Evolutionary Computing for Multi-Objective Spatial Optimisation

Daniel Caparros-Midwood, Stuart Barr and Richard Dawson

School of Civil Engineering and Geosciences, Newcastle University

Summary

During the transition to more resilient and sustainable cities, planners require robust planning tools to ensure sustainability efforts do not conflict and negatively affect one another. In this paper spatial optimisation is used to provide best trade-off spatial plans between conflicting real world sustainability objectives during the spatial planning process. Using Pareto-optimal optimisation a series of spatial development strategies are derived that outperform all other possible development strategies in at least one objective. When applied to a case study for a north east local authority the resulting spatial Pareto-optimal strategies were found to significantly outperform the local authorities proposed development plan.

KEYWORDS: Sustainability objectives, spatial planning, optimisation.

1. Introduction

The processes of urbanisation and climate change are necessitating the transformation of cities towards sustainable cities that are robustly adapted to natural (and other) hazards, while simultaneously reducing energy and resource usage to mitigate further climatic change. However the policies required to achieve these frequently conflict with each other, negatively affecting sustainability as a whole. For example, urban intensification with the intention of lowering transport energy costs (Newman and Kenworthy, 1989; Williams, Burton et al., 2000) has been found to exacerbate urban heat islands and increase flood risk as well lead to poor health outcomes for residents (Hunt and Watkiss, 2011; Melia, Parkhurst et al., 2012; Holderness et al., 2013).

Therefore decision makers require robust planning tools to achieve the trade-offs necessary to ensure optimal sustainability (Dawson, 2011). This paper presents the use of a spatial optimisation framework as one method by which multiple positively and negatively correlated sustainability objectives can be evaluated in time and space to assist urban planning. A case study, applied to Middlesbrough Borough Council, a local authority area in the North East of England (Figure 1), demonstrates how a spatial Pareto-optimisation based on a Genetic Algorithm (GA) framework (Goldberg, 1989) can be employed to derive spatial development patterns that are sensitive to climate induced hazards such as heat and flood while accounting for current planning policies that seek to avoid fragmented urban growth and development on green space.

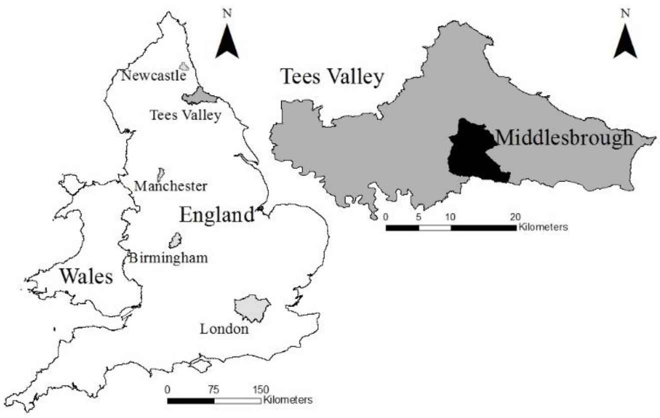
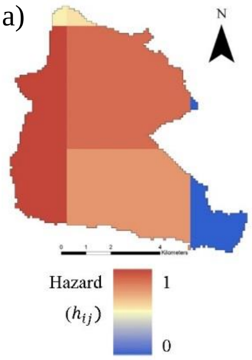
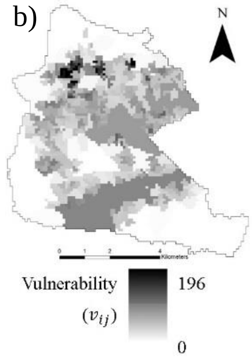
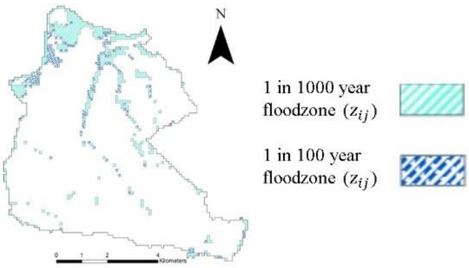
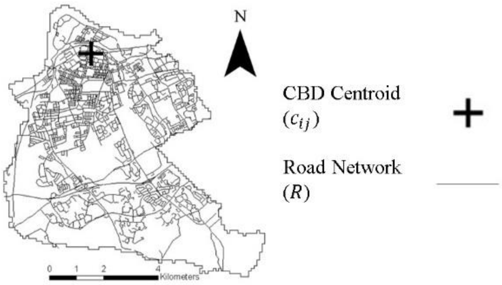
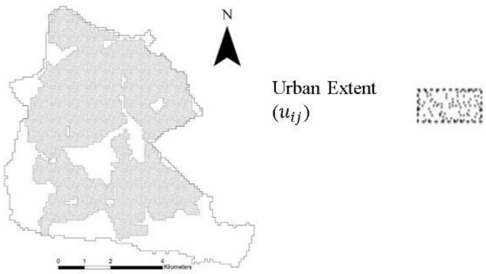
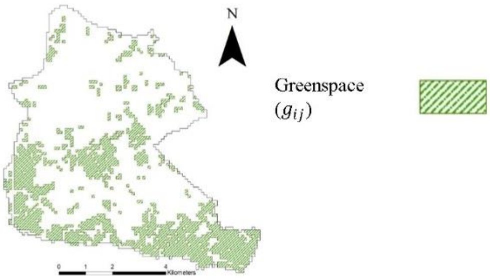


Figure 1 The case study area of Middlesbrough within the Tees Valley.

2. Methodology

A subset of key, real world sustainability objectives were derived from a review of spatial planning and urban sustainability literature: namely; (1) minimizing risk from heat waves; (2) minimizing risk from flooding; (3) minimizing the distance of new development to the current CBD to minimize travel costs; (4) minimizing urban sprawl to prevent increased travel costs; and (5) preventing the development of green-space. Table 1 summarises their parameterisation and the spatial fields used in their calculation.

Table 1 Parameterisation of Sustainability Objectives

Parameterisation	Inputs
1. Minimise risk from heat waves: f_{heat} Characterised by the increase in heat risk in the future relative to the baseline date based on the spatial assignment of new development sites. Heat risk is defined as the cross product of the probability of a heat hazard event and population vulnerability. **Data Source**: a) Spatially disaggregated 2020 heat wave frequency projections (Jones et al., 2009); & b) 2011 census (ONS, 2012) population figures at lower super output area (density per hectare).	a)  b) 
2. Minimise risk from flooding: f_{flood} Characterized by a proportional risk assessment of development within 1 in 100 and 1 in 1000 year flood zones represented **Data Source**: UK's Environmental Agency's (EA) Flood zone maps at a 100 meter resolution.	
3. Minimise the distance of new development to CBD to minimise travel costs: f_{dist} Characterised by a shortest path between proposed development sites and designated CBD centroid. **Data Source:** Roads and CBDs represented by Ordnance Survey Meridian 2 roads and digitised town centre centroid respectively.	
4. Minimise expansion of urban sprawl: f_{sprawl} Calculated as a proportion of new development which falls outside the currently defined urban extent. **Data Source:** Ordnance Survey Meridian Developed Land Use Area.	
5. Prevent development of greenspace: Spatial constraint prevents solutions locating development on areas designated as greenspace **Data Source:** Rasterised Ordnance Survey MasterMap data with Natural theme, reduced to greenspace areas which exceed 2 ha as per Natural England guidelines.	

2.1 Spatial Optimisation Framework

The developed framework utilises a genetic algorithm which exploits the evolutionary operators of selection, crossover and mutation to converge on superior spatial configurations of development (Figure 2). The framework initialises with a series of random spatial configurations which are modified by the genetic algorithm operators for a set number of generations. The initial spatial plans are evaluated against the objective functions outlined before a selection operator chooses superior solutions to breed a new set of solutions. The selection operator is based on the NSGA-II (Deb et al., 2002) selection method which uses a unique crowding distance metric to ensure that a wide Pareto-front is maintained.

The resulting superior solution-set is then exposed to a crossover operator which combines features from two selected solutions using a two point crossover algorithm. Elements of each solution are exchanged around two randomly selected crossover points along the list of sites to generate two new solutions. This is done with the intention that sliced and merged solutions will lead to superior spatial development plans. Lastly a mutation operator is applied on a small probability which randomly alters the location of a site in order to maintain a diversity of sites in the solutions and prevents premature convergence.

After the prescribed number of GA generations is achieved, a set of Pareto-optimal solutions are returned. These are defined as spatial development plans that out perform all other spatial development strategies in at least one objective function. For a set of objective functions, $f \in F$ a solution $s^{(1)}$ is said to dominate solution $s^{(2)}$ if:

1. The solution $s^{(1)}$ is no worse than $s^{(2)}$ in all objectives; $f(s^{(1)}) \leq f(s^{(2)}) \forall f \in F$;
2. The solution $s^{(1)}$ is strictly better than $s^{(2)}$ in at least one objective; $f(s^{(1)}) < f(s^{(2)})$ for at least one $f \in F$. (Deb, 2001)

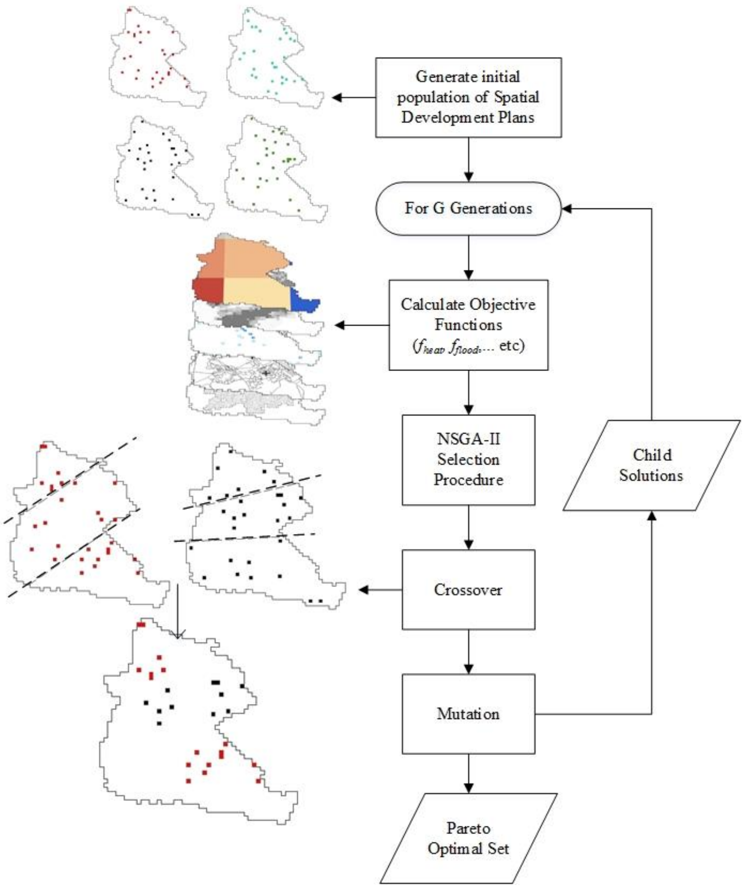


Figure 2 Genetic Algorithm flowchart.

3. Results and Discussion

Figures 3 and 4 present the results of the analysis over the case study. The performance of the local authorities development plan (Middlesbrough Council, 2013) is highlighted for comparison, demonstrating that the spatial optimization framework significantly improves upon this in terms of the sustainability objectives investigated. Figure 3 presents the Pareto-fronts (best trade-offs) between sustainability objectives highlighting conflicts between f_{heat} and both f_{flood} (Figure 3a) and, to a much greater extent, f_{sprawl} (Figure 3b). The latter is a result of urbanized areas having higher vulnerability. Despite these conflicts, the spatial optimization is able to identify plans which are best trade-offs. Alternatively f_{dist} and f_{sprawl} are simultaneously optimized (Figure 3c) as locations close to the CBD correspond with being within the urban extent.

A major strength of this approach is the ability to co-present sustainability scores alongside the spatial configuration. Figure 4 highlights a series of Pareto-optimal optimised spatial configurations of future development which occur on the Pareto front between f_{heat} and f_{dist}. To fully minimise f_{heat} (Figure 4a) the optimal plan assigns development in the south east of the study at the expense of f_{dist} whilst to optimize f_{dist} (Figure 4c) development is assigned to areas surrounding the CBD at the expense of poor f_{heat} performance. Interestingly, the median solution in the Pareto front (Figure 4b) assigns development in the north of the study area, a trade-off location which avoids the most vulnerable areas whilst being located relatively close to the CBD. By combining mapped results with the Pareto front plot it becomes possible to understand spatially the outcome of selecting a particular optimal solution.

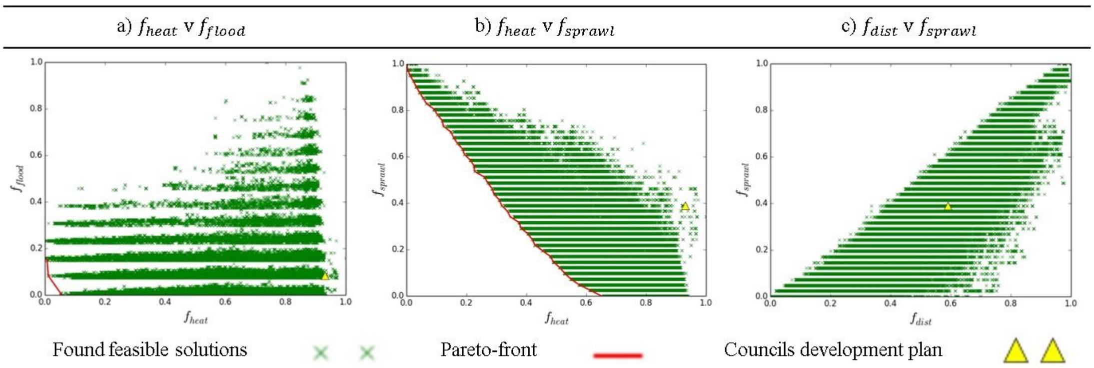


Figure 3 Pareto front between pairs of objectives

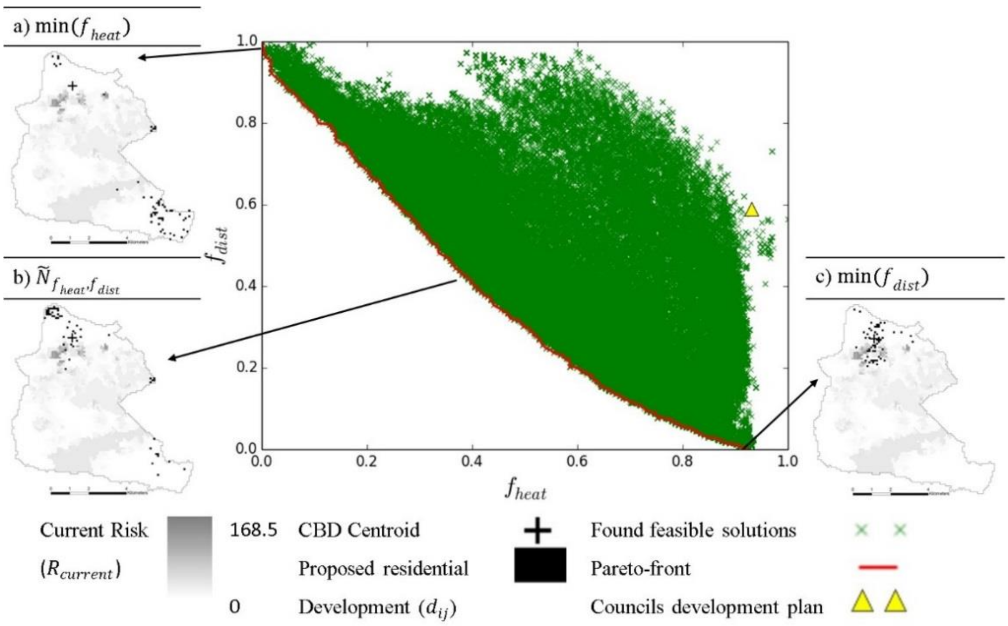


Figure 4 Pareto-front and resulting Pareto-optimal spatial plans.

4. Conclusion

Spatial optimisation provides a powerful decision support tool to help planners to identify spatial development strategies that satisfy multiple sustainability objectives. The application of the spatial optimization framework demonstrates for the real-world case study the ability to recognize potential development patterns that are potentially more sustainable than the current development plan. Extraction of non-dominated Pareto-optimal spatial configurations provides planners with a clear quantitative and visual characterization of the potential conflicts present between sustainability objectives. Moreover, the use of the Pareto-optimal approach provides a rich set of diagnostic information on possible trade-offs, with the potential to constitute a spatial decision support tool. In-conjunction with further qualitative examination these results could directly inform final planning decisions.

5. Acknowledgements

The research was funded by the UK Engineering and Physical Sciences Research Council, grant EP/H003630/1.

6. Biography

Daniel Caparros-Midwood (daniel.caparros-midwood@ncl.ac.uk) is a PhD student in the School of Civil Engineering, Newcastle University. Daniel's research focuses on the use of optimised spatial planning to manage climate risks and achieve sustainable development. Previously a GIS graduate from Newcastle University.

Stuart Barr (stuart.barr@newcastle.ac.uk) is a senior lecturer in Geographic Information Science in the School of Civil Engineering and Geosciences, Newcastle University.

Richard Dawson (richard.dawson@newcastle.ac.uk) is the Chair of Earth Systems Engineering (www.ncl.ac.uk/ceser) at Newcastle University. Richard's research focuses on the analysis of risks associated with urban and infrastructure systems and the development of adaptation solutions that ensure our infrastructure and cities are resilient and sustainable in the face of intensifying global change.

References

Deb K. (2001) *Multi-Objective Optimization using Evolutionary Algorithms*. John Wiley & Sons Ltd, Chichester.

Deb K, Pratap A, Agarwal S and Meyarivan T (2002). A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, 6(2), 182-197.

Dawson R (2011). Potential pitfalls on the transition to more sustainable cities and how they might be avoided. *Carbon Management*, 2(2), 175–188.

Goldberg, D. E. (1989).*Genetic Algorithms for Search, Optimization and Machine Learning*. Addison-Wesley, Reading.

Holderness T, Barr S, Dawson R and Hall J (2013) An evaluation of thermal Earth observation for characterising urban heatwave event dynamics using the urban heat island intensity metric. *International Journal of Remote Sensing*, 34(3), 864–884.

Hunt A and Watkiss P (2010). Climate change impacts and adaptation in cities: a review of the literature. *Climatic Change*, 104(1), 13-49.

Jones P, Kilsby C, Harpham C, Glenis V and Burton A (2009) *UK Climate Projections Science Report:*

Projections of Future Daily Climate for the UK from the Weather Generator, University of Newcastle, UK.

Melia S, Parkhurst G and Barton H (2012). The Paradox of Intensification. *Journal of Transport Policy,* 18(1), 46–52.

Middlesbrough Council (2013). *Local Development Framework Housing Review Preferred Options: Sustainability Appraisal*. Middlesbrough, UK.

Newman, P. and Kenworthy J.R. (1989). *Cities and automobile dependence: a sourcebook*. Gower, Aldershot.

ONS (Office of National Statistics) (2012). *2011 Census: Population Estimates for the United Kingdom*. London.

Williams K, Burton E and Jenks M (2000). Achieving Sustainable Urban Form: Conclusions. In Williams K, Burton E. and Jenks, M. (ed.), *Achieving Sustainable Urban Form*. Routledge, London, 347-55.