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Participatory multi-objective optimization for planning dense and green cities

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The consideration of urban ecosystem services becomes increasingly important when planning compact cities. We implement a multi-objective optimization approach to support decision-makers in their efforts to develop green and dense cities. Embedded in a participatory process, the applied genetic algorithm allows us to assess spatial tradeoffs between urban ecosystem services and compactness. The optimization model is embedded in a decision support system for interactive analysis and communication of the results, facilitating the engagement of planners to support sustainable development. We illustrate the process in a multi-level case study in Singapore, a tropical city state aiming to pursue its distinct greening strategy. The whole process, from the problem definition to the obtained solution set, is evaluated using a feedback loop with stakeholders. Using this approach, we identify robust and best-suited urban development locations as well as temporal prioritization schemes evolving around future public transportation nodes.

Keywords: Urban Ecosystem Services (UES); urban densification/compactness; multi-objective optimization; land use allocation; participatory process; decision-making/decision support system

1. Introduction

While the world's urban population is rapidly growing, sustainable development increasingly depends on the successful management of urban growth (United Nations 2018). Coping with the growing number of urban dwellers challenges urban living conditions and calls for synthetic and holistic solutions (Acuto, Parnell, and Seto 2018). Densification processes have been suggested as an effective strategy to reduce urban sprawl (Wolsink 2016) and related environmental impacts (Stone, Hess, and Frumkin 2010). Planning for compactness, however, often entails the loss of urban green space (Haaland and van den Bosch 2015), negatively influencing the supply of ecosystem services (Grêt-Regamey *et al.* 2020) and ultimately well-being (Tzoulas *et al.* 2007), as well as urban sustainability (Elmqvist, Mcdonald, and Seto 2013) and resilience (McPhearson *et al.* 2015). Securing urban green spaces in the context of

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densification becomes increasingly difficult in compact cities (Wolsink 2016), as land is limited and this scarce resource is contested by competing land uses, such as housing, commercial interests, and transportation. On the one hand, the integrity and connectivity of natural and semi-natural ecosystems within the urban landscape are continuously threatened by new housing and infrastructure developments. On the other hand, the demand for services from such ecosystems is growing due to the growth of the urban population, as well as exacerbated environmental issues due to global warming and anthropogenic heat.

The conservation, restoration, and creation of urban ecosystem services (UES) are known to decrease the detrimental impact of cities, while creating a more resilient and livable space for city dwellers (Gómez-Baggethun and Barton 2013). The benefits that cities obtain from green spaces include drinkable water, microclimate regulation, food, biodiversity and recreation, to name but a few (Luederitz *et al.* 2015). By buffering against more frequent climate-related disturbances exacerbated by human activities such as flooding and heat waves, UES have an increased insurance value (Gómez-Baggethun and Barton 2013; McPhearson *et al.* 2015). At the same time, green spaces contribute to meeting recreational needs (Jim and Chen 2006), supporting physical and psychological health benefits (Mark *et al.* 2017), embodying aesthetic appreciation (Jim and Chen 2006), and allowing spiritual experience, sense of place (Daniel *et al.* 2012) and education (Wolsink 2016). Ultimately, all these benefits have been proven to contribute to better socio-economic conditions for urban communities (Tzoulas *et al.* 2007).

As the amount of green spaces decreases, the number and variety of interests for the multiple services provided by the remaining open spaces increase. Integrating UES into urban planning (Grêt-Regamey *et al.* 2017) thus increasingly requires the consideration of tradeoffs and conflicting or diverging values (Elmqvist, Mcdonald, and Seto 2013; Haaland and van den Bosch 2015). Several computational tools have been developed to support decisions in contexts of tradeoffs between single or multiple conflicting objectives. Approaches range from multi-criteria decision analysis (MCDA) to multi-objective optimization problems. Both approaches pursue different strategies to structure, search and evaluate solutions to decision problems (Jankowski, Fraley, and Pebesma 2014). Polasky *et al.* (2008) studied tradeoffs between biodiversity and economic values regarding land use, utilizing a heuristic search algorithm. Grêt-Regamey *et al.* (2017) applied a MCDA approach using a web-based platform to allocate a requested amount of urban development areas on the basis of UES and locational factors. Elliot *et al.* (2019) used multi-objective integer linear programming to model scenarios that optimize UES supply. Seppelt and Voinov (2002) used genetic algorithms for optimizing land use patterns. Holzkämper and Seppelt (2007) showed that a genetic algorithm can be used to tradeoff habitat requirements of bird species and the cost-effectiveness of management actions for species conservation. They also demonstrated the applicability of the genetic algorithm to various spatial planning problems and identify tradeoffs between conflicting values.

Multi-objective optimization aims at solving combinatorial decision problems without giving undue weight to individual objectives or depending upon weighting schemes (Schwaab, Deb, Goodman, Kool, *et al.* 2018). Multi-objective genetic algorithms are stochastic optimization procedures that were developed to identify Pareto-optimal solutions. These solutions are optimal as the improvement of one objective leads to the decline of another objective (Pareto 1964). Several multi-objective optimization techniques have been developed, among them genetic or evolutionary algorithms. Genetic algorithms mimic natural selection and evolutionary principles. The Non-Dominated Sorting Genetic Algorithm NSGA-II (Deb *et al.* 2002) has been proven to be effective and efficient as a multi-objective search technique for various application scenarios (Bekele and Nicklow 2007). It's described as a powerful and effective algorithm for multi-objective land use allocation optimization (Shaygan *et al.* 2014). The NSGA-II algorithm is widely applied in optimization processes in forest planning (Fotakis *et al.* 2012), spatial allocation of natural resources (Lautenbach *et al.* 2013; Jankowski, Fraley, and Pebesma 2014; Hu *et al.* 2015), renewable energy sources (Karakostas 2015), water management (Bekele and Nicklow 2007) or land use allocation (Fonseca *et al.* 2007; Cao *et al.* 2011; Shaygan *et al.* 2014; Schwaab, Deb, Goodman, Kool, *et al.* 2018). Problems evolving around the allocation of land uses are often complex because multiple stakeholders with conflicting goals and objectives are involved (Aerts *et al.* 2005). Multi-objective optimizations allow integration of various stakeholder perspectives (Schwaab, Deb, Goodman, Kool, *et al.* 2018), which makes optimization procedures well-suited for integration in participatory approaches. Participatory approaches comprise contributions of stakeholders and allow the consideration of a range of viewpoints (Elliot *et al.* 2019). They have been applied in UES research to map intangible cultural values in the marine spatial planning context (Klain and Chan 2012) or they have been used for the exploration of the social perceptions of conditions, trends, tradeoffs, and the future of UES to propose management strategies (Palomo *et al.* 2011). Participatory approaches have been found to add value to urban planning decision-making and stimulate discussions (Elliot *et al.* 2019) that can foster different visions and consensual management strategies (Palomo *et al.* 2011). Feedback loops represent the mechanism to integrate participatory information in the modeling process. For example, Boumans *et al.* (2015) used successive cycles of observation, stakeholder engagement, mediated modeling, and model run updates in an iterative flow across multiple scales. Piemonti *et al.* (2017) applied human-in-the-loop optimization methods using a web-based approach. Despite the number of UES studies including participatory aspects, there is still a gap in studies outside the EU and the US (Haase *et al.* 2014). Furthermore, a gap in multi-level studies (de Groot *et al.* 2010) has been identified, especially in a participatory context (Haase *et al.* 2014).

This paper describes a participatory multi-objective optimization approach to support minimization of UES loss and maximization of compactness in planning of new developments in cities. The approach is illustrated in a case study in Singapore, an island nation located in the tropical climate. We implement a stakeholder feedback loop to gain insights into local constraints and objectives. The framework is applied to simulate temporal development options evolving around future transportation nodes. We finally discuss how the integration of stakeholders in the modeling process facilitates the development of legitimate, credible and salient solutions for more sustainable development in cities.

2. Methods

2.1. Modeling framework

We rely on a multi-objective optimization approach developed by Schwaab, Deb, Goodman, Kool, *et al.* (2018) to assist decision-making in urban planning. We trade off compact development of future residential areas with minimizing the loss of UES due to this development. Since the employed optimization procedure is stochastic, there is no guarantee that the true Pareto-optimal solutions can be identified. However, a set of non-dominated solutions is defined, which is usually close to, or even identical to, the Pareto-optimal solutions. To avoid any misunderstanding, we will henceforth speak of non-dominated solutions, when referring to the set of optimal solutions identified in the evolutionary optimization process. In the following, we present the modeling framework with the algorithmic structure of the genetic operators, and the implementation of the optimization procedure in a stakeholder process.

The two-dimensional land use matrix constituted the chromosome of the evolutionary optimization process being evolved within a vast space of candidate solutions. The input and output maps featured a resolution of 100 m. This pixel size was chosen to respect the approximate needed size for construction sites. Based upon population growth in previous decades, we estimated a hypothetical 10%-growth of the residential area until 2030.

We implemented the NSGA-II (Figure 1) using the Python (Rossum 1995) framework called DEAP *Distributed Evolutionary Algorithms in Python* (Fortin *et al.* 2012). The crossover and mutation methods shown to be most effective in the work of Schwaab, Deb, Goodman, Lautenbach, *et al.* (2018) were consequently applied to our optimization problem. In the crossover procedure, the parent solutions are halved by drawing a line in randomly varying angles through the center of the polygon of our area of interest. The mutation process consists of a combination of uniform and biased mutation operators. The starting population size was chosen to be 100 analog to

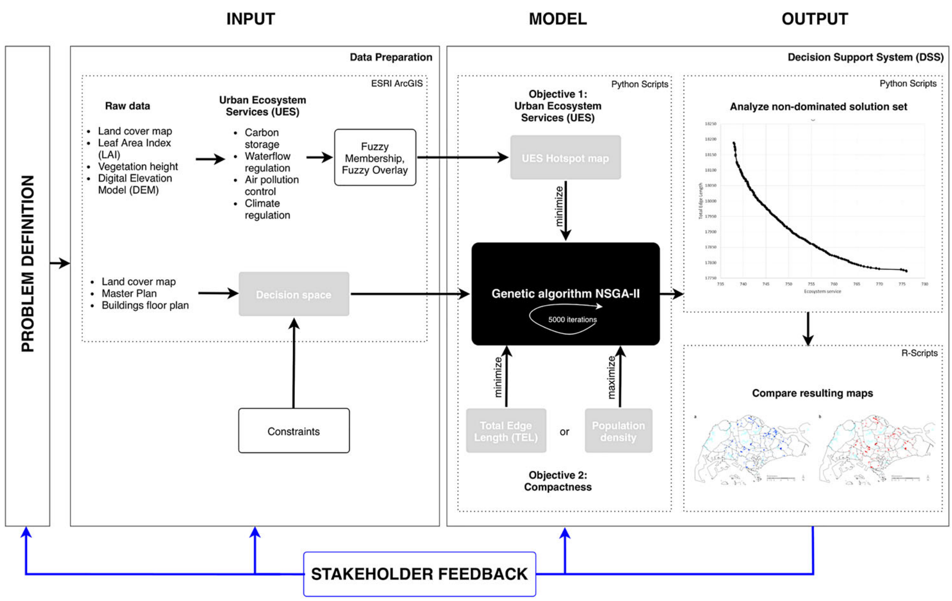


Figure 1. Flow chart of the optimization procedure. Problem Definition: together with stakeholders the problem and the required steps were defined. Input: The input consists of raw data processed to urban ecosystem service layers. These layers are combined to form the urban ecosystem service hotspot map. The decision space is mapped using Land cover, Master Plan and Buildings floor plan. Model: The core of the model (NSGA-II algorithm) minimizes loss of urban ecosystem services and maximizes compactness simultaneously. Output: After 5,000 iterations, the produced output data is further inspected. The resulting graphs and maps are analyzed and compared using the features of a decision support system. Stakeholder Feedback: The parameters are adapted depending on the feedback of the stakeholder. The iterative loop with the stakeholders is indicated in blue. Colour online.

Schwaab, Deb, Goodman, Kool, *et al.* (2018). To monitor the fitness after every iteration, the hypervolume indicator (Zitzler 1999) was used. The increase in hypervolume after 5,000 generations (i.e. iterations) was minor. Thus, 5,000 iterations were chosen for each run, resulting in a computation time of around 30 min per run. More details on the modification of the crossover and mutation operators can be found in Schwaab, Deb, and Goodman (2017).

In order to identify growth areas that are robust in terms of meeting both objectives in every section of the solution set of the non-dominated front, we produced an overlay of the pixel patterns. The pixel values of each solution on the non-dominated front were summed up and divided by the total quantity of pixel patterns to obtain the average per pixel. The mean value of every pixel determined its robustness measure. A threshold of 1 was applied to exclusively obtain pixels recurring in every solution and filter out the non-robust pixels. Among all the solution pixels, robust pixels can be considered as preferable by decision-makers. We chose two time steps (2020–2025 and 2025–2030) to account for a 10 year planning approach to urban development. The chosen time steps are for illustrative purposes only and do not directly correspond with time frames used by the local urban planning agencies. In each consecutive step, the optimization model was executed based on the new decision space resulting from the previous time step, constraining the decision space with fewer allocation possibilities.

We embedded the optimization process in an interactive participation procedure with local stakeholders in a *three phases process* (Figure 1). The stakeholders consisted of representatives from science (Singapore-ETH Center (SEC), National University of Singapore (NUS), Swiss Federal Institute of Technology (ETH Zurich), Nanyang Technical University (NTU), and the Singapore-MIT Alliance for Research and Technology (SMART) as well as stakeholders from Singaporean government agencies (National Parks Board [NParks], Urban Redevelopment Authority [URA], Housing and Development Board [HDB], and Singapore Land Authority [SLA]). The stakeholders were keen, among other interests, to see the development of a tool to support the allocation of future development areas to maintain dense and green city structures. In *the input phase (2018–2019)*, stakeholders had to identify key challenges related to urbanization. In the same workshops, the stakeholders identified essential UES related to the problem definition. The *model phase (2019)* focused on the development of the modeling process. We defined the objectives most suited to meet the problem definition. In the *output phase (2019–2020)*, the results were shown to, and discussed with, the stakeholders. Stakeholders made suggestions for improving the approach, two of which are highlighted: (1) using a higher resolution for the optimization to help identify the distribution of new built-up locations per Planning Area (urban planning and census divisions of Singapore), (2) incorporating further datasets such as ecological connectivity and locations of future MRT-stations.

To facilitate the visual communication of the results, the optimization model was integrated in *Singapore Views*. *Singapore Views* is a 3D-4D GIS platform for visualizing, analyzing and presenting scientific geospatial data (Burkhard *et al.* 2018). It has been developed by the Collaborative Interactive Visualization and Analysis Laboratory (CIVAL) group at the Singapore ETH-Center (SEC).

2.2. Case study

Singapore is a tropical island city-state situated near the equator in Southeast Asia (Figure 2). Its area covers about 724.2 km^2 (SLA 2018) and the current population

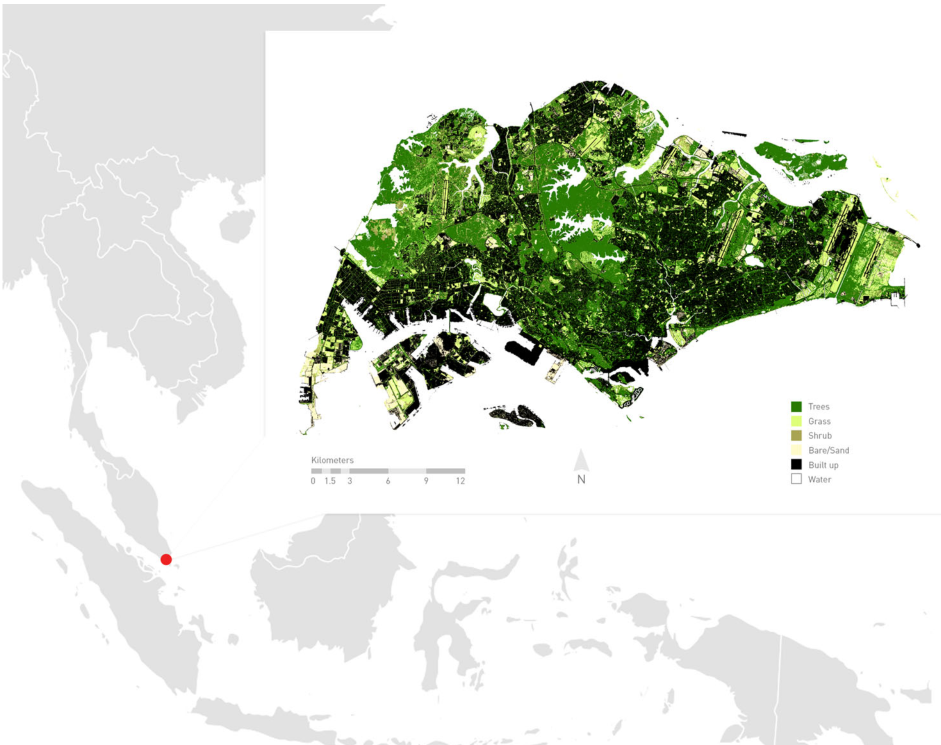


Figure 2. Map of the island city-state of Singapore, located south of the Malayan Peninsula. The land cover map shows 6 land cover classes based on Dissegna *et al.* (2019).

amounts to about 5.64 million inhabitants (Singstat 2018). With 7,804 people/km^2 (Singstat 2018), Singapore has one of the highest population densities in the world. Singapore has a highly developed infrastructure and industry and is considered a compact, high-rise, and high-density city (Tan, Wang, and Sia 2013). For our case study, we used an estimated growth of 10% from 2020 until 2030 that would lead to an expected population size of approx. 6.28 million (Statista 2019).

The ecological transformation of Singapore can be divided into two phases: (1) deforestation, mainly in the 19th century, and (2) urbanization, beginning in the 19th century and lasting until today (Corlett 1992). Urbanization and modernization were the main drivers of a major shift in land use changes after the independence of Singapore in 1959 (Yee *et al.* 2011). Singapore's extensive land reclamation programs have led to a growth of the land area of 24.5% in the past 60 years (SLA 2018), partially meeting the increasing demand for new land areas. Nevertheless, the rate of urbanization and growth of the built-up area raised the competition for urban space and increased pressure on green spaces. For instance, between 2007 and 2011 a population rise of 16% was observed, while vegetation cover had significantly declined by 7% (Tan 2016). The new town planning concept of Singapore successfully provides living space for a large and growing number of inhabitants. At the same time, the large-scale developments lead to a loss of extensive green areas. Despite the constant and successful efforts to green the city, the heavily modernized and densely developed urbanity characterizes the cityscape of Singapore. This urban form of multifunctional

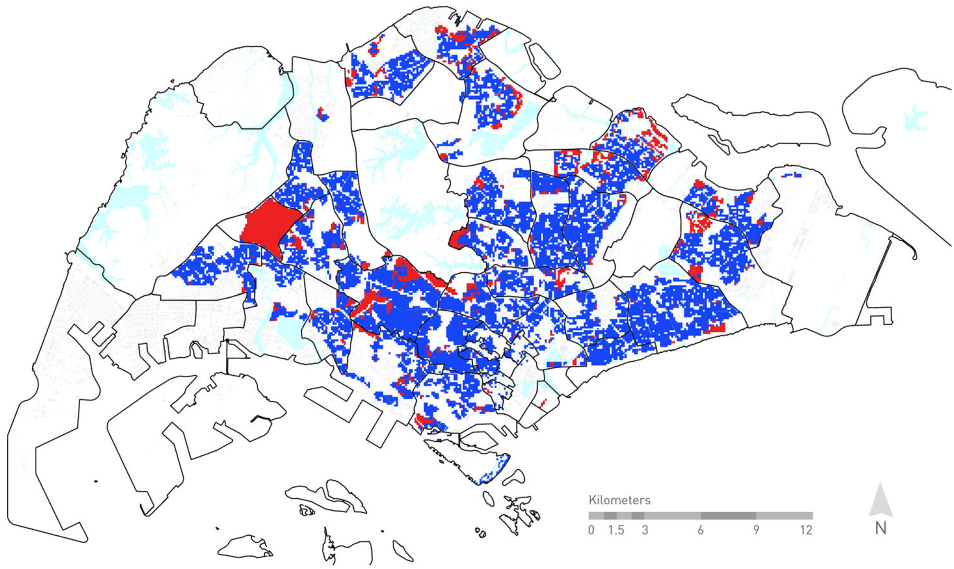


Figure 3. The total area zoned as residential area on the mainland of Singapore according to the Master Plan 2014 (blue and red pixels combined). The non-built-up residential area of Singapore's mainland (red pixels) constitutes the decision space where allocation of new residential pixels is considered. Colour online.

areas shapes the types and quantities of UES provided in Singapore in manifold respects.

The framework includes optimization runs on two scales, the national level of Singapore (100 m resolution) and the Planning Area level of Tengah (30 m resolution). The Planning Area of Tengah covers an area of 7 km^2 and is reserved for future housing developments. In Tengah, we considered the influence of future Mass Rapid Transport (MRT) stations on the development patterns. Pixels overlapping with the approximate locations of future MRT-stations were turned into built-up area to simulate urban patches and act as urban growth seeds.

2.3. Data

The decision space was defined by comparing the residential area of the Master Plan 2014 of Singapore (URA 2014) with the building floor plan of Singapore for 2016 (Dissegna *et al.* 2019). The Master Plan describes the land use plan that guides Singapore's development over the next 10 to 15 years. Areas zoned as *residential* in the Master Plan are set aside for possible future developments. Using the residential area of the Master Plan 2014 as the basis for the possible decision space ensured congruence with the goals of the spatial planning authorities in Singapore. The decision space includes only unbuilt-up residential areas on the mainland of Singapore (Figure 3, red) within the country's boundary to date and thus consisted of 2,402 pixels. Offshore islands and future to be reclaimed land were not taken into account due to the lack of UES data at these locations.

The first objective of the optimization was to minimize the impact on UES, including air pollution control, carbon storage, climate control and water flow regulation. These UES were determined together with stakeholders and are considered highly

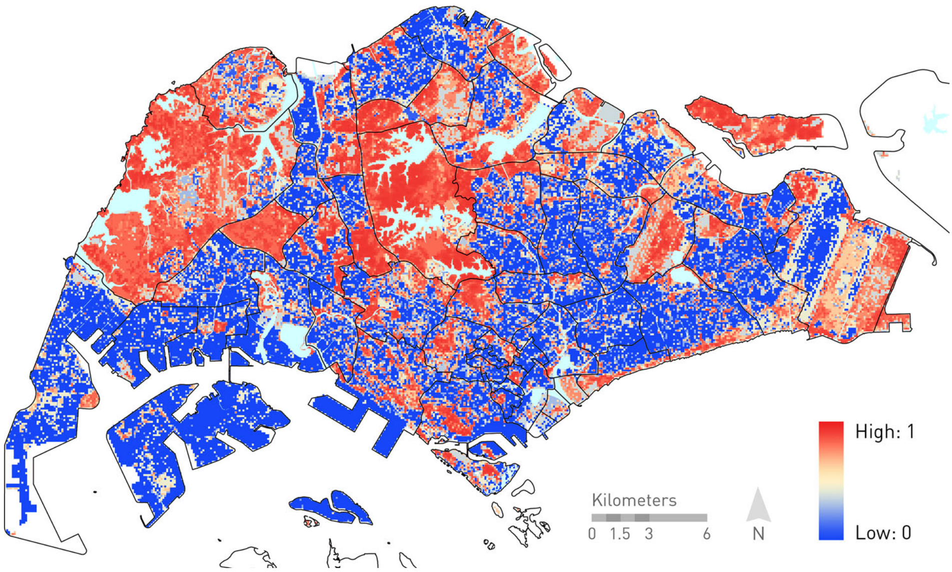


Figure 4. The urban ecosystem service hotspots were mapped using ecosystem service models of air pollution control, carbon storage, climate control and water flow regulation. Low values (blue) indicate low ecosystem service provision while high values (red) indicate high provision of multiple ecosystem services.

relevant for Singapore (Grêt-Regamey *et al.* 2020). All UES maps were estimated using the land cover map (Figure 2) developed by Dissegna *et al.* (2019), vegetation layers, Digital Elevation Model (DEM), and the Master Plan of Singapore. Details about the modeling of the four UES maps are provided in Appendix 1 (online supplemental data).

Areas where multiple UES are generated, were considered as UES hotspots (Figure 4). The hotspots were calculated following a two-step procedure: In a first step, the individual UES maps were constructed using fuzzy membership in ArcMap (ESRI 2016). The fuzzy representation considers the indication of the strength of membership in a set (Bick, Bardhan, and Beaubois 2018). In a second step, under the assumption of equal importance of every UES (Larondelle and Lauf 2016), the layers were aggregated using a fuzzy sum overlay method. Fuzzy sum is a linear combination function producing results larger than the inputs (Bick, Bardhan, and Beaubois 2018).

In order to operationalize the second objective, we selected two compactness measures. The first measure was based on the population density map. Using the population density increases the allocation likelihood of new residential areas in proximity to existing populated residential zones. The population density was calculated using the dataset *Singapore Residents by Subzone and Type of Dwelling* (MTI 2016). The mean population density per subzone was computed and distributed evenly among the residential pixels per subzone. As a second compactness measure, we applied the Total Edge Length (TEL) of all urbanized area. All edges neighboring any class other than urban were counted (Schwaab, Deb, Goodman, Kool, *et al.* 2018). Compactness indicators encourage the neighboring allocation of pixels of equal land use (Aerts *et al.* 2005), with low TEL corresponding to a compact urbanization pattern (Schwaab, Deb, and Goodman 2017). We ran the optimization model with the UES hotspot map and with both compactness measures, population density and TEL (see Figure 1). We

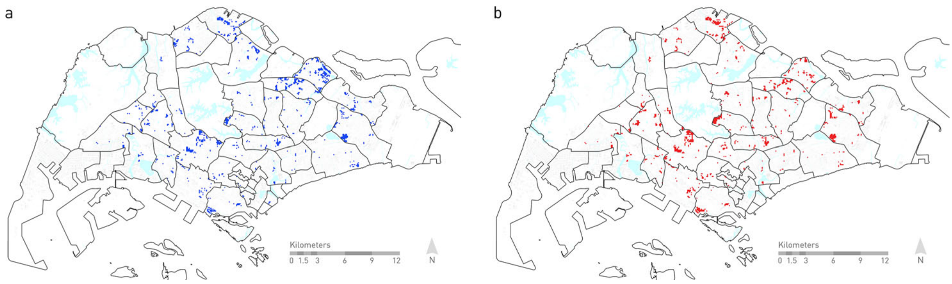


Figure 5. Robust optimal solutions for possible new residential development areas in Singapore, based on (a) minimizing urban ecosystem service loss and maximizing areas of high population density (leading to 1,158 robust solution pixels in blue) or (b) minimizing urban ecosystem service loss and reducing the Total Edge Length of all built-up areas (resulting in 1,077 robust solution pixels in red). Colour online.

Table 1. Changes in the amount of urban (built-up) pixels in the present (Baseline 2020) compared with two allocation scenarios of new residential areas until 2030. The comparison is presented for two compactness measures, population density and Total Edge Length (TEL).

	Urban (built-up)	Decision space (non-built-up)	New residential	Increase urban (built-up)
Baseline (2020)	38,253	2402	–	–
Population density compactness (2030)	38,253	1244	1158	3.03%
Total Edge Length (TEL) compactness (2030)	38,253	1325	1077	2.82%

compared the results using R (R Core Team 2018) and the R-Package diffeR (Pontius and Millones 2011) to calculate omission and commission pixels.

3. Results

Using the optimization procedure presented above, we allocated new residential areas in the decision space. We identified robust optimal locations that minimize UES losses and maximize closeness to high population density (Figure 5a) as well as minimize UES losses and minimize TEL (Figure 5b).

The results of both compactness measures show a concentration of new residential pixels around existing residential areas, strengthening the urban fabric. The similarity of the spatial pattern of the allocation maps in Figure 5 is quantitatively confirmed with an agreement indicator of 1,015, with an omission of 232, and commission of 229 pixels (Table 2.1, Appendix 2 [online supplemental data]).

Using the population density as a compactness measure leads to 1158 robust pixels and an increase of 3.03% in the overall built-up area compared to the current situation. TEL as a compactness measure leads to 1,077 robust pixels and an increase of 2.82% of the overall built-up area compared to the current situation (Table 1).

A deeper understanding of the influence of the compactness measures on the allocation procedure is provided when comparing the non-dominated fronts of both optimizations (Figure 3.1, Appendix 3 [online supplemental data]). Exploring the tradeoffs

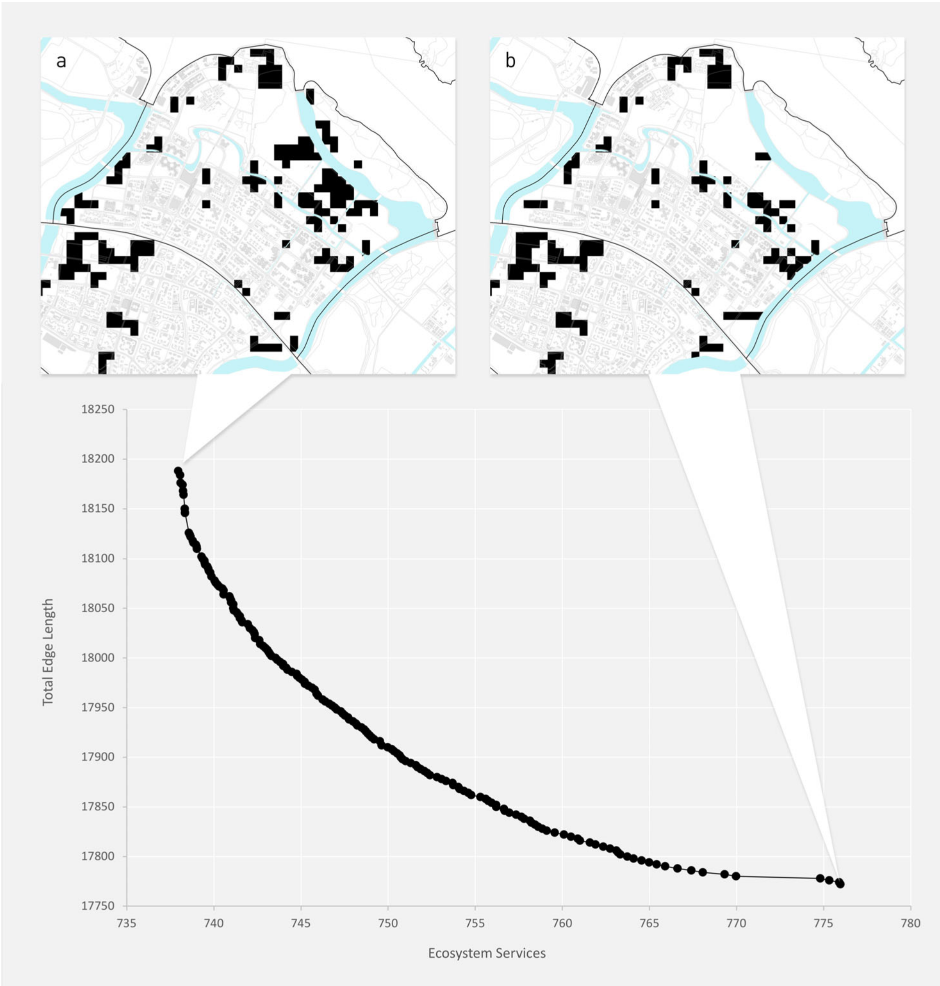


Figure 6. Mapping the distribution of optimal new residential areas in the Planning Area of Punggol using the minimization of the two objectives loss of urban ecosystem services (UES) and Total Edge Length (TEL). (a) In the solution on the left side of the non-dominated front 122 pixels are converted to new residential areas. (b) In the right side of the non-dominated front 82 pixels are converted to new residential areas. The analysis of the solutions along the non-dominated front allows to launch a discussion about allocation possibilities among decision-makers.

between the two objectives UES and compactness in Planning Areas in Singapore shows certain areas to be more optimal than others for residential development, depending on the emphasis on minimizing the loss of UES (left side of the non-dominated front, Figure 6a) or on compactness (right side of the non-dominated front, Figure 6b). Punggol, for example, shows a large difference in the number of converted pixels between the left and the right side of the non-dominated front (Figure 6).

An increase of 26.67% on the left side (Figure 6a) and an increase of 18.22% on the right side of the front (Figure 6b) was simulated for built-up areas in Punggol until 2030 compared to the Baseline (2020) (Table 2). This difference indicates that

Table 2. Comparison of the amount of pixels allocated to new residential areas between the present situation (Baseline 2020) and the left side of the non-dominated front or the right side of the non-dominated front in Punggol until 2030.

	Urban (built-up)	Decision space (non-built-up)	New residential	Increase urban (built-up)
Baseline (2020)	450	159	–	–
Left side of the non-dominated front (2030)	450	39	120	26.67%
Right side of the non-dominated front (2030)	450	77	82	18.22%

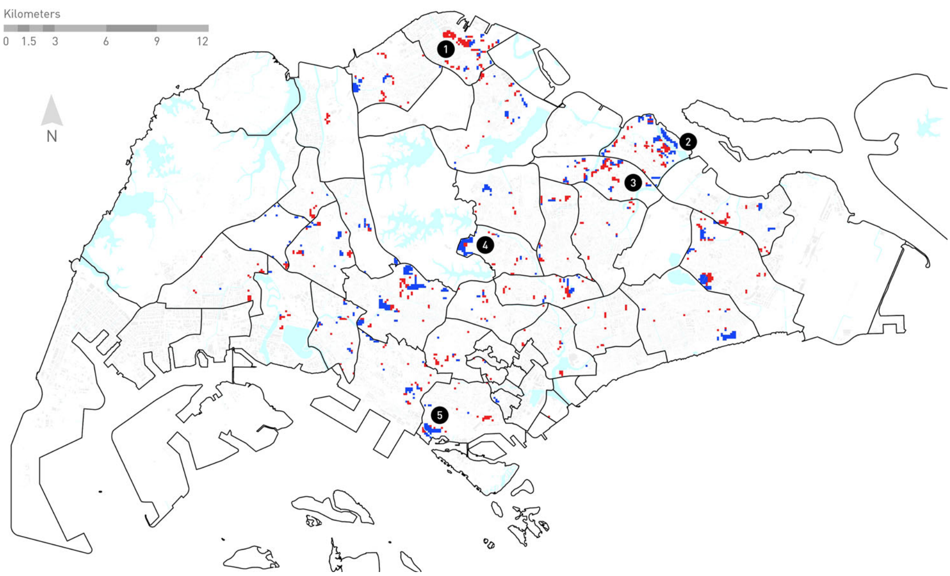


Figure 7. The allocation of new residential areas modeled in two time steps: in time step 1 from 2020-2025, there were 622 new residential pixels allocated (red), and in time step 2 from 2025-2030, there were 622 new residential pixels allocated (blue). Areas in (1) or (3) predominantly get converted in time step 1, whereas areas in (2) or (4) as well as (5) are predominantly converted in time step 2. Colour online.

reaching a compact development is difficult, but minimizing the loss of UES is more achievable in Punggol compared to other Planning Areas.

As not all development areas will be planned and realized at once, we investigated the use of an allocation by time steps to prioritize areas for development. The model simulation was partitioned into two steps, namely time step 1 referring to 2020–2025 and time step 2 referring to 2025–2030 (Figure 7). In time step 2, the amount of options in the decision space is reduced, increasing the pressure on the remaining free areas. The development areas (1) or (3), on the one hand, illustrate clusters of residential pixels that get converted in time step 1 (Figure 7, red). The area of (2) or (4) as well as (5), on the other hand, are only considered under increasing pressure (Figure 7, blue).

To analyze the tradeoffs between UES and compactness values in different time steps, their non-dominated fronts were compared (Figure 4.1, Appendix 4 [online

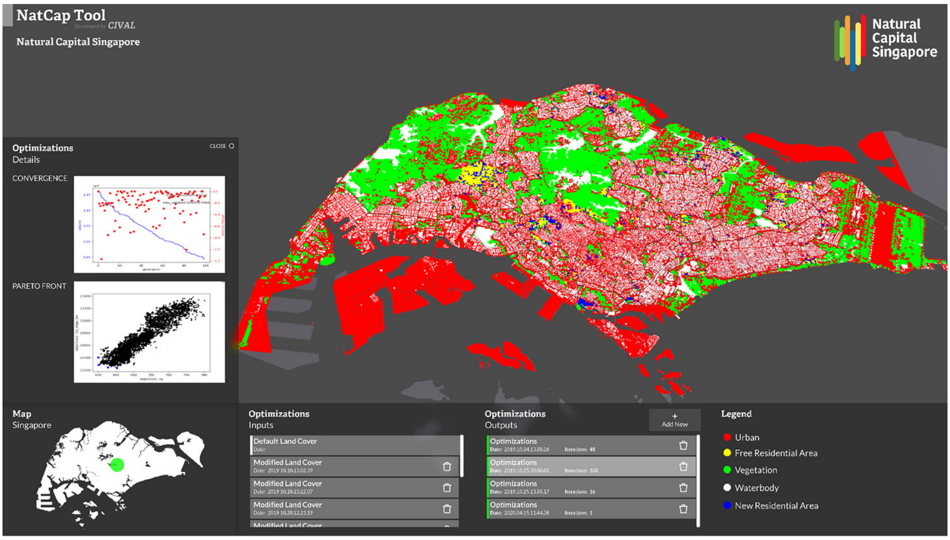
Figure 8. Temporal urban growth simulation patterns in the Planning Area of Tengah from black (pixels converted in the first time step, higher in priority) to bright gray (pixels converted in the last time step, lower in priority). (a) The temporal urban growth pattern simulated on a blank space, without consideration of future transportation nodes. (b) The temporal urban growth pattern simulated including approximate locations of future transportation nodes as urban growth seeds (blue points). Colour online.

supplemental data]). The options of retaining UES decrease considerably with time, while the decrease is less pronounced for compactness. The successive optimization was further applied to the Planning Area of Tengah in a higher temporal resolution of ten time steps. The result of the map on Planning Area level in Figure 8a shows that the very southern part of Tengah was prioritized, similarly to the national-level map. In both the national- and Planning Area-level maps, the remaining lower priority pixels are scattered around the boundary of the Planning Area of Tengah (Figures 7 and 8a).

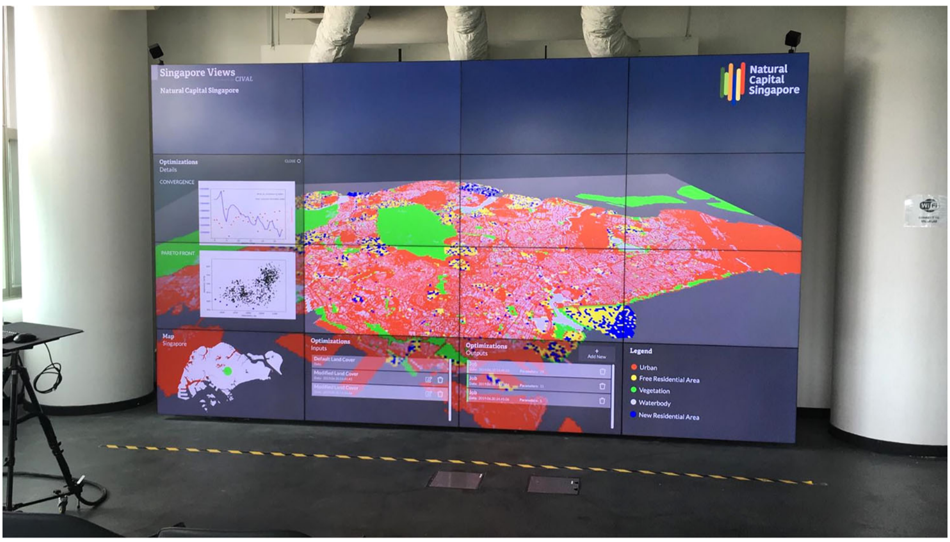
The time-partitioned model runs of the optimization in Tengah without transportation nodes (Figure 8a) and with transportation nodes (Figure 8b) revealed significant differences in the urban growth patterns (from black to bright gray). In Figure 8a, the urban growth simulation follows a pattern of optimal minimization of ES loss and maximization of compactness. This leads to new residential patches that dock onto the existing built-up area around the boundary of Planning Area Tengah. Whereas in Figure 8b new residential patches incrementally expand toward areas with low UES values and in proximity to future MRT-stations. This case study simulates how future transportation nodes could be combined with UES information to simulate hypothetical urban growth patterns.

4. Discussion

Our multi-objective optimization approach helped to successfully identify urban development areas (Figure 5) that meet the requirements of dense and green development efforts in a case study in Singapore. To our knowledge, this is the first study that shows that targeting tradeoffs between minimizing UES losses and maximizing urban compactness can aid in prioritizing urban development locations. We propose successive optimization model runs to obtain time steps simulating a prioritization scheme for the development of new residential areas (Figure 7). Implementing the suggestions of stakeholders, we linked future transportation nodes with the optimization model to investigate their effect on urban growth simulations (Figure 8). We argue that the presented collaborative workflow can be applied to a broad variety of spatial decision problems. In particular, integrated into a participatory process, such an iterative solution-finding process (Elliot *et al.* 2019) can support negotiation of sustainable



(a)



(b)

Figure 9. (a) The multi-objective optimization was integrated into the interactive 3D GIS platform Singapore Views and (b) displayed in the Value Lab Asia at the Singapore ETH-Center (SEC).

development goals (Seppelt *et al.* 2013). The stakeholder feedback loop can be used to gain innovative insights on boundary conditions or constraints, such as scarcity of the decision space and its effect on the solution set. This allows a learning process by the stakeholders (Grêt-Regamey *et al.* 2013), while including their preferences in the modeling process (Stewart, Janssen, and Van Herwijnen 2004). In dense cities with strong resource constraints, the quantification of tradeoffs (e.g. between UES and compactness) will gain importance as urbanization processes are expected to increase over time.

While we identified new optimal locations for development, we did not consider other densification possibilities such as (1) conversion of former industrial sites, or (2) building high-rise instead of low-density buildings, as described in Haaland and van den Bosch (2015). These densification procedures have less impact on existing UES and should therefore be considered first when development efforts are pursued. However, if the circumstances pressure decision-makers to develop new buildings in non-built-up areas, a deliberate and data-driven allocation as proposed in our work is crucial, even more so when taking into account the high degree of irreversibility of the urbanization process (Haaland and van den Bosch 2015). This is essential in Singapore with its new town planning strategy and current high level of greenery. But it could be even more important for other compact cities that are facing drastic declines in UES (Haaland and van den Bosch 2015).

While we used two objectives to define our spatial optimization problem, addressing complex questions in urban planning usually requires the consideration of more than two dimensions. However, increasing the number of objectives is known to restrict the use of simple visualization techniques for decision-makers (Blasco *et al.* 2008). This can hinder valuable feedback from stakeholders and impede the decision-makers' choice (Blasco *et al.* 2008). Nevertheless, considering more objectives seems promising and requires further investigation. As suggested by stakeholders, we highlight the possibility of including ecological connectivity. Habitat corridors connecting green spaces are known to provide a high value for biodiversity and intact ecosystems (van Strien and Grêt-Regamey 2016), especially in compact cities such as Singapore, where the integrity of habitats is threatened by settlements and roads. To ensure that new residential developments do not disrupt vital habitat corridors, maps of ecological connectivity could be taken into account.

The drivers of the UES modeled in this work obey very different spatio-temporal dynamics, but also the dependencies and interactions among the drivers of the UES change with varying dynamics (Stürck, Schulp, and Verburg 2015). These dynamics are expected to change with future land use changes (Stürck, Schulp, and Verburg 2015) and climate change (Shaw *et al.* 2011). Awareness of the simplification of these dynamics in the applied UES models is essential in the interpretation of the results. Further, the modeling includes uncertainties stemming from various sources such as errors of sensor measurement or incomplete simulations of computational models (Goh and Tan 2009). To improve the reliability of the results, modeling uncertainty or external drivers such as climate change, could be integrated into an assessment involving different future scenarios (Lautenbach *et al.* 2013). The robustness assessment presented in this work, which selects locations that score highly on both axes (compactness and UES), could thus be considered as a first step in this direction. The robustness measure could be used to assess the impact of other driving forces on urban development, facilitating the generation of more resilient solutions (McPhearson *et al.* 2015).

Scales are known to significantly influence spatial modeling results (Gotway and Young 2002) and several authors have called for analyses at multiple scales (Seppelt *et al.* 2013; de Groot *et al.* 2010; Larondelle and Lauf 2016). Upon request by the stakeholders, the resolution of 100 m for the city-wide analysis was expanded by a 30 m resolution analysis at the Planning-Area scale. However, we only compared our results visually without an in-depth quantitative analysis. A deeper investigation of the issues originating from cross-scale approaches has been called for in studies on spatial multi-objective optimization (Seppelt *et al.* 2013).

A lot of real-world systems, including urbanization, feature time-varying components with changing conditions operating in a constant state of flux (Goh and Tan 2009). The time steps applied in this work (Figures 7 and 8) only partially account for such changes. Multiple time-partitioned runs of optimizations allow an update of the objective maps after every time step, thereby approximating toward more dynamic and realistic temporal representation. A high degree of integration of stakeholder feedback as suggested in the work of Piemonti *et al.* (2017) provides the basis for an important next step in research.

Integrating multiple stakeholders into the optimization process calls for interactive decision support systems (DSS) to be used in planning processes (Stewart, Janssen, and Van Herwijnen 2004). We integrated our optimization model into the stand-alone DSS *Singapore Views* (Figure 9). The dialogue with the stakeholders is simplified as outputs can be discussed and viewed in a realistic 3D-space of Singapore, aiming toward a data-driven DSS for informed decision-making. The usage of such a DSS can raise awareness of UES integration in urban planning as shown by Grêt-Regamey *et al.* (2017).

An in-depth decision-making analysis using an interactive DSS with effective visuals can help identify key areas of the solution set as well as preferred solutions within the key areas (Jankowski, Fraley, and Pebesma 2014). Enabling a participatory solution-finding process can support the understanding of land use impacts and tradeoffs, essentially leading to innovative insights and paving the way for more effective decision-making (Haase *et al.* 2014). For example, Elliot *et al.* (2019) illustrated a proof-of-concept of a participatory spatial optimization process to explore land use compositions that maximize UES. Concurrent with Elliot *et al.* (2019), we recommend a participatory approach to integrate local expert knowledge and engage stakeholders in the modeling process.

Similarly to Schwaab, Deb, Goodman, Kool, *et al.* (2018), we were able to show that multi-objective optimization using two objectives can be applied to simulate development options. While Schwaab, Deb, Goodman, Kool, *et al.* (2018) focus on agricultural productivity and soil loss to make conclusions about zoning practices, we showed that the method is adaptable to UES and residential development. A similar optimization approach was implemented by Yoon, Kim, and Lee (2019) using NSGA-II to optimize cooling effect, connectivity and cost for urban greening in a hypothetical landscape at a neighborhood scale. Their results showed synergistic relationships between cooling and connectivity. The resulting optimal plans are sought to contribute to the feedback loop with stakeholders, as suggested in our work. Yoon, Kim, and Lee (2019) aim to maximize UES through the allocation of new green space, while we target minimizing the UES loss due to future developments. The merits of our study are embedding of the multi-objective optimization into a participatory approach with a feedback loop. To our knowledge, this is the first study to use this method to develop temporal multi-level urban growth simulations tied to future transportation nodes to support the allocation of new residential areas.

5. Conclusion

Participatory optimization procedures have the potential to support sustainable land allocation processes. Rather than providing a single solution, the optimization approach delivers a solution set, supporting a negotiation process of conflicting demands for the remaining green areas in dense cities. As shown in this work, the method delivers geographically explicit development options and it can be applied to develop temporal multi-level urban growth simulations linked to future transportation nodes. In order to provide clear and coherent visual information on complex development challenges, we embedded our approach in an interactive 3 D visualization DSS to support the collaborative and iterative solution-finding process. Exhausting the full potential of these advancements toward participatory problem-solving can reveal salient and credible urban development prioritization schemes that were not initially apparent. Such an approach not only fosters the acquisition of interdisciplinary knowledge but allows tradeoffs between UES and densification efforts to be addressed explicitly, which is pivotal for shaping the growing cities across the world.

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Disclosure statement

The authors declare that there is no conflict of interest regarding the publication of this article.

Supplemental data

Supplemental data for this article can be accessed here.

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