Multi-Criteria Spatial Optimisation of Christchurch's Urban Development

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Final Year Projects, 2020
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Keywords: *Spatial planning, Urban optimisation, Climate risks, Sustainability objectives, Planning synergies & conflicts*

ABSTRACT

Currently, local authorities are unequipped to quantitatively assess areas for future development in a manner that can consider multiple planning objectives. In this paper, we continue the development of a multi-criteria spatial optimisation framework that uses a genetic algorithm. As a case study, the framework is applied to Ōtautahi Christchurch, New Zealand, to identify areas of priority for urban intensification. This will help aid decision-makers where to guide future growth whilst taking into account multiple hazard adaption and sustainability objectives and their trade-offs and synergies. We observe such synergies and trade-offs between the selected objective functions, indicating that urban planners can both take advantage of co-benefits, but also must make compromises, between criteria when choosing areas for development. The algorithm was observed to not entirely neglect unfit development plans; however, it does converge on superior regions when averaging the best spatial plans of the final generation. These maps could guide urban planners by providing evidence for decisions when choosing regions for future strategic growth.

1. INTRODUCTION

Cities are widely recognised as a solution to many of societies challenges, but they are not without problems (Lehmann 2019; OECD 2010; United Nations 2019). Issues arise around where cities are built and how they are planned. Urban planners are faced with the complex task of assessing areas for future development. However, through the careful design of cities, they can develop sustainable and resilient urban environments. In the face of projected increases in the frequency and intensity of extreme events, it is widely accepted that urban areas must focus on adapting to exacerbated natural (and other) hazards to enhance sustainability, quality of life and resilience.

Urban planners measure the quality of spatial development plans by creating objectives they wish to fulfil. Objectives that aim to mitigate or adapt to climate-related issues are termed sustainability planning objectives. However, attempting to target one sustainability objective exclusively can undermine and cause conflicts among the other objectives (Caparros-Midwood et al. 2019; Floater et al. 2016; Lehmann 2019; Meerow 2019; Sethi et al. 2018; Smith 2013; Viguié and Hallegatte 2012). Conversely, there is potential for objectives to have co-benefits where induced increases in one objective result in a secondary benefit of another objective. For example, reducing vehicle use will have supplementary benefits on public health and greenhouse gas emissions (Floater et al. 2016). This presents urban planners with a conundrum, where a multi-dimensional spatial optimisation problem is encountered to balance potential compromises and utilise co-benefits between risk and other sustainability objectives (Caparros-Midwood et al. 2019).

By 2038, it is predicted that an additional 600,000 dwellings will be required to house Aotearoa New Zealand residents, with 50,000 of these dwellings being needed in Ōtautahi Christchurch (Stats NZ 2013; Stats NZ 2018). The Ministry for the Environment (2020) requires local authorities to prepare a Future Development Strategy (FDS) as part of the National Policy Statement on Urban Development (NPS-UD). The NPS-UD focuses on policies for strategic growth planning through evidence-based decision-making methods in order to form well-functioning environments. Thus, urban planners have the responsibility to make design decisions for urban areas for these future populations.

According to the 2018 Census (Stats NZ 2018), 99% of Christchurch is occupied by low-density private housing (Figure 1) of which is not sustainably densified, as defined by (Lehmann 2016). Therefore, the first question that arises is how planners can implement an FDS to guide Christchurch's projected urban growth. Moreover, when applying qualitative criteria to fulfil the requirements of the NPS-UD, the more important question for planners is where to build next?

To address that question, a novel multi-objective spatial optimisation framework was developed (Caparros-Midwood 2016). This framework combined several objectives to identify urban areas for intensification in European cities (Caparros-Midwood 2016). Subsequent journal articles Caparros-Midwood et al. (2019) have further refined the optimisation approach to efficiently search for urban development strategies that optimise the objective functions chosen. This framework is both critical to, and appropriate for addressing future intensification through quantitative-based decision-making procedures, and covers the significant policies of the NPS-UD.

We created a modified genetic algorithm multi-objective spatial optimisation model, developed initially by Caparros-Midwood et al. (2019), and applied it to Ōtautahi Christchurch, New Zealand. Christchurch City Council urban planners (and other stakeholders) will be able to identify a range of suitable areas for sustainable future development. This framework equips urban planners with an evidence-based method for their decisions that considers both the trade-offs and synergies between multiple planning objectives, to aid them in fulfilling their requirements under the NPS-UD.

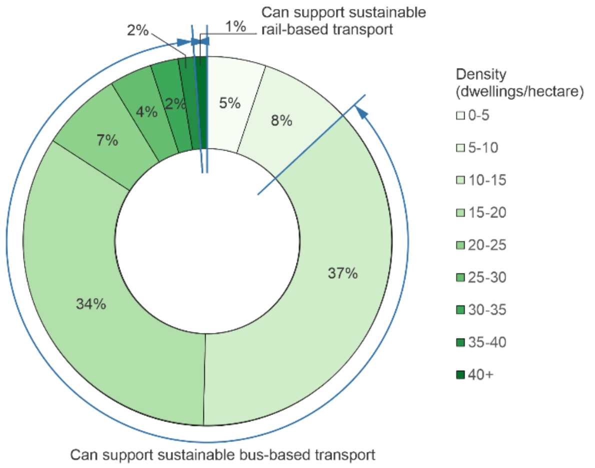

Figure 1. Proportions of existing urban densities of Christchurch in 2018, by statistical area, indicating where different transport methods can be supported as outlined by Chakrabarti (2013). A 3D interactive spatial map can be found at urutau.co.nz/research/spatial_optimization

2. LITERATURE REVIEW

An answer to the question of where to best build requires the choice of a good algorithm. Many variants of possible algorithmic approaches exist within the literature, and each methodology has limitations. For the algorithm to efficiently locate improved solutions, it is vital to choose a method that creates a vast range of spatial plans, each different from the last iteration. We chose a genetic algorithm because it is ideal based on its ability to escape converging on local optima (Caparros-Midwood 2016) whilst creating diverse development plans. Figure 2 outlines the steps of the genetic algorithm implemented using the Python software language. We expand on this in the following sections.

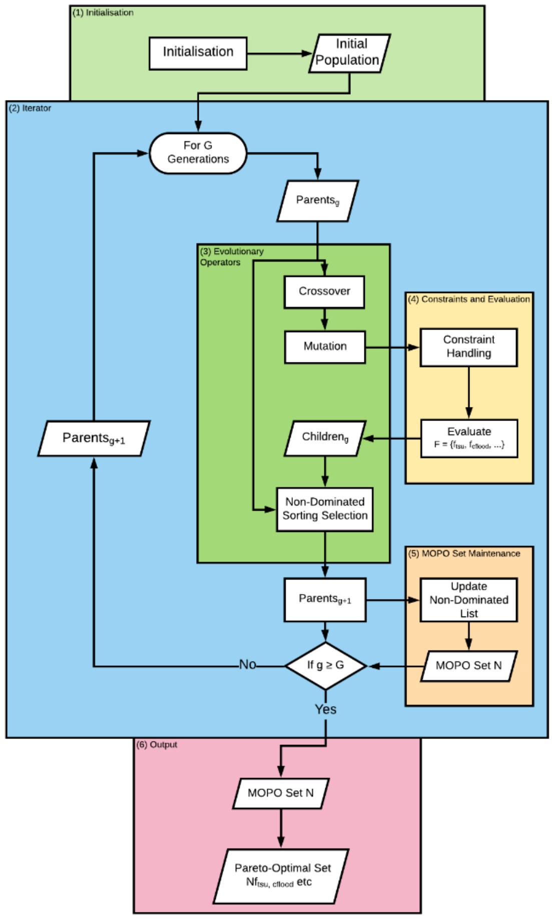

Figure 2. Computational flowchart of the genetic algorithm used to implement the multi-objectional spatial optimisation framework. (Modified from Caparros-Midwood et al., 2016).

When designing sustainable and resilient urban environments, a careful choice of unique densities that are feasible and sustainable is needed. One particular study (Jasmax 2011) investigated the practicality of residential densification for the city of Auckland, New Zealand. A range of possible design solutions, from 42 to 520 dwellings per hectare, were considered viable for the current Auckland market conditions. Several authors (Chakrabarti 2013; Ministry for the Environment 2005; Tauranga City Council 2018) promote a minimum threshold of approximately 40 dwellings per hectare to promote a viable public transportation network in cities, infrastructure cost savings and land economy gains. Lehmann (2016) argues that a more generous lower limit of 70 dwellings per hectare comprises a benchmark for authentic, sustainable development. Possible design solutions by Jasmax (2011) over 155 dwellings per hectare were comprised of high-rise apartment-style structures. Therefore, a maximum bound of 140 dwellings per hectare was enforced to persevere the current character of neighbourhoods in Christchurch. Thus, the achievable sustainable design densities between 70 and 140 dwellings per hectare recommended by Jasmax (2011) were used.

It is important to choose appropriate objectives that are spatially quantified to represent the planning goals of Christchurch best. A review was conducted of the City Plan (Christchurch City Council 2016) and various reports (Christchurch City Council 2017; Christchurch City Council n.d.; Todd et al. 2017) to identify planning objectives and hazards implemented in the current urban planning context. From this investigation and the availability of data, the objectives implemented in our Christchurch case-study are as follows:

- to minimise exposure to inundation from a tsunami resulting from a 1 in 2500-year earthquake event situated in South America
- to minimise exposure to a 1 in 100-year coastal flooding surge in addition to increments of future sea-level rise
- to minimise exposure to the risk of future river flooding for a 1 in 500-year event
- to minimise liquefaction susceptibility
- to minimise the distance of new development to key activity areas
- to minimise the expansion of urban sprawl in rural zones.

Further objectives can be prescribed in the framework for Christchurch, as well as other future case studies. However, for illustrative purposes, we believe the six objectives chosen are adequate to showcase the developed framework.

The quantity of required dwellings for future generations is needed through projections under multiple scenarios. Three central forecasts follow low, medium and high growth due to differing rates of fertility, mortality and migration. It is argued by Stats NZ (2013) that the medium projection is best suited for assessing future dwelling required. In order to identify robust regions for development regardless of the scenario, three alternative projections will be considered (ten, thirty, and fifty thousand dwellings) (Stats NZ 2013).

3. METHODOLOGY

3.1. Initialisation

To enforce the genetic algorithm to allocate future dwellings to regions that can be intensified, constraints are applied to prevent uninhabited areas from being considered. The choice of regions to develop in Christchurch is based on statistical areas defined by the 2018 Census (Stats NZ 2018), detailed at urutau.co.nz/research/spatial_optimization. The constraints imposed upon each statistical area in the genetic algorithm are: (i) Red Zones identified after the Canterbury Earthquake Sequence, (ii) public recreational parks and green spaces, and (iii) areas identified as specific purpose, transport or open space as per the District Plan. A further constraint was to ensure chosen statistical areas are contained within the urban extent boundary set by the District Plan.

Creating a successful quantitative framework involves each statistical area to be evaluated against each of the six chosen objective functions. Each objective was parameterised from a spatial dataset into a function, as outlined at urutau.co.nz/research/spatial_optimization. User-defined weightings for each objective were then correspondingly multiplied by each objective function score to calculate an overall score of the statistical area (Eqn 1).

$$F = \sum_i (w_i \times f_i) \tag{1}$$

where:

F = Overall objective score for the statistical area
w = User-defined weighting for an objective function
f = Associated quantitative objective function score.

An efficient method of retrieving these evaluations is required. Each modified statistical area was indexed with a unique integer to create a 'look-up table', which is called upon each iteration. This guarantees statistical areas that satisfy all constraints were selected by the algorithm, which eliminated the need for a penalty function.

The creation of the initial spatial development plans is crucial to the success of optimisation problems. We chose to form initial plans by randomly selecting a statistical area and increasing its density to a randomly chosen feasible sustainable design density. This process continues until the number of dwellings in the spatial plan reaches the required amount needed for future development under the specified projection pathway, and the resulting set of plans is labelled parents_0. Thus, each development plan, D_i, is a collection of statistical areas (that are specific development locations) called d_i, with randomly added density.

3.2. Iterator

We iterate over successive generations to create diverse and unique spatial plans in order to evolve towards the optimum configuration. The algorithm runs for a user-defined amount of iterations and takes the previous set of selected development plans (parents_g) and updates it to create a new set of development plans (parents_{g+1}) using evolutionary operators.

3.3. Evolutionary Operators

Evolutionary operators randomly alter individual development plans to create new ones, each with a slightly different selection and densification of statistical areas. The new set of children_g is generated through a modified mu-plus-lambda evolutionary strategy, implemented by the Distributed Evolutionary Algorithms in Python (DEAP) module. This produces a child by probabilistically choosing one of three evolutionary methods until the number of children matches that of $parents_g$. Specifically, the algorithm is chosen to use a 2-point cross-over operator, a mutation operator by shuffling attributes (d_i's), or a cloning operator. For all three methods, the strategy implements a roulette selection procedure to select the required amount of D_i's from the set of $parents_g$ before applying the evolutionary operator to the selected parent(s). The probabilities for crossing-over and mutating operators are assigned to be 0.7 and 0.2, respectively, with the remaining 10% of children being created through cloning. This improves convergence on objectives whilst demonstrating more diverse solutions being generated Caparros-Midwood et al. (2017).

3.4. Constraints and Evaluation

After a child is created through an evolutionary operator, each d_i is verified to be under the sustainability density threshold of 140 dwellings per hectare. If found to have exceeded the limit, then a new child is created to replace the unacceptable child.

The critical requirement of finding optimal locations to densify is to rank the performance of each development plan. The approach undertaken was to use a weighted sum of all statistical areas identified for intensifying, as outlined in Equation 2.

$$fitness = \sum_i (F_i \times dw_i) \quad (2)$$

where:

fitness = Objective score for the development plan

F = Overall objective score for a statistical area

dw = Associated dwellings to be added to a statistical area

3.5. Selection

In order to choose the individuals with the best fitnesses for the next iteration, a selection tool is used after constraint handling and evaluation. Several authors have discovered that the use of the Non-dominated Sorting Genetic Algorithm II (NSGA-II) process performs well compared to other selection methods when utilised in optimisation problems (Cao et al. 2011; Jaeggi et al. 2008; Zhang and Fujimura 2010). Hence, we used NSGA-II as the method of selection Deb et al. (2002).

3.6. Multi-Objective Pareto-Optimal (MOPO) Set Maintenance

Keeping a record of spatial plans that are shown to have the best fitness in at criteria is essential. It was chosen to implement a multi-objective Pareto-optimal (MOPO) sets that appends newly formed plans after every iteration that dominate in at least one objective score.

3.7. Output

To best visualise a range of optimal development plans and associated trade-offs in two objective functions requires the use of a scatter plot. This shall show the optimal points that are the best in one of the objectives, without negatively impacting on the other, i.e. Pareto-optimal points. For example, in Figure 3, Point A lies on the "Pareto-front" as it cannot get any smaller in f_1(X) without increasing in f_2(X). This plot is used to indicate a range of robust future spatial development plans which show clear evidence of synergies & conflicts between risk and sustainability objectives.

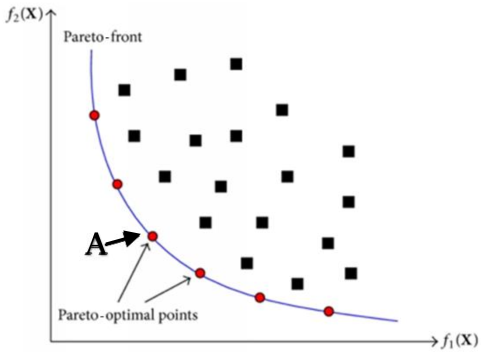

Figure 3. Demonstration of the Pareto front for two objectives. (Reproduced from Wang et al., 2015)

Urban planners must consider the implications and necessary compromises of exclusively minimising one objective function. We chose to showcase this through a parallel coordinate plot, where each line represents the fittest spatial development plan discovered for each objective.

To answer the central question of this research of where to build for future urban growth in Christchurch, displaying the locations of optimal development plans is essential. We chose to define the best D_i's ever created to be those that were simultaneously a part of the MOPO set and located on the Pareto-front of the last generation. Moreover, the statistical areas indicated to be more frequently densified on average are to show urban planners priority areas in order to guide and support evidence-based decisions for future urban growth.

4. RESULTS AND DISCUSSION

4.1. Observed relationships among objective functions

Two main types of relationships exist between objectives, as depicted in Figure A1. The first is the interaction and simultaneous minimisation of at least two objective functions. For example, this synergy exists between the risk of tsunami inundation and coastal flooding for statistical areas in Christchurch (Figure A1). Figure 4 indicates that both hazards are co-located along the eastern coastline. When multiple objectives are synergistic, this supports mitigative action to occur as the relative cost is greatly reduced. As the algorithm seeks ideal locations, statistical areas inland are chosen due to this co-location to minimise multiple objectives simultaneously.

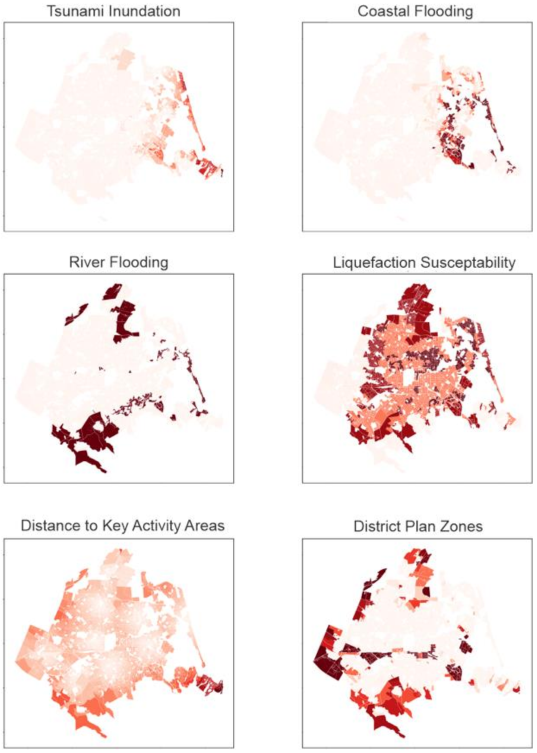

Figure 4. Parametrized spatial dataset for each objective function of the Ōtautahi Christchurch case study. A darker shade of red indicates that the statistical area has a high objective function score.

Approximately half of the objective pairs demonstrate a synergistic relationship that converges to the minimum in both objectives simultaneously. However, as expected for many pairs of objective functions, a clear Pareto-front of optimal spatial plans exists (Figure A1). Similarly, when assessing the development plans that were superior in each objective function (the MOPO set), as depicted in Figure 5, there is significant variability among objective function scores for the optimal plans. Both results indicate that no development plan is capable of entirely minimising all objective functions simultaneously, but rather conflicts occur between objective functions. The existence of Pareto-fronts regrettably dismisses the notion that a single development plan can fully minimise all objective functions. The key to future urban densification for Christchurch based on the criteria and weightings chosen, therefore, lies with the awareness that there will be no one perfect answer to the question of where to build next, but rather a range of solutions along the Pareto-fronts should be considered.

Due to the presence of both synergistic and conflicting relationships, decision-makers need to be aware of the potential for maladaptation. It can be tempting to choose a plan which minimises multiple objectives simultaneously. However, in doing so, other objectives may end up much higher and push the total fitness score above what it would be otherwise. This is evident when attempting to minimise the liquefaction objective exclusively (Figure 5), where an unintended increase in river flooding is produced.

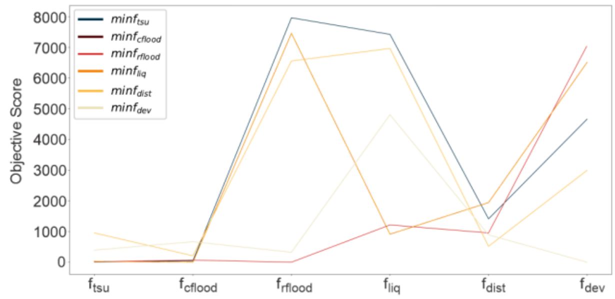

Figure 5. Performance of Pareto-optimal spatial plans that dominate in one objective across all objectives. (Parents = 1000, Generations = 200, Balanced weightings, High dwelling projection)

4.2. Convergence

Increasing the number of parents and generations further defines the Pareto-front; however, this comes at the cost of an extreme run-time. This imposes a new constraint upon the research: to evaluate the trade-off between the discovery of accurate solutions and the time taken to find them. Through running numerous simulations with varying ranges of both parameters, it was concluded that the optimal arrangement was to create 2500 parents and iterate for 400 generations to gather a precise Pareto-front.

As the initial development plans were constructed by randomisation of location, we noticed that all statistical areas were picked by at least one D_i in $parents_0$. However, at progressively larger numbers of iterations, statistical areas with notably bad scores are neglected for further use in successive iterations. This results in more densified development in certain areas that better achieve the objective functions. In this regard, the behaviour of the genetic algorithm is as intended and indicates the framework is successful at converging on superior development plans. This convergence, where some regions are discarded from all development plans, is not nearly as noticeable when more parents are used. This is believed to be due to more parents meaning each statistical area has a higher probability of still being selected after each generation. This indicates the genetic algorithm is not great at converging, as it still chooses almost every statistical area for development across all the parents at higher parent numbers. Multiple sources have found that seeding the algorithm with reasonable solutions during initialisation can lead to development plans converging on optimal solutions quicker due to using a biased starting position (Caparros-Midwood 2016; Harik and Goldberg 2000; Keedwell and Khu 2005).

Although unfit locations are not entirely dismissed, the genetic algorithm can be seen in Figure 6 to converge on particular regions. Sites that are darker in colour appear in a higher percentage of development plans that are in the MOPO set, meaning they are a common theme in development plans that have performed well. These statistical areas are, therefore, a good indication as to where urban planners should consider for intensify residential areas.

Figure 6. Ranked Pareto-optimal development sites. Darker blue signifies where statistical areas appeared more often in the MOPO sets. (Parents = 1000, Generations = 200, Balanced weightings, High dwelling projection)

4.3. Distinctive patterns of densification methods of the genetic algorithm

Development plans from the final iteration shown to lie within the top 1% of the overall objective function score are overlaid on top of the current densities in Christchurch (Figure 7). This shows where the genetic algorithm converged that is ideal for urban intensification, given the chosen weightings. It indicates what Christchurch would spatially look like if the recommended urban areas were densified.

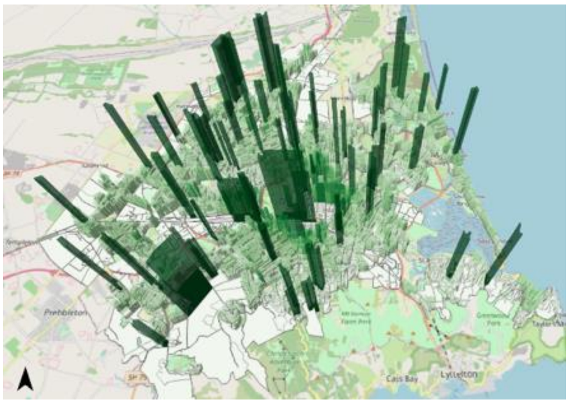

Figure 7. Spatial variability of envisioned urban densities of Ōtautahi Christchurch, by statistical area, where the height and colour of the extruded statistical areas indicate relative urban density. (Parents = 1000, Generations = 200, Balanced weightings, High dwelling projection). A 3D interactive map can be found at urutau.co.nz/research/spatial_optimization

5. CONCLUSION

To assist urban planners to undertake a multi-objective evidence-based assessment, we set out to build a framework that addresses the question of where to build for future growth in cities. This paper presented a genetic algorithm to search for optimal spatial development plans in Christchurch whilst considering the trade-offs and synergies between multiple planning objectives.

The framework relies upon several assumptions of parameter inputs to characterise future development. Despite these limitations, the methods proposed in this paper is credible at locating areas of cities to densify to accommodate future development sustainably.

With the given illustrative criteria and weightings for Christchurch, our findings demonstrate that both synergies and trade-offs exist between objectives. These results indicate that Christchurch urban planners are faced with a range of optimal spatial plans, instead of one superior solution that completely satisfies all objectives. This leads us to believe that when collating a Future Design Strategy, an evidence-based approach to decision-making is necessary to address multiple objectives whilst ensuring maladaptive actions are not undertaken.

Our findings highlight that the algorithm is not efficient at neglecting regions with poor fitnesses, as all statistical regions are shown to be developed on among the summation of all parents. However, it was discovered that when averaging a select sub-set of superior parents from the last generation, the algorithm converges on particular regions. Based on these preliminary results, it is in these statistical areas that we recommend urban planners to focus on developing and densifying for increased residential capacity. The recommendation of areas to densify shall serve as a guide for urban planners to base and support their choices for future urban growth in cities. More importantly, this framework is to be a tool for urban planners to utilise in order to make evidence-based decisions for sustainable and resilient development, as required under the NPS-UD.

6. FURTHER WORKS

We have developed a framework that is suitable for any city based on geographic constraints and dwelling count data. Objective functions need to be written based on what objectives the user wants to achieve based on data availability; however, the rest is versatile. Currently, the framework considers six objectives, only one of which relates to a positive amenity. A further step is to include positive objectives, such as minimising the distance to schools, supermarkets and medical centres to design urban areas for quality of life measurements.

As we use the best performing development plans of the genetic algorithm, a stability check is to be completed to ensure the statistical areas that are recommended for development each time is consistent.

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8. ACKNOWLEDGEMENTS

We thank Dr Tom Logan (University of Canterbury), as our journey would not have been possible without you guiding us. Your critique, encouragement, discussion and assistance has been most helpful.

We thank Dai Kiddle and Mitchell Anderson (University of Canterbury) for their contribution to data manipulation and methods.

9. DATA AND CODE AVAILABILITY

Data used and source code is available from Dr Tom Logan (tom.logan@canterbury.ac.nz) upon request.

Interactive maps, all figures created in the code and a database detailing the data used and where it was sourced from can be found at:
urutau.co.nz/research/spatial_optimization

APPENDIX – PARETO PLOTS

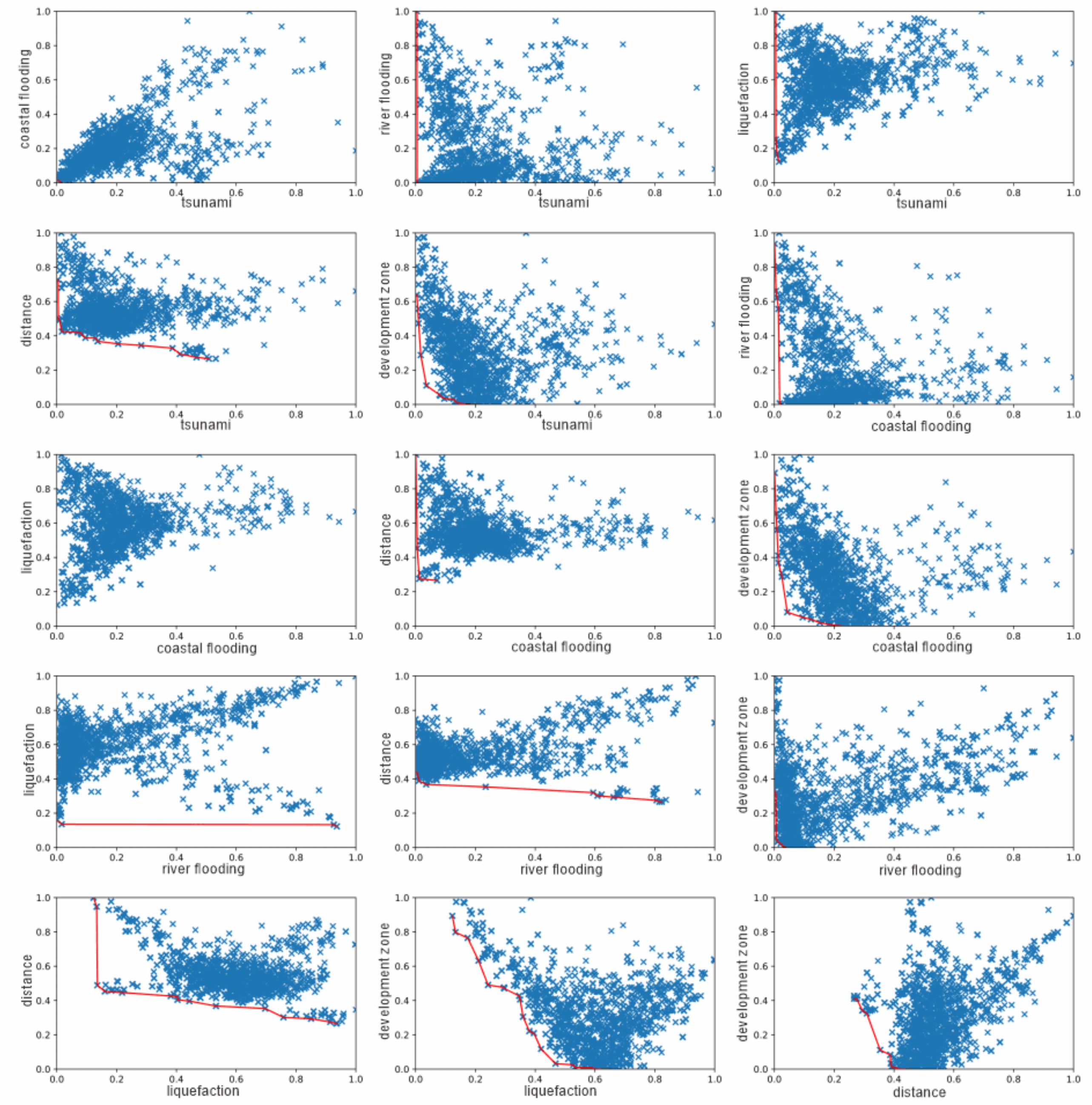

Figure A1. Scatter plot of every spatial development plan's fitness in two competing objective functions analysed in the entirety of the genetic algorithm for the Ōtautahi Christchurch case study. Highlighted is the Pareto-optimal plans along the Pareto-front curve. (Parents = 1000, Generations = 200, Balanced weightings, High dwelling projection)