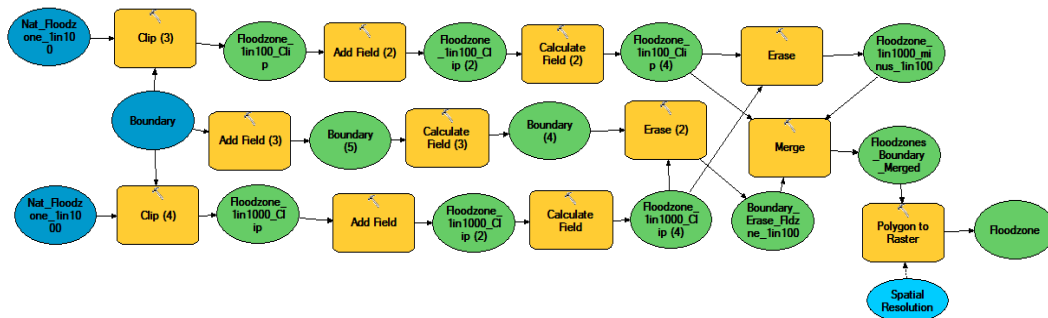


Figure D.2 Pre-processing model for flood hazard input raster

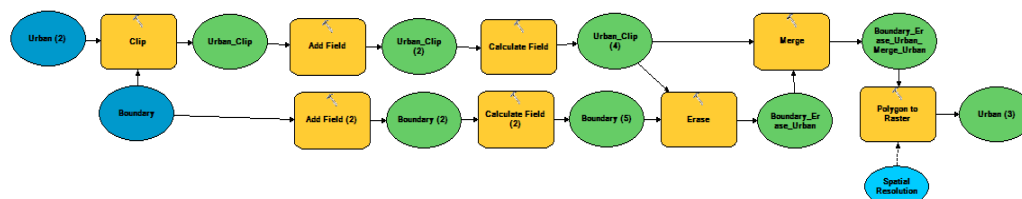


Figure D.3 Pre-processing urban extent input raster