Metaheuristic Algorithms for Spatial Multi-Objective Decision Making

Niyomubyeyi, Olive

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OLIVE NIYOMUBYEYI
DEPARTMENT OF PHYSICAL GEOGRAPHY AND ECOSYSTEM SCIENCE | LUND UNIVERSITY

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Olive Niyomubyeyi

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Abstract

Spatial decision making is an everyday activity, common to individuals and organizations. However, recently there is an increasing interest in the importance of spatial decision-making systems, as more decision-makers with concerns about sustainability, social, economic, environmental, land use planning, and transportation issues discover the benefits of geographical information. Many spatial decision problems are regarded as optimization problems, which involve a large set of feasible alternatives, multiple conflicting objectives that are difficult and complex to solve. Hence, Multi-Objective Optimization methods (MOO) — metaheuristic algorithms integrated with Geographical Information Systems (GIS) are appealing to be powerful tools in these regards, yet their implementation in spatial context is still challenging. In this thesis, various metaheuristic algorithms are adopted and improved to solve complex spatial problems. Disaster management and urban planning are used as case studies of this thesis.

These case studies are explored in the four papers that are part of this thesis. In paper I, four metaheuristic algorithms have been implemented on the same spatial multi-objective problem — evacuation planning, to investigate their performance and potential. The findings show that all tested algorithms were effective in solving the problem, although in general, some had higher performance, while others showed the potential of being flexible to be modified to fit better to the problem. In the same context, paper II identified the effectiveness of the Multi-objective Artificial Bee Colony (MOABC) algorithm when improved to solve the evacuation problem. In paper III, we proposed a multi-objective optimization approach for urban evacuation planning that considered three spatial objectives which were optimized using an improved Multi-Objective Cuckoo Search algorithm (MOCS). Both improved algorithms (MOABC and MOCS) proved to be efficient in solving evacuation planning when compared to their standard version and other algorithms. Moreover, Paper IV proposed an urban land-use allocation model that involved three spatial objectives and proposed an improved Non-dominated Sorting Biogeography-based Optimization algorithm (NSBBO) to solve the problem efficiently and effectively.

Overall, the work in this thesis demonstrates that different metaheuristic algorithms have the potential to change the way spatial decision problems are structured and can improve the transparency and facilitate decision-makers to map solutions and interactively modify decision preferences through trade-offs between multiple objectives. Moreover, the obtained results can be used in a systematic way to develop policy recommendations. From the perspective of GIS - Multi-Criteria Decision Making (MCDM) research, the thesis contributes to spatial optimization modelling and extended knowledge on the application of metaheuristic algorithms. The insights from this thesis could also benefit the development and practical implementation of other Artificial Intelligence (AI) techniques to enhance the capabilities of GIS for tackling complex spatial multi-objective decision problems in the future.

Key words: Geographic Information System (GIS), Multi-Objective Optimization (MOO), Spatial Decision Making, Metaheuristic Algorithms, Disaster Management, Urban Planning.

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Olive Niyomubyeyi

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MADE IN SWEDEN

To my beloved family

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This Thesis is based on the following papers, which will be referred to in the text by their Roman numerals. The papers are appended at the end of the thesis.

I. **Niyomubyeyi, O.**, Sicuaio, T.E., Díaz González, J.I., Pilesjö, P., Mansourian, A. A Comparative Study of Four Metaheuristic Algorithms, AMOSA, MOABC, MSPSO, and NSGA-II for Evacuation Planning. *Algorithms* 2020, 13, 16. https://doi.org/10.3390/a13010016

II. **Niyomubyeyi, O.**, Pilesjö, P., Mansourian, A. Evacuation Planning Optimization Based on a Multi-Objective Artificial Bee Colony Algorithm. ISPRS Int. J. Geo-Inf. 2019, 8, 110. https://doi.org/10.3390/ijgi8030110

III. Sicuaio, T., **Niyomubyeyi, O.**, Shyndyapin, A., Pilesjö, P., Mansourian, A. Multi-Objective Optimization Using Evolutionary Cuckoo Search Algorithm for Evacuation Planning. *Geomatics* 2022, 2, 53–75. https://doi.org/10.3390/geomatics2010005

IV. **Niyomubyeyi, O.**, Veysipanah, M., Sarwata, S., Pilesjö, P., Mansourian, A. An improved Non-dominated Sorting Biogeography-based Optimization Algorithm for Multi-Objective Land-Use Allocation: A case study in Kigali-Rwanda. (*Under review for publication in Geo-spatial Information Science*)

Author contributions

I. **ON** conceived the idea and designed the methodology mainly together with co-authors. **ON** prepared the data and implemented the methods. **ON** interpreted the results together with co-authors and led the writing.

II. **ON** led the study design, data preparation, and implemented the method, performed the analysis, interpreted the results with co-authors, and led the writing.

III. **ON** participated in the study design, interpretation of the results, and writing of the paper.

IV. **ON** led the study design, performed the analysis, interpreted the results with co-authors and led the writing of the manuscript

Abstract

Spatial decision making is an everyday activity, common to individuals and organizations. However, recently there is an increasing interest in the importance of spatial decision-making systems, as more decision-makers with concerns about sustainability, social, economic, environmental, land use planning, and transportation issues discover the benefits of geographical information. Many spatial decision problems are regarded as optimization problems, which involve a large set of feasible alternatives, multiple conflicting objectives that are difficult and complex to solve. Hence, Multi-Objective Optimization methods (MOO)—metaheuristic algorithms integrated with Geographical Information Systems (GIS) are appealing to be powerful tools in these regards, yet their implementation in spatial context is still challenging. In this thesis, various metaheuristic algorithms are adopted and improved to solve complex spatial problems. Disaster management and urban planning are used as case studies of this thesis.

These case studies are explored in the four papers that are part of this thesis. In paper I, four metaheuristic algorithms have been implemented on the same spatial multi-objective problem—evacuation planning, to investigate their performance and potential. The findings show that all tested algorithms were effective in solving the problem, although in general, some had higher performance, while others showed the potential of being flexible to be modified to fit better to the problem. In the same context, paper II identified the effectiveness of the Multi-objective Artificial Bee Colony (MOABC) algorithm when improved to solve the evacuation problem. In paper III, we proposed a multi-objective optimization approach for urban evacuation planning that considered three spatial objectives which were optimized using an improved Multi-Objective Cuckoo Search algorithm (MOCS). Both improved algorithms (MOABC and MOCS) proved to be efficient in solving evacuation planning when compared to their standard version and other algorithms. Moreover, Paper IV proposed an urban land-use allocation model that involved three spatial objectives and proposed an improved Non-dominated Sorting Biogeography-based Optimization algorithm (NSBBO) to solve the problem efficiently and effectively.

Overall, the work in this thesis demonstrates that different metaheuristic algorithms have the potential to change the way spatial decision problems are structured and can improve the transparency and facilitate decision-makers to map solutions and interactively modify decision preferences through trade-offs between multiple objectives. Moreover, the obtained results can be used in a systematic way to develop policy recommendations. From the perspective of GIS - Multi-Criteria Decision Making (MCDM) research, the thesis contributes to spatial optimization modelling and extended knowledge on the application of metaheuristic algorithms. The insights from this thesis could also benefit the development and practical implementation of other Artificial Intelligence (AI) techniques to enhance the capabilities of GIS for tackling complex spatial multi-objective decision problems in the future.

Sammanfattning

Beslut grundade på rumsliga parametrar görs dagligen, såväl av individer som av organisationer. Det kan också noteras att intresset för rumsliga beslut-system ökat markant under senare år. Fler och fler beslutsfattare inser betydelsen av hållbarhet, ur såväl sociala, ekonomiska, miljörelaterade, markanvändningsrelaterade som infrastrukturella perspektiv. Inom alla dessa områden spelar rumslig, eller geografisk, information en viktig roll.

Generellt kan man säga att alla rumsliga beslut innefattar någon form av optimering. De inkluderar i många fall ett stort antal möjliga alternativ, och ett antal av dessa alternativ är ofta motstridiga vilket ökar komplexitet och därmed svårighet att komma fram till bästa tänkbara lösning. En möjlig ansats för att lösa dessa problem är att använda sig av Multipel Objekts-Optimering (MOO), där metaheuristiska algoritmer integreras i Geografiska Informations-System (GIS). Ett sådant angreppssätt ger stora möjligheter, men det är även en stor utmaning att implementera rumsliga parametrar. I denna doktorsavhandling tillämpas och utvecklas olika metaheuristiska algoritmer med syfte att lösa komplexa rumsliga problem. Fallstudier inom katastrofhantering och stadsplanering har använts som exempel på sådana problem.

Avhandlingen inbegriper fyra publikationer. I den första har fyra metaheuristiska algoritmer anpassats till samma rumsliga multi-objektiva problem, evakuering, för att undersöka algoritmernas prestanda och potential. Resultaten visar att alla fyra algoritmer är effektiva för att lösa det givna problemet, men med variationer avseende anpassningsflexibilitet och prestanda. Den andra publikationen spinner vidare på detta, och testar effektiviteten hos algoritmen ”Multi-Objektiv Artificiell Bi-koloni” (MOABC) när den anpassats för att lösa evakueringsproblem.

I den tredje publikationen föreslår vi en multi-objektiv optimerings-ansats för att lösa ett urbant evakueringsproblem med tre rumsliga begränsningar (objektiv). Algoritmen som används är en ”Multi-Objektiv gök (”Cuckoo”) - Sökning” (MOSC). Båda algoritmerna (MOABS och MOSC) visade sig vara effektiva för att lösa evakueringsproblem, i jämförelse med såväl standardversioner som andra algoritmer.

I publikation fyra genomfördes en studie av allokering av markanvändning som inbegrep tre rumsliga begränsningar. En ”Icke(”Non”)-Dominerande Sorterande

Biogeografisk-baserad Optimerings algoritm" (NSBBO) implementerades framgångsrikt för att lösa problemet.

Sammanfattningsvis kan konstateras att arbetet som presenteras i denna avhandling demonstrerar att olika metaheuristiska modeller har potential att förändra hur olika rumsliga beslutsproblem kan struktureras, och därmed förbättra transparens och resultat. De kan ge beslutsfattare möjligheter att få överblick över olika lösningar, och interaktivt modifiera betydelsen av olika begränsningar genom avvägningar mellan dessa. Resultaten kan sedan användas för att systematiskt utveckla bl.a. policys och rekommendationer.

Inom forskningsområdet GIS – multi-kriterie-beslutsförfarande (Multi Criteria Decision Making (MCDM) tillför avhandlingen kunskaper inom optimering av rumslig modellering samt användning av meta-heuristiska algoritmer. Resultaten kan också främja utveckling och implementering av andra tekniker inom Artificiell Intelligens (AI) för att utnyttja GIS i syfte att lösa komplexa rumsliga multi-objektiva problem.

Introduction

Many real-world problems with spatial concepts have to handle multiple criteria that are often conflicting. One example would be deciding on where and how to optimally allocate various land use activities such as schools, industries and residences within an area to promote sustainable urban development. Such a problem is not only complex but also involves multiple interest groups who might be affected by the final decision arrived at (e.g. decision-makers, individuals, organizations). In such an example, there is no single "best" solution that satisfies all involved decision-makers and stakeholders. Nevertheless, supporting methods and techniques to solve such problems are usually integrated within tools known as *geographic information systems (GIS)*. The ultimate goal of GIS functions is to provide support for making spatial decisions, by using either fundamental or advanced functions. However, GIS has a limited capacity for solving complex spatial decision problems and cannot stand alone. Accordingly, spatial decision-making problems are multi-faceted challenges. Not only do they often involve technical requirements, but their formulation to appropriately abstract or represent the issue of interest is typically not an easy task. Decisions to be made and properties of the spatial problem need to be structured using mathematical principles and logic (Krzanowski and Raper 2001). It is even more complicated for instance when a problem considers economic, environmental, and political dimensions that could involve conflicting objectives.

Solving a spatial decision problem is therefore complicated for several reasons. First, the problem requires highly complex spatial data analysis processes. Second, the number of decision variables and constraints associated with the problem could make it difficult to solve and computationally intensive. Scientists and practitioners, therefore, suggested merging GIS with advanced techniques to enhance its capabilities for supporting spatial decisions (Malczewski 1999; Church 2002). From this idea, the integration of two distinctive fields: GIS and Multi-Criteria Decision Making/Analysis (MCDM) was initiated (Jankowski 1995). On one hand, GIS provides the tools for storing, manipulating, and analysing spatial data and relationships to be an input of MCDM. On other hand, MCDM provides a collection of techniques and procedures for structuring decision problems. Thus, the combination of GIS and MCDM is regarded as a collection of methods and tools for transforming and combining spatial data and preferences to obtain information for decision making, where the purpose is to evaluate a set of alternatives in terms of number of conflicting objectives (Chakhar and Martel 2003; Malczewski and Rinner 2015).

Over the last three decades, the integration of GIS-MCDM has been then widely and strongly adopted within the GIScience field and the great benefits have been recognized (Thill 1999; Malczewski and Rinner 2015). The major application areas of GIS-MCDM include environmental planning/management, transportation, urban and regional planning, waste management, agriculture, forestry, natural hazard, and other diverse domains (Malczewski 2006; Greene et al. 2011; Rinner 2018). Methods of MCDM that have been applied to GIS are classified into two groups: Multi-Attribute Decision Making (MADM) and Multi-Objective Decision Making (MODM), also known as Multi-Objective Optimization (MOO).

The MADM methods are those concerned with the evaluation of a relatively small number of alternatives characterized by attributes (or feasible solutions) and the evaluation process searches for how well the alternatives satisfy the objectives. The Weighted Linear Combination (WLC) and Analytic Hierarchy/Network Process (AHP) are the best examples of this type of methods (Hamilton et al. 2016; Özkan, Özceylan, and Sarıçiçek 2019).

In contrast, MOO methods involve the simultaneous evaluation of multiple objective functions along with a set of constraints defined for each decision variable, to search for the best alternative (Ehrgott, Figueira, and Greco 2010). This thesis focuses on GIS-MOO methods (therefore, the terms, GIS-MODM, GIS-MOO, are used interchangeably).

While there is a wide range of approaches available for solving multi-objective optimization problems (Gunantara 2018), two categories of MODM methods have typically been applied in GIS. The first category corresponds to the exact or deterministic methods that are based on mathematical principles of transforming the multi-objective problem into a scalar function and then solved as a single-objective problem. When using this approach, the best possible, or optimal solution is guaranteed to be identified. However, many MOO problems, specifically in a spatial context, cannot be approached using exact methods. Because most of the problems have an infinite number of feasible solutions, evaluating each solution is almost impossible. The most popular exact approaches used in GIS-MODM include weighting and constraint methods, goal programming, linear programming, Dijkstra's algorithm, and others (Tong and Murray 2012).

The second category of MODM methods corresponds to the heuristic/metaheuristic algorithms, which involve the use of algorithms to find good solutions by using trial and error approaches. Unlike the exact methods, heuristics/metaheuristics are problem-oriented ad hoc strategies, they use procedures to explore the solution space from which a near-optimal solution can be found. Although heuristic and metaheuristic algorithms have been applied to many spatial decision problems (e.g., Krzanowski and Raper 2001; Mladenović et al. 2007; Xiao, Bennett, and Armstrong 2007; Xiao and Murray 2019; Liang, Minanda, and Gunawan 2021), the choice of the suitable algorithm to handle a given problem can be a challenge to the users. In addition, several factors may affect the selection of the algorithm for a particular spatial problem such as the spatial arrangement of feasible alternatives, the number of objectives, the type of decision variables, and last but not least, computational requirements and capacities of the algorithm. It is therefore of great importance that metaheuristic algorithms are implemented and modified so that they fit the problem at hand.

Rationale of the research

As already outlined in the introduction section, many spatial decision problems are not directly solvable through straightforward approaches. Such problems often require the participation of several stakeholders and consideration of multiple factors. In urban planning, for example, the task of locating land use activities may require decision-makers to maximize suitability, minimize economic cost, and also minimize negative environmental effects (Zander and Kächele 1999). This is in a way similar to evacuation planning in disaster management, where the incorporation of multiple objectives into decision-making and the search for efficient evacuation plans are critical to the safety of people exposed to hazards (Sherali, Carter, and Hobeika 1991; Ma et al. 2019).

These and other types of multi-objective problems represent significant challenges for researchers and decision-makers. To solve spatial multi-objective decision problems efficiently and effectively, metaheuristic algorithms have proven to be efficient, and provide a set of optimal solutions with low computation complexity. However, Malczewski and Rinner (2015) noted that the available studies which applied heuristic/metaheuristics represented less than 10% of the total research on GIS-MCDM yet these techniques have a great potential to be used for decision making and planning. Moreover, among the used metaheuristic methods, evolutionary algorithms, specifically genetic algorithms, have been used to a greater extent than other algorithms to tackle spatial decision problems (Schwaab et al. 2018; Masoumi et al. 2020; Ding, Zheng, and Zheng 2021). So far, very few researchers have used other methods such as swarm intelligence algorithms and hybrid algorithms in GIS applications (Hu, Xu, and Li 2012; Mi et al. 2015; Bui et al. 2016; Jaafari et al. 2019).

Many challenges that exist in spatial multi-objective decision making are also related to the limited number of studies within the field. Murray (2010) reflected on the contribution of GIS and optimization techniques to solve location modelling. This study/review highlighted the research gap in terms of theory, application, and solution to support the decision-making process. A study by Lidouh (2013) explored the reasons for integrating MCDA and GIS and gave an overview of the concrete works that have been achieved in terms of technical and operational aspects. The author revealed a lack of multi-criteria tools that are useful for the development of an integrated system that can offer robustness and higher interactivity with the decision processes. Zheng, Chen, and Ling (2015) provided an overview of evolutionary algorithms applied to disaster relief operations. The findings of this survey highlighted the need for more metaheuristics methods to be applied and demonstrate their performance on more real-world applications. This could be a solution to overcome the true challenge of soft computing in general, that convinces decision-makers that the new methods are capable of producing results worthy of application and win their trust. Consequently, the application of metaheuristic algorithms in different GIS domains is increasing and their efficiency is continuously being proved by several researchers (Boussaïd et al. 2013; Castillo-Villar 2014; Memmah et al. 2015; Razavi Termeh et al. 2018; Ding et al. 2021).

Moreover, there are many reasons for metaheuristics' success. First, they have the potential to formalize knowledge concerning how to appropriately structure and solve an optimization problem. The use of stochastic operators allows metaheuristics to escape from local optima and converge to approximate global optima. The aim here is not to find the best optimal solution to the given problem but to find a set of optimal solutions of good quality within a reasonable computational time. To achieve such an objective, a suitable balance between exploration and exploitation must be maintained. In exploration operation, the algorithm is searching for new solutions in the most promising new regions in a search space, while exploitation means using already existing solutions and making refinement to find solutions of high quality. The better a given algorithm performs in the balance of these two operators, the better its performance will be (Boussaïd et al. 2013). Second, hybrid metaheuristics combine two or more algorithms to take advantage of each other while avoiding as much as possible their weaknesses (Marić et al. 2015; Mohammadi et al. 2016). The third, reason for metaheuristics' success is due to their flexibility and robustness which make them easy to use in practice. Therefore, the use of metaheuristic algorithms for spatial decision making is technically interesting and timely issue for research to explore.

Research aim and objectives

The aim of this thesis mainly focuses on adopting and improving metaheuristic multi-objective optimization techniques for solving complex spatial problems. The study intends to present the efficiency and effectiveness of metaheuristic algorithms when solving spatial decision problems. Evacuation planning and urban land use planning have been used as two case study problems for application of efficient and effective metaheuristic algorithms to solve spatial decision problems.

The aforementioned aim will be achieved by following these objectives:

1. To investigate the performance and efficiency of different multi-objective optimization techniques to solve multi-objective evacuation planning model (Paper I).
2. To adopt and improve a recently developed metaheuristic algorithm to solve the multi-objective evacuation planning model (Paper II).
3. To develop an evacuation planning model that optimizes three conflicting spatial objectives and proposes an efficient metaheuristic algorithm to solve the problem (Paper III).
4. To develop a hybrid algorithm based on the existing metaheuristic algorithms for solving a multi-objective land-use allocation problem in urban planning (Paper IV).

Structure of the thesis

The thesis is structured as follows: after this introductory chapter, chapter 2 presents a theoretical background of GIS and MCDM in general, as well as the concept of GIS-based MCDM methods. In addition, the most popular metaheuristic algorithms applied in GIS-MODM are reviewed. Chapter 3 provides a detailed description of the methods and data used in the thesis. Chapter 4 summarises the results and discusses the research findings. The concluding remarks and outlook are given in Chapter 5.

Theoretical Background

The geospatial decision-making research field is often defined as interdisciplinary. It combines decision-making concepts and methods and relates them to spatial context. Accordingly, many spatial decision problems give rise to GIS and MCDM. At the most fundamental level, GIS-MCDM is a process that includes geospatial data (input maps) and the decision maker's preferences into a resultant decision (output map). Whether it concerns the development of new methods, analysis and improving the existing methods, or the simple application of fundamental methods in the GIS context, it will rely on both decision making and geographical information science. Hence, the research presented in this thesis does fall into these categories.

Geographic Information System

Geographic Information System (GIS) also known as a spatial information system, is defined as an integration of several components: hardware, software, and procedures designed to provide support for making decisions. The system is devoted specially to capturing, storing, managing, manipulating, analysing, modelling, and display of spatially referenced data. Data input refers to the process of identifying and gathering the data required for a specific application. Such a process involves the acquisition, reformatting, georeferencing, compiling, and documenting of the data. These functions of storing and retrieving data make most GIS systems to be database-oriented.

GIS utilizes two types of data: *spatial* data and *attribute* data. The spatial data describe the absolute and relative locations of spatial entities (e.g., building, street, tree, river, state, country, etc.). The attributes (e.g., tabular data) refer to the properties of spatial entities. These properties can be qualitative or quantitative. Spatial data are stored in GIS using one of two models: *raster* and *vector*. Raster models are represented by grid cells identified by rows and columns of the same size. Each element is called a pixel or cell and has its information and geographic reference assigned to it. A group of cells forms an image of the area. In vector models, the geographic features are represented by the geometric features (e.g. points, lines, polylines, and polygons). Vector data are used to define boundaries and spatial geometries such as houses, represented by points; rivers, roads, streams, etc., are represented by polylines; and villages, towns, cities, etc. are represented by polygons.

One of the advantages of GIS is the way spatial data are organized so that a user can select the necessary information for a particular purpose or task by reading a map. A thematic map with spatial data allows a user to add layers of information to a base map of real-world locations (see Figure 1). This shows the major potential GIS has for manipulating spatial data to promote a Decision Support System (DSS).

For many spatial problems, however, GIS presents some difficulties to become the general tool for solving all types of problems. For instance, GIS does not support the decision making process effectively (Densham and Goodchild 1989; Zerger and Smith 2003). Most of these difficulties arise from the lack of spatial analysis and modelling capacities required in the design of the decision-making process, as it involves investigating, developing, and analysing the diverse number of decision variables, considered spatially. This form of geographic information management allows multi-criteria decision making, giving the possibility to provide the capacity of manipulating data using statistics and mathematic models.

Furthermore, several alternatives were studied for the development of Spatial Decision Support Systems (SDSS). The SDSS is defined as a computer-based system designed to expand GIS capabilities for tackling complex spatial decision problems (Malczewski 1999). The concept of SDSS evolved in research the development of many different approaches and frameworks including planning support systems (Geertman, de Jong, and Wessels 2003), group SDSS (Jankowski and Nyerges 2001), spatial knowledge-based systems (Zhu, Healey, and Aspinall 1998), spatial multi-agent systems (van Leeuwen, Hagens, and Nijkamp 2007). The common aim of all these spatial information systems is to improve the performance of decision-makers, managers, and citizens when they deal with spatial decision problems (Keenan and Jankowski 2019).

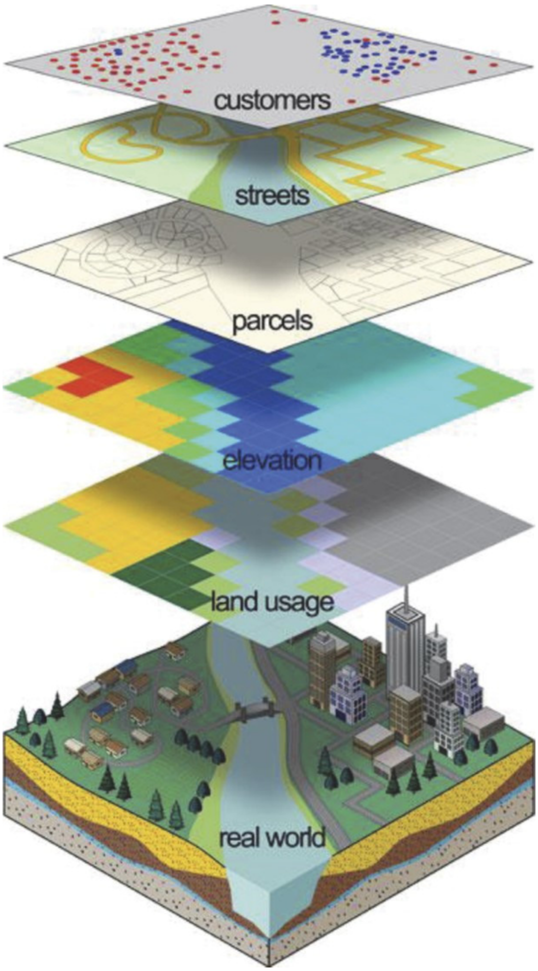

Figure 1. GIS Layers. Source: www.gembc.ca

Multi-Criteria Decision Making

Decision analysis is a valuable tool in solving the issue as characterized by multiple actors, criteria, and objectives (Triantaphyllou 2000). A decision-making process is therefore an act of selecting the most suitable action to fulfil the desired goals and objectives (Clemen and Reilly 2014). Because decision-making is a daily task in our everyday routines, effective tools should be used to analyse all aspects of decision-making problems. Hence, Multi-Criteria Decision Making (MCDM, also known as Multi-Criteria Decision Analysis, MCDA) has been widely used to perform mathematical optimization to analyse multi-objective decisions and incorporate the varying opinions of decision makers (Colorni et al. 1996; Sánchez-Lozano et al. 2013). MCDM is intended to reduce the impact of biased decisions from decision-makers relying on their interests, and also group decision-making failures, that almost inevitably afflict intuitive decision-making. By making the weights and associated trade-offs between the criteria explicit in a structured way, MCDM results in more transparent and consistent decisions.

In short, any multi-criteria decision involves these three elements: decision-maker(s), whose preferences are to be presented with the responsibility of decision making, decision alternatives to be ranked or chosen between, and criteria include a set of objectives and attributes, by which decision alternatives are evaluated and compared (Zarghami and Szidarovszky 2011). While decision-making process, in general, follows six steps including, problem formulation, identifying the requirements, setting the goals, identifying various alternatives, (5) developing criteria, and (6) identifying and applying the decision making techniques.

MCDM is a procedure that consists in finding the best alternative among a set of feasible alternatives. In particular, a spatial decision alternative consists of at least two elements: action (what to do?) and location (where to do it?). The spatial components of a decision alternative can be specified explicitly or implicitly (Malczewski 2006). In addition, many spatial decisions are made by multiple decision-makers, who have different preferences, goals, objectives, and criteria. In this case, there is no single solution that is likely to satisfy every decision-maker completely. When there is one decision-maker and one criterion then one is dealing with a single-objective optimization problem. On other hand, the MCDM problem arises when the decision-maker or group of decision-makers consider several criteria simultaneously.

GIS-based Multi-Criteria Decision Making methods

According to Malczewski (1999), a criterion is a generic term including both the concept of objective and attribute. An objective is a statement about the desired and favourable state of the system under consideration (e.g., a spatial pattern of accessibility to school). It indicates the direction of improvement of one or more attributes. The statement about the desired goal to achieve can be interpreted as either maximization or minimization of an objective function. Thus, an objective is defined as operational by assigning to each objective at least one attribute, which measures the level of achievement of the objective. While, an attribute can be described as a property of elements in an applied system (e.g., location-allocation system, vehicle routing system).

It is a measurable quantity or quality of a spatial entity or relationship between entities. For example, the objective of maximizing the accessibility of fire stations, shelters, hospitals, public facilities can be measured by attributes such as cost, time, travel distance, and capacity of the area, etc. Therefore, Multi-criteria decision methods are classified based on the criteria used during the decision process to search for the solutions, which can be attributed for multi-attribute decision making (MADM) and objectives for multi-objective decision making (MODM) (Hwang and Yoon 1981; Malczewski and Rinner 2015) as shown in Table 1.

MADM methods are data or outcome-oriented. They deal with the evaluation of a limited number of alternatives that are predetermined (known in advance by the decision maker). Multi-attribute techniques are referred to as discrete methods because the alternatives are given explicitly rather than implicitly as in MODM. The MODM approach is a model or process-oriented design and search. Here, alternatives are either not known in advance, or there are many so that the problem cannot be solved with the evaluation method. Instead, these types of problems can be solved by applying mathematical optimization. Unlike multi-attribute approaches, multi-objective methods define the set of alternatives in terms of a decision model consisting of two or more objectives and a set of constraints imposed on the decision variables. The alternatives are implicitly defined as decision variables (see Table 1). In MODM, the attributes can be used implicitly as information sources available to the decision maker to formulate and measure the achievement of his/her objectives (Kaim, Cord, and Volk 2018). Although MADM is referred to as discrete and in GIS they use vector-based data structure, while MODM are continuous decision problems and they use raster-based data structure (Malczewski 2006), it is also important to note that the MODM problems can be defined in terms of a set of continuous and/or discrete decision variables (Zarghami and Szidarovszky 2011).

Table 1. Multi-attribute and multi-objective decision making approaches

Condition	Multi-attribute decision making (MADM)	Multi-objective decision making (MODM)
Criteria	Attributes	Objectives
Objectives	Implicitly	Explicitly
Attributes	Explicitly	Implicitly
Constraints	Implicitly	Explicitly
Alternatives	Explicitly	Implicitly
Decision modeling paradigm	Outcome-oriented evaluation/choice	Process-oriented design/search
Examples of multi-criteria methods	Weighted linear combination Analytic hierarchy/network process Outranking methods Ideal point methods	Linear/integer programming Goal programming Compromise programming Heuristics/metaheuristics
Examples of spatial decision problems	Site selection Land use/suitability Vulnerability analysis Environmental impact Assessment	Site search Location-allocation Transportation problem Shortest path problem Districting

Sources: Based on (Hwang and Yoon 1981; Malczewski 1999); cited in (Malczewski and Rinner 2015).

This research specifically focused on the metaheuristics subgroup of MODM methods, although the next section briefly presents a summary of the relevant literature for both MADM and MODM approaches, to give an overview of the distinction between these two types of GIS-MCDM methods. Multi-attribute decision making, MADM related methods, as well as exact methods are out of the scope of this thesis.

Multi-Attribute Decision Making methods

A large number of multi-attribute decision-making methods have been described in the GIS-based MCDM literature as highlighted in (Malczewski and Rinner 2015; Malczewski and Jankowski 2020; Abdullah, Siraj, and Hodgett 2021). The most widely used GIS-MADM methods are the weighted linear combination (WLC), ideal point methods, the analytic hierarchy/network process methods (AH/NP), and outranking methods (see Table 1). Research by (Ehrgott, Figueira, and Greco 2010) reviewed the percentage of GIS-MCDM research by type of methods and the study shows that around 71% of the total research belonged to the MADM approach and only 39.4 was about WLC methods.

In short, the WLC and related models are composed of a set of criterion weights (w_k) and value functions ($v(a_{ik})$). Each ith decision alternative is associated with a set of criterion weights combined with the attribute values $a_{i1}, a_{i2}, \dots, a_{in}$.

(with $i = 1, 2, \dots, n$) (Malczewski and Rinner 2015). The mathematical expression of the WLC method is summarized as follows:

$$V(A_i) = \sum_{k=1}^{n} w_k \, v(a_{ik})$$

where in spatial terms $V(A_i)$ is the overall value of the ith alternatives at a certain location i, and $v(a_{ik})$ is the value of the ith alternative concerning the kth attribute. The alternative with the highest value of $V(A_i)$ is the best among the evaluated alternatives (Malczewski and Rinner 2015)

The main reason behind the extensive usage of WLC in the GIS context is that WLC-related methods are easy to implement, just by considering map algebra operations and cartographic modelling (Malczewski 2000). The method is also easy-to-understand to decision-makers. A variety of application domains have applied GIS-WLC for analysing decisions and management (Jankowski 1995; Geneletti 2005). Some GIS systems (e.g., IDIRIS (Eastman 2009)) have built-in routines for the WLC method, and there is other GIS desktop software (e.g. ArcGIS, QGIS) that have modules or scripts to perform the WLC procedure. More details about this method can be found in the literature (Jankowski 1995; Malczewski 1999; 2006; Greene et al. 2011; Malczewski and Rinner 2015). Other MADM methods such as the Analytic network process (ANP) for flood vulnerability model can be found in de Brito, Almoradie, and Evers (2019), and AHP applied in urban land use planning (Hao Wang, Shen, and Tang 2015; Kazemi and Akinci 2018).

Multi-Objective Decision Making methods

Multi-objective decision making methods (MCDM) or Multi-objective optimization (MOO) define a problem in terms of a mathematical model that includes decision variables, a set of objective functions to be optimized, and parameters representing a set of constraints subjected to decision variables. In general, a MODM problem can be mathematically expressed as follows:

$$\begin{aligned} &Minimize/maximize \qquad F(x) = \{f_1\,(x), f_2\,(x), \dots f_m\,(x)\} \qquad (1) \\ &Subject\ to \qquad g(x) \leq 0 \end{aligned}$$

where x is the vector of decision variables, $f_i(x)$ is the ith objective functions to be minimized, and $g(x)$ is the constraint vector.

The decision variables strongly influence the formulation of objective functions. In other words, an objective function is a function of decision variables. The objective function is either minimized or maximized to find the optimal values of decision variables, which are solutions to the problem. In an optimization problem, objective function space is determined by the decision variable space. For each solution in the decision variable space, there is a point in the objective space as illustrated in Figure 2. In most optimization problems, there are always restrictions imposed by particular conditions or available resources. These restrictions also called constraints must be satisfied to find an acceptable solution.

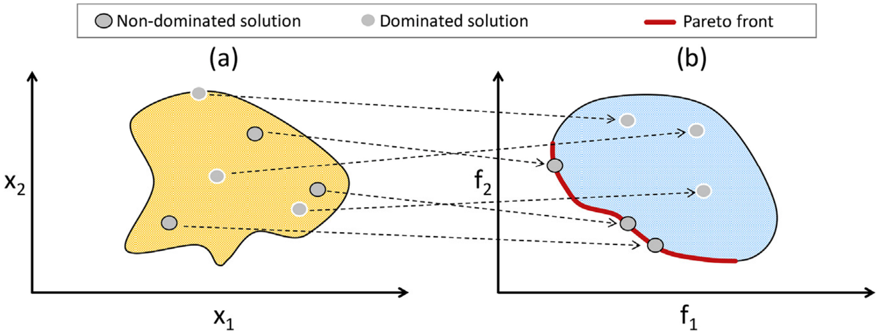

Figure 2. Relationship between (a) m-dimensional decision variable space, and (b) n-dimensional objective function space of two-objective problem. Both objectives are to be minimized. Source: Maier et al. (2019).

In the context of spatial optimization problems, there must be at least one set of spatially explicit decision variables (e.g., location, distance, size, capacity, direction, connectivity, shape, etc.). For example, in the case of land use optimization problems, four main decision variables are considered: land-use type, size, location, and capacity (Mohammadi, Nastaran, and Sahebgharani 2016). By combining these variables, the goal of any land use optimization problem is to find the appropriate (size) of specific land use (type) which needs to be allocated in a particular site (location) to maximize or minimize a specific objective (e.g. maximize environmental, and or economic benefits) (Rahman and Szabó 2021).

The optimization model expressed in equation (1) is considered as a general formulation that can be extended in many different ways. There are two categories of solving a MOO problem: Scalarization (exact methods) and Pareto front-based (heuristics/metaheuristics) method. Scalarization methods combine multiple objectives into a single-objective scalar function. The most common under scalarization techniques in GIS-MODM are: the weighted sum method (Kennedy et al. 2016), Goal programming (Praneetpholkrang, Huynh, and Kanjanawattana 2021), and Reference point method (Stewart and Janssen 2014). On other hand, Pareto front-based methods attempt to find a set of non-dominated solutions also called Pareto optimal solutions. According to this concept, a solution x^* is Pareto optimal if there exists no feasible vector x which would decrease some objective without causing a simultaneous increase in at least one other objective function(s) (in case of minimizing (Coello Coello, Van Veldhuizen, and Lamont 2007). Figure 2 illustrates non-dominated solutions on the Pareto front line, which are trade-offs among two conflicting objective functions f_1 and f_2. From the set of trade-off solutions, decision-makers can select or prioritize an alternative according to their preferences and then plan.

There is a wide range of Pareto front-based methods, specifically nature-inspired metaheuristic algorithms which have been used in GIS-based multi-objective optimization problems. The following section gives examples of the most used metaheuristics, and some of them were applied in this thesis.

Nature-inspired metaheuristic algorithms

Overview

The concept of metaheuristic originates from two words in Greek "meta" and "heuristic", where "meta" means "high level" or "beyond" and heuristic means "to find" or "to know" (Gandomi et al. 2013). Metaheuristics give guidance (strategies) on how to design and apply heuristics to solve real-world problems. The popularity and success of metaheuristics can be attributed to many reasons, and one of the main ones is that these algorithms have been developed by mimicking the most successful processes in nature, including biological, physical, and chemical processes (Abdel-Basset et al. 2018). This thesis focused on the two subgroups of evolutionary and swarm intelligence-based algorithms, both classified in the family of bio-inspired algorithms and simulated annealing classified as physics-based algorithms. The two selected groups are known as population-based algorithms and are efficient to solve multi-objective optimization problems (Coello Coello, Van Veldhuizen, and Lamont 2007). Figure 3 presents the classification of nature-inspired metaheuristic algorithms.

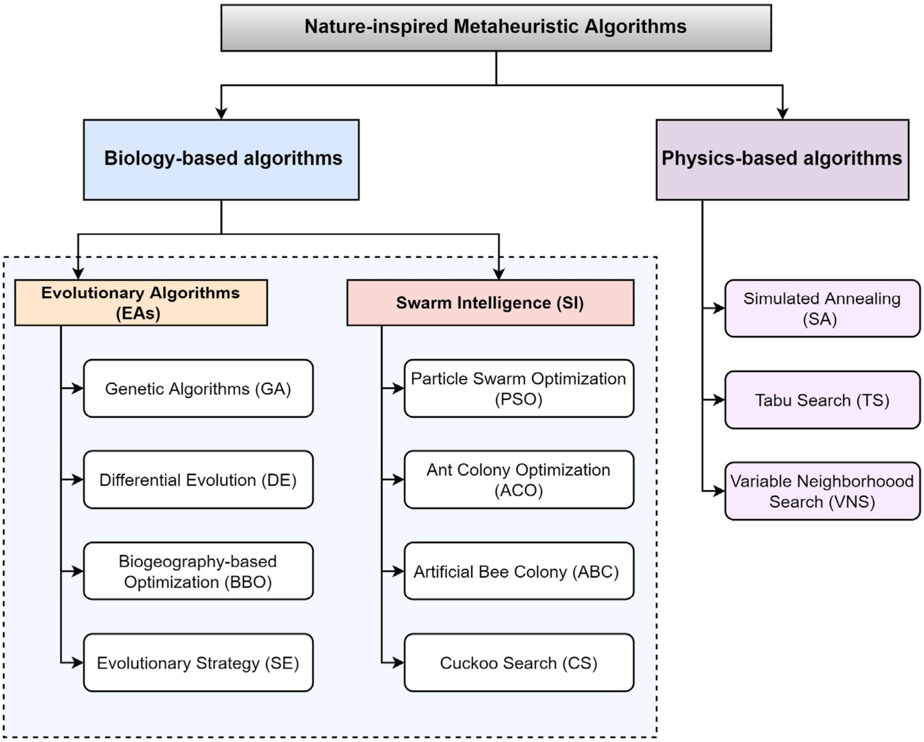

Figure 3. Classification of nature-inspired metaheuristic algorithms. These are examples of algorithms used in GIS-based multi-objective optimization.

The metaheuristics methods presented in Figure 3 were applied in GIS-MOO research due to their reputation of being efficient and/or accurate to solve multi-objective optimization problems with complicated factors, including huge solution space, non-linearity, and non-standard underlying objective functions, which make them potentially suitable for spatial multi-objective optimization problems. The common concept of these algorithms is that they all start by identifying multiple feasible solutions from which the best solutions can be found. For these reasons, they are called population-based algorithms. According to the specific search rule of the heuristic, new solutions are identified and the current solutions are updated. The search process ends when the termination condition is satisfied. The set of high-quality solutions, also known as optimal solutions, is found through many iterations (Talbi 2009). In addition, most of the illustrated algorithms in Figure 3 have their variants that are proposed to solve multi-objective optimization problems in general, and for solving spatial decision problems in particular.

Biology-based algorithms

The majority of metaheuristics are based on biological evolution principles (Abdel-Basset, Abdel-Fatah, and Sangaiah 2018). They are concerned with simulating various biological metaphors which differ from the representation schemes (structuring, components, etc.). The following two main paradigms are the most popular: evolutionary and swarm intelligence.

- *Evolutionary algorithms (EAs):* are metaheuristic methods that simulate the biological principles of natural selection and survival of the fittest. Specifically, the family of evolutionary algorithms includes (i) Genetic Algorithms (Krzanowski and Raper 2001; Mi et al. 2015; Xin Li and Parrott 2016), (ii) Differential Evolution (Chen, Panahi, and Pourghasemi 2017), (iii) Biogeography-based optimization (Ahmadlou et al. 2019), and (iv) Evolution Strategy (Schröder, Lauven, and Geldermann 2018). Genetic algorithms (GAs) are the most used metaheuristics for dealing with multi-objective optimization problems. They are also by far the most popular methods for tackling spatial multi-objective optimization problems (Yang 2014).

  Many GAs variants have been suggested, with different schemes of chromosome representation (encoding of solutions), evaluation of fitness function, selection, crossover, and mutation (Yang 2014). Extended literature on GA procedures can be found in (Malczewski and Rinner 2015). Among the GAs variants, the most popular MOO is known as the Non-dominated Sorting Genetic Algorithm (NSGA-II) developed by Deb and associates (Deb et al. 2002). NSGA-II is also the most used method in GIS-based applications of genetic algorithms. Examples of NSGA-II application in land-use optimization (Song and Chen 2018; 2018; Schwaab et al. 2018; Lubida et al. 2019), and in evacuation planning (Ghasemi et al. 2019; Ransikarbum and Mason 2021).
- *Swarm intelligence (SI):* These optimization methods are inspired by the collective, emerging, and social behaviour of multiple agents such as flocks of birds, schools of fish, colonies of ants, and bees. This type is among the most recently popular and widely used algorithms in multi-objective optimization. Some examples of most used SIs in GIS applications are (i) Particle Swarm Optimization-PSO (Zhao et al. 2015; Chen, Panahi, and Pourghasemi 2017; Razavi Termeh et al. 2018; Song and Chen 2018a), (ii) Anti Colony Optimization-ACO (Castillo-Villar 2014; Razavi Termeh et al. 2018; Masoumi, Van Genderen, and Niaraki 2021), (iii) Artificial Bee Colony-ABC (L. Yang et al. 2015; Fang et al. 2017), and Cuckoo Search-CS (M. Cao et al. 2015; Talib et al. 2020). In this thesis, four variants of swarm intelligence algorithms are applied, namely Multi-objective Standard Particle Swarm

Optimization Algorithm (MSPSO); Multi-objective Artificial Bee Colony (MOABC); and Discrete Multi-objective Cuckoo Search algorithm (DMOCS).

Physics-based algorithms

These types of algorithms mimic certain physical and/or chemical phenomena, including instance electrical charges, temperature changes, gravity, or river systems. Within this group, the most popular algorithm is Simulated Annealing (SA), which mimics the annealing process of metals, cooling and freezing them into a crystalline state with the minimum energy and larger crystal sizes, which reduces the defects in metallic structures. Bandyopadhyay et al. (2008) extended the SA algorithm to a multi-objective optimization version and named it the Archived Multi-Objective Optimization Simulated Annealing algorithm (AMOSA). AMOSA has been improved and applied to solve complex geographical spatial sampling in the study by (Xiaolan Li et al. 2020). Duh and Brown (2007) developed a knowledge-informed Pareto simulated annealing approach to solving multi-objective allocation problems. The ordered capacitated multi-objective location-allocation problem for fire stations has been solved and evaluated using SA and GA (Bolouri et al. 2018).

Tabu search (TS) is another physics-based algorithm, which is inspired by the mechanics of human memory (Boussaïd, Lepagnot, and Siarry 2013). TS was initially developed to solve single-objective combinatorial optimization problems, but it can also be applied for multi-objective optimization problems when coupled with other heuristic algorithms. Mohammadi, Nastaran, and Sahebgharani (2016) developed and compared various hybrid metaheuristic algorithms including TS for urban land-use allocation problems. The variable neighbourhood search (VNS) is a type of metaheuristic developed with aim of solving hard optimization problems. It has been applied in the GIS application studies such as waste management problems (Delgado-Antequera et al. 2020), traveling salesperson problems (Polacek et al. 2007), and humanitarian logistics model for disaster relief operations (Ahmadi, Seifi, and Tootooni 2015).

Methodology

The methods employed in this study were primarily influenced by the nature of the problems in disaster management and urban planning, which gave rise to the use of Geographic Information System (GIS) and Multi-criteria Decision Making (MCDM). To achieve the objectives of this thesis, various data and methods have been used (Table 2). Evacuation planning problem in two countries, Rwanda and Mozambique as well as urban land-use allocation problem in Rwanda were considered as case studies. The spatial data were prepared and analysed in a GIS environment as input data to the metaheuristic algorithms implemented using python scripts.

Table 2. An overview of spatial objectives, data, and methods by paper and research applications as case studies.

	Research applications	**Spatial Objectives**	**Study area**	**Methods**	**Datasets**
Paper I	Evacuation planning	Total travel distance Capacity of shelters	Kigali, Rwanda	Network analysis Four metaheuristic algorithms: AMOSA, MOABC, NSGA-II, MSPSO	The road networks location of shelters Population data DEM
Paper-II	Evacuation planning	Total travel distance Capacity of shelters	Kigali, Rwanda	Network analysis Dijkstra's algorithm MOABC algorithm	The road networks location of shelters Population data DEM
Paper III	Evacuation planning	Total travel distance The capacity of shelters risk on evacuation routes	Maputo, Mozambique	Network analysis, Dijkstra's algorithm MOCS algorithm	The road networks location of shelters, and bridges Population data
Paper IV	Urban Land-use allocation	Spatial accessibility Spatial compactness Space syntax integration	Kigali, Rwanda	Network analysis Space syntax analysis MOBBO algorithm	Road networks Land use dataset Kigali master plan (2013)

Case studies

Evacuation planning (Papers I, II, and III)

The urban evacuation planning scenarios presented in this thesis were conducted in two study areas; one in the city of Kigali, Rwanda, and the other in the city of Maputo, Mozambique. Both cities (Kigali and Maputo) are the capitals of the two sub-Saharan African countries. These cities are experiencing an increase in frequency and intensity of natural disasters including floods, landslides, droughts, and cyclones (Fraser et al. 2017). Flooding, in particular, is one of the major threats to these cities. Climate change effects, combined with migration toward cities, lead to high demand for housing and promote urbanization. Given the insufficiency of adequate planning and infrastructure, many people live in flood-prone zones. This makes them vulnerable. Therefore, development of effective urban evacuation planning is needed in these two cities. Moreover, the effective planning and scheduling of emergency operations such as evacuation planning, play a key role in saving lives and reducing damages in disasters, which promote the sustainability development goals (SDGs), specifically for Disaster Risk Reduction (Zheng, Chen, and Ling 2015).

Spatial data including road networks, administrative boundaries, and location of bridges were provided by authorities of the city of Kigali, Rwanda and of Maputo, Mozambique (Table 2). The population data was provided by the National Institute of Statistics of Rwanda (paper I, and II). The selection of appropriate shelters and their capacities of accommodating evacuees were determined based on global standards documented in The Sphere Project (2011). A digital elevation model (DEM) with 10 m resolution was used to conduct the slope analysis for the selection of shelters' locations. Dijkstra's algorithm and road networks extracted from Open Street Map were used to calculate the shortest path and to generate the distance matrix that was used in the computation of the total travel distance. The Risk function was formulated to calculate the total risk in the evacuation planning process. Thus, datasets including roads, bridges, shelters, and residential were used to estimate the risk on the evacuation path between the point of origin and destination, that is prone area and shelter.

Urban land-use allocation (Paper IV)

With the rapid increase in urbanization and population growth, urban land-use planning is becoming a major concern for governments and municipalities, particularly in developing countries (United Nations 2018). This rapid demographic and spatial transformation may be difficult for most of the African cities, where the capacity is typically inadequate to cope with major challenges including increased demand for housing, resource scarcity, increased poverty, and climate change (Keivani 2010; Sakka 2016). However, the well planned urban land uses, based on policies and principles of sustainable development can help to address these challenges (Van et al. 1994; Satterthwaite 2017).

Therefore, paper IV of this thesis addressed the problem of land-use allocation in the city of Kigali, Rwanda. The main goal of the proposed land-use planning model is to generate land use allocations that lead to the balance of social integration and economic benefits in urban design areas via three objectives: maximizing accessibility, maximizing compactness, and maximizing space syntax integration. The Land-use (LU) data of the study area was extracted from a dataset of the Kigali master plan (Kigali 2013). Detailed master plans and recommendations were used to classify different land-use activities and to determine the proportion of each land use type (REMA 2013). Road networks were analysed using GIS tools to generate a distance matrix for calculating the accessibility index and performing the space syntax analysis. The Depthmap software was used to generate a segment map of the integration attribute.

The space syntax analysis employed in paper IV, was used to assess the spatial relationship between street networks and the distribution of land uses of residential and commercial in particular. According to Hillier (2009), the space syntax can be described as a set of techniques that are used for analysing spatial layouts and human activity patterns in buildings and urban areas. Moreover, the space syntax concept enables us to understand the spatial properties of a sustainable city. Therefore, the possible spatial distribution/ arrangement of commercial land use within residential areas was measured using the space syntax integration attribute.

Methods

Development of MOO methods and tools in the context of spatial multi-objective decision making is typically an iterative process of identifying the spatial problem, spatial multi-objective optimization modelling, implementing algorithms, and evaluating solutions. The methodological approach employed in this thesis has been adopted and extended by several researchers starting with Malczewski (1999), Jankowski and Nyerges (2001), followed by Chakhar and Martel (2003), Xiao, Bennett, and Armstrong (2007), and Xiao (2008).

The design cycle of GIS-MODM, which constitutes the core of the decision-making process, consists of three phases: intelligence, design, and selection/choice as suggested in the study by Simon (1960). Problem definition, data acquisitions, processing, and analysis are done in the intelligence phase; and spatial modelling is the design phase to develop a set of solutions as spatial decision alternatives. The selection phase, also called choice phase involves the sensitivity analysis of the model, results visualisation, and gives recommendations. The integration of MODM techniques and GIS functions supports the design phase significantly. The selection phase involves the choice of particular alternatives from optimal solutions (Malczewski 1999). Furthermore, the sensitivity analysis supports parameter configuration and testing of robustness of the model. At the end of the analysis, the analyst is expected to provide a recommendation and its justification to the decision-maker concerning the problem and explain how to implement it.

In this thesis, the conceptual framework of decision-making process includes problem formulation, design and implementation of the algorithms, and determining optimal solutions to the problem. Specifically, the conceptual framework employed for spatial multi-objective decision-making models is created from the perspective of metaheuristic algorithms and GIS tools for data structure, analysis, and visualization. Figure 4 illustrates the fundamental elements of this framework, as well as the three phases suggested in Simon (1960).

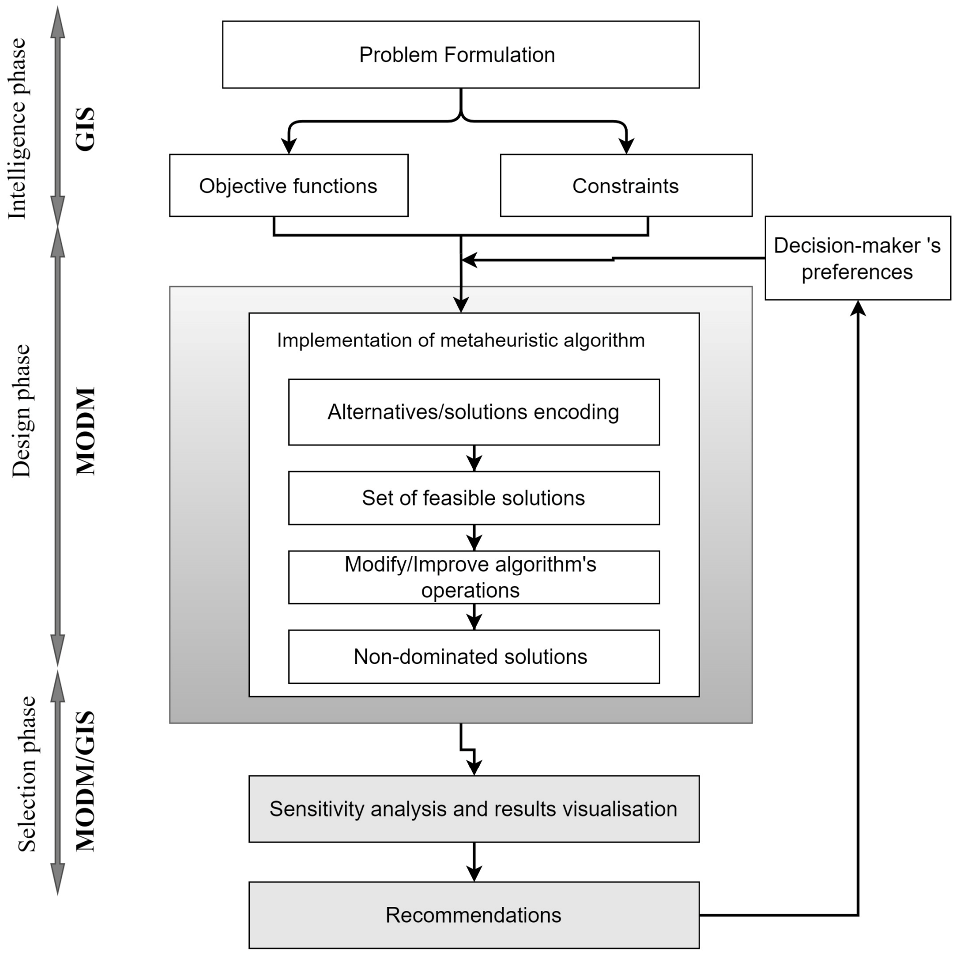

Figure 4. A conceptual framework of spatial multi-objective decision making and analysis. Adopted from Xiao, Bennett, and Armstrong (2007) and extended by the author.

Spatial multi-objective optimization problem formulation

The first step in structuring any GIS-based MODM technique is to define a goal that a group of individuals attempts to achieve, along with its associated evaluation criteria (objectives), from which the decision-maker evaluates alternatives. In the context of MODM, problems are formulated differently than they are in traditional methods (e.g. linear programming models), though the general mathematical form as explained by the equation (1).

The evacuation planning and urban land-use allocation problem tackled in this thesis are types of location-allocation problems, which means that the solutions to such problems depend on the spatial arrangements of the feasible alternatives. The alternatives are defined geographically and contain spatial concepts explicitly. For instance, the concept of location, distance, connectivity, and adjacency was used to define the decision alternatives. Based on the type of decision variables of these problems, they were formulated and tackled as combinatorial optimization problems. Decision variables are discrete when their values are fixed. Similar structuring of the spatial multi-objective optimization model has been suggested in the literature (Jankowski 1995; Malczewski 1999; Chakhar and Martel 2003).

In spatial modelling of evacuation planning and urban land-use allocation using MODM, the decision-makers and experts were involved in the conceptualization of the problems. The decision maker's preferences were used to set the goal and assign the weights to different objective functions, and also to set the target values that should be satisfied with any feasible solution. Moreover, they helped to indicate the nature of optimization for each defined objective function, e.g., maximization or minimization. The goal and the nature of optimization are the most required information to define a set of *non-dominated solutions*. This set contains solutions that are not *dominated* by any other solution in the objective space on which experts base their decisions.

The solutions to the spatial multi-objective optimization problems were generated using metaheuristic methods. These methods seek to find the best solutions by trial and error and incorporate strategies aimed at efficient exploration of a solution space. For a metaheuristic algorithm, a problem is more directly formulated algorithmically: an appropriate data structure is designed to encode solutions, and searching strategies are specified to handle objectives and constraints subjected to them. Then, the fitness evaluation techniques are applied to generate the optimal solutions. Figure 5 demonstrates an example of a discrete encoding structure employed in Papers I and II (Niyomubyeyi et al. (2020), Niyomubyeyi, Pilesjö, and Mansourian (2019), and Sicuaio et al. (2022)). This encoding strategy was used based on vector data representation.

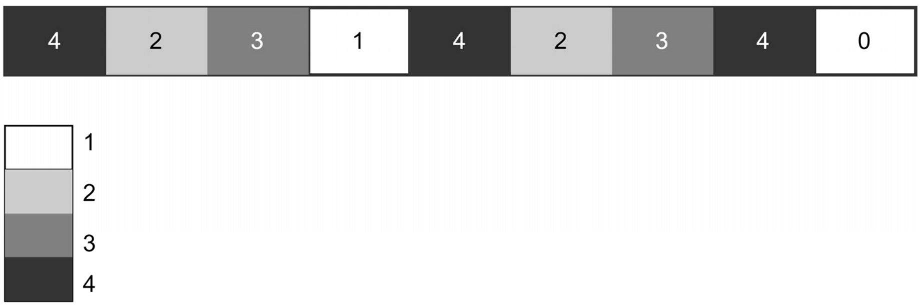

Figure 5. Example of discrete/integer encoding of a potential land-use plan.

Each land-use variable is represented by an integer value from 0 to 4. These values correspond to the four land uses. The whole string is a numeric code describing the details of the land use pattern (alternative solution) of the study area consisting of nine sites of land. (adopted from Malczewski and Rinner (2015)).

Non-dominated Sorting Genetic Algorithm II

The Non-dominated Sorting Genetic Algorithm II (NSGA-II) developed by Deb et al. (2002), is one of the most popular multi-objective optimization algorithms. It was proposed to improve the original version of NSGA initially developed based on the concept of the Genetic Algorithm (GA). The structure of NSGA-II is based on the four principles, which are, non-dominated sorting, elite preserving operator, crowding distance, and selection operator.

The procedure of NSGA-II start with generating an initial random population P_0 of size N and then is sorted using the concept of Pareto dominance. After evaluating objective functions, the process of non-dominated sorting begins with assigning the first rank (or fitness) to the non-dominated solutions of the P_0 at initial time $t = 0$. The first ranked solutions are stored in the first front and then removed from the initial population. The procedure continues until all members of the population P_0 are assigned to different fronts based on their ranks. At the beginning of the main loop, operators such as binary tournament selection, recombination (crossover), and mutation are applied over P_0 to create the offspring population Q_0 of size N. The parents and offspring populations, P_t and Q_t, are combined and form a new combined population R_t of size $2N$, which is also sorted according to the non-domination procedure. Figure 6 illustrates this process.

Next, the elitism selection method is applied to select the best candidate for next-generation and must reduce the number of individuals in a combined population of $2N$ to get the size of N. As Figure 6 demonstrates the process, all solutions of the first two Pareto fronts F_1 and F_2 are selected and included into P_{t+1}. However, if the number of solutions in P_{t+1} is less than the size of P_t, then some solutions in F_3 must be included. The crowding distance sorting method is used to rank the solutions in the Pareto front F_3. Then the solutions with higher ranking value of crowding distance are included in the new population P_{t+1}. The crowding distance sorting method introduces more diversity into the population. The selection, evaluation, recombination, and non-dominated sorting procedures repeatedly continue until the stopping criteria are met (e.g., the maximum number of iterations).

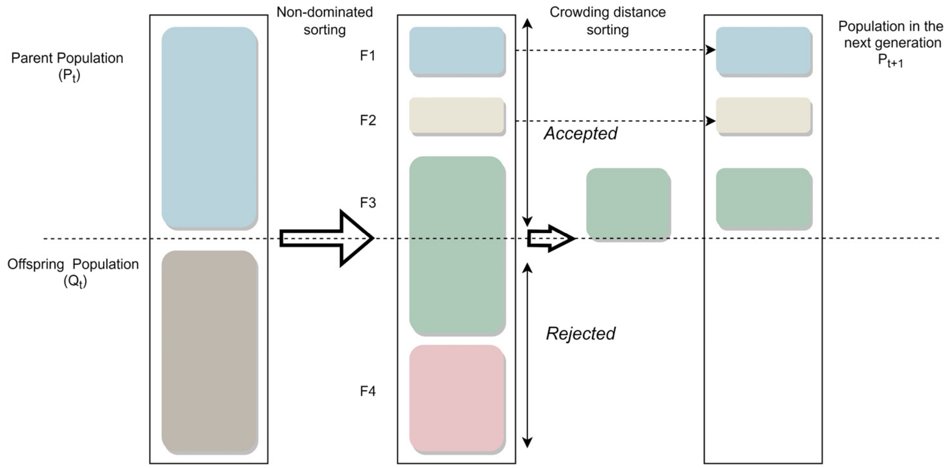

Figure 6. The NSGA-II evaluation of non-dominated solutions procedure. P_t = parent population; Q_t = offspring population; P_{t+1} = parent population in the next generation; $(F_1, F_2, \ldots F_m)$ = Pareto front. Adopted from Deb et al. (2002).

The previously described procedures are for a standard or classic NSGA-II algorithm as proposed in the original work by Deb et al. (2002). Similar procedures of NSGA-II have been applied to optimize the total travel distance and overload capacity of shelters as two objective functions for the evacuation model in Paper I (Niyomubyeyi et al. (2020)) where all objectives were to be minimized.

The implementation of NSGA-II starts with encoding the potential solutions into the form of genes and chromosomes. According to the genetic terminology, a solution vector of decision variables is referred to as a chromosome or an individual. Chromosomes are made of discrete units as demonstrated in Figure 6. Each unit in a chromosome is called a "gene", which controls the features of the chromosome. Once an encoding solution is done, the next step is to apply NSGA-II procedures as described in the previous texts.

NSGA-II has been widely applied to solve evacuation planning models. Goerigk, Deghdak, and Heßler (2014) proposed a comprehensive urban evacuation planning model which was solved using the standard NSGA-II algorithm. Furthermore, a standard NSGA-II was applied and compared with other algorithms in solving multi-period dynamic emergency resource scheduling problems (Zhou et al. 2017). A study by Ghasemi et al. (2020) showed the efficiency of the NSGA-II algorithm in solving the problems of logistic distribution and evacuation planning. Moreover, many researchers continue to modify and improve the performance of standard NSGA-II to fit better to the spatial problem (e.g., García et al. 2017; Masoumi, Coello Coello, and Mansourian 2020; Verma, Pant, and Snasel 2021).

Multi-objective Standard Particle Swarm Optimization algorithm

The Particle Swarm Optimization algorithm is a population-based metaheuristic algorithm proposed by Kennedy and Eberhart (1995). The algorithm is inspired by animals' social behaviours, including fishes, birds, and insects. Members of the swarm called particles organize themselves and work together in a multi-dimensional space searching for food, and each member of the swarm adjusts its movement and distance for better search according to its own previous experience and with those of neighbouring particles in the swarm.

Numerous variants of the PSO algorithm have been proposed in the literature, aimed at improving the performance or solving a specific problem. Among the variants, Standard PSO (SPSO-2011) was proposed to provide common procedures and guidance to improve the original PSO (Clerc 2012). However, the developed SPSO was not intended to be the best PSO variant but only to be considered as the reference level of future improvements (Zambrano-Bigiarini, Clerc, and Rojas 2013).

The SPSO algorithm begins with generating a random initialization of each particle's position and velocity (particle displacement) within the search space. By considering a D- dimensional search space, position and velocity of the i^{th}particle is represented by a vector $X_i^{\rightarrow} = x_{i1}, x_{i2}, \dots, x_{iD}$ and velocity $V_i^{\rightarrow} = v_{i1}, v_{i2}, \dots, v_{iD}$. The performance of each particle is therefore assessed based on its fitness value, which is the basis for updating $X_i^{\rightarrow}$. A particle memorizes its best position found so far, which is named as personal/previous best and represented as $P_i^{\rightarrow} = p_{i1}, p_{i2}, \dots, p_{iD}$, whereas the best position within the particle's neighbourhood, is named local best and presented by $G_i^{\rightarrow} = g_{i1}, g_{i2}, \dots, g_{iD}$. In SPSO-2011, velocity, and position of the i^{th} particle is updated using the following equations:

$$V_i^{\rightarrow t+1} = \omega V_i^{\rightarrow t} + \mathcal{H}_i(G_i^{\rightarrow t} \left\| G_i^{\rightarrow t} - X_i^{\rightarrow t} \right\|) - X_i^{\rightarrow t} \quad (3)$$

$$X_i^{\rightarrow t+1} = X_i^{\rightarrow t} + V_i^{\rightarrow t+1} \quad (4)$$

where $i = 1, 2, \dots, N$ with N equal to the size of the swarm, and $t = 1, 2, \dots, T$, with T equal to the maximum iterations. ω is the inertia weight that controls the increase of particle velocity to prevent swarm explosion. The $G_i^{\rightarrow t}$ represents the centre of gravity for each particle at three positions: a personal position $X_i^{\rightarrow}$, the best previous position ($P_i^{\rightarrow}$), and the best previous position in the neighbourhood ($G_i^{\rightarrow}$), respectively. Figure 7 presents the main procedures of the SPSO algorithm applied in paper I.

```
For i = 1 to N do {for each particle in the swarm}
        Initialise particles' position (X_i→) and velocity (V_i→)
        Initialise personal/previous best position, P_i→, and local best, G_i→
End for
Repeat
   For i = 1 to N  do
        Update particles' velocity using equation (3)
        Update particles' position using equation (4)
        If f(X_i→) < f(P_i→) then {minimization of f}
              Update particles' best known position P_i→ = X_i→
              If (V_i→) < f(G_i→) then {minimization of f}
                    Update the neighbourhood's best-known position G_i→ = P_i→
                    End if
              End if
        End for
Until (number of iterations (T) or tolerance error is met)
```

Figure 7. Pseudocode for the SPSO-2011 algorithm. source: (Zambrano-Bigiarini, Clerc, and Rojas 2013).

In this thesis, a multi-objective version of standard particle swarm optimization (MSPSO) algorithm was implemented to optimize two conflicting objective functions for the evacuation planning problem addressed in paper I. Nevertheless, the original SPSO algorithm was designed for a continuous problem with real numbers, while the solved evacuation problem was defined as a discrete problem. To solve this issue, the rounded value method was used for mapping a continuous space transforming to a discrete problem space. The encoding procedure illustrated in Figure 5 was employed to design the SPSO solutions. To solve the evacuation model, every possible spatial arrangement to evacuate people from the risk zone to a safe place was considered as a potential particle in the search space. Thus, a neighbourhood topology (ring topology) was used to determine the global best ($\vec{G_i}$) for each particle among its neighbors (see the modelling of MSPSO in in paper I).

Other variants of the PSO algorithm have been adapted in other studies related to evacuation planning. For example, Lin and Lucas (2015) proposed a PSO model of emergency airplane evacuations with emotion. The results from this study showed the efficiency of PSO in simulating the evacuation of airplane. The PSO has also been modified and hybridized in many studies in order to better fit the problem at hand (Song and Chen 2018a; Xu et al. 2018; Hua Wang et al. 2020).

Multi-objective Artificial Bee Colony algorithm

The Multi-objective Artificial Bee Colony (MOABC) is a multi-objective optimization variant of original Artificial Bee Colony (ABC) developed by Karaboga (2005). ABC algorithm mimics the behaviour of the colony of bees in nature. This algorithm was selected to solve the evacuation problem based on its efficiency and flexibility. It is also known to have well-balanced exploration and exploitation operators, which promote diversity among optimal solutions (Karaboga et al. 2014).

In the standard MOABC algorithm, the colony consists of three artificial bees: employed, onlookers, and scout bee. In nature, each bee in the colony carries in its memory the food source, the quality of the food, and the location of the food source. While in the optimization problem, the food source represents the fitness value assigned to each artificial bee and the food source position corresponds to the solution position in the search space. First, some scout bees (initial solutions) are randomly generated to explore the search space of the problem. After initializing solutions and evaluating their fitness values, the best solutions are stored in an external archive. The employed bees and onlooker bees are sent in the search space to exploit the best solutions and improve their quality through the following equations:

$$v_{id} = x_{id} + w.rand[0,1](x_{id} - x_{kd}) \tag{5}$$

$$p_i = \frac{f(X_i)}{\sum_{i=0}^{n} f(X_i)} \tag{6}$$

where i represents the food source which is going to be updated, $d \in \{1, 2, \ldots, D\}$ is the $D -$ dimension (number of decision variables), and $k \in \{1, 2, 3 \ldots, K\}$ represents the new position of x bee. Note that k and d are randomly chosen indices.

Standard MOABC uses a roulette wheel selection method to select the onlooker bees for next-generation after evaluating the fitness of employed bees and updating the archive with the best solutions. An onlooker bee is selected based on the probability p_i, found by calculating the proportion of solution fitness $f(x_i)$ in relation to the total fitness of the n population, as shown in equation (6). Both employed and onlooker bees perform the neighbourhood search using the expression in equation (5). The greedy selection method is then applied to evaluate the solution with the best fitness value. Further exploration is carried out by scout bees that generate new random solutions. The algorithm is terminated when the given termination criterion (maximum generations) is attained. Similar procedures of standard MOABC have been adopted to solve the evacuation model in paper I.

However, the standard MOABC has a weakness of local search, where the solutions tend to be trapped in a local optimum. To solve this issue, paper II proposed an improved MOABC for solving the evacuation model with two objectives. Three strategies and Pareto front-based approach from NSGA-II were employed. First, a discrete random procedure was used for solution representation and initialization. The second proposed searching strategy combined two random searches (swap and insertion) to improve the selection of new solutions in the search space. This strategy improved the exploration process of MOABC and maintained the diversity of the solutions. Third, the crossover operator was used to enhance the recombination process of parents and offspring solutions (employed bees and onlooker bees in the case of MOABC). Finally, the concept of Pareto dominance was used to sort non-dominated solutions (see the detailed improved MOABC in paper II (Niyomubyeyi, Pilesjö, and Mansourian 2019).

In addition, many studies have applied and or improved MOABC in GIS applications (e.g., L. Yang et al. 2015; Shao et al. 2015; Naghibi, Delavar, and Pijanowski 2016). Pérez et al. (2017) applied MOABC to design water quality monitoring networks in river basins, and the obtained solutions were insightful and valuable information to decision-makers. Also, a land partitioning model was proposed using a MOABC algorithm, and the model outperformed the designer's land-use plan in terms of land-use compatibility and agriculture conditions (Bijandi et al. 2021)

Multi-objective Cuckoo Search algorithm

The Multi-objective Cuckoo Search (MOCS) is a nature-inspired metaheuristic algorithm extended from the original Cuckoo Search (CS) developed by Yang and Deb (2009) to solve a single-objective function. The CS mimics the reproductive breeding behaviour such as brood parasitism of certain species of cuckoos. In CS for single-objective optimization, the following three idealized rules are used; 1) each cuckoo lays an egg at a time and dumps it in a randomly chosen nest; 2) the best nests with high-quality eggs will continue to the next generations; 3) the number of the available host is fixed, and a host can discover an alien egg with a probability $p_a \in [0,1]$. In this case, the host bird can either throw the egg away or abandon the nest to build a completely new nest in a new location. Here the egg represents a decision variable of optimization problem and the nest represents a solution to the problem.

The procedure of the proposed discrete MOCS algorithm in paper III is mainly based on three parameters: (i) the probability to abandon the worst nest, p_a, (ii) a non-negative step size, α, that should be associated with the scale of the problem, in most cases is greater than one. For the evacuation model, the step size corresponds to the current solution x_i^t, and (iii) the random step length, λ. Then, a Lévy flight operator is applied when generating a new solution x_i^{t+1}. The following equation expresses the Lévy flight operator:

$$x_i^{(t+1)} = \left\lfloor x_i^{(t)} + \alpha \oplus \text{Lévy}(\lambda) \right\rfloor \%(1+5) \quad (7)$$

where $\oplus$ means entry wise multiplication, and % is the modulus arithmetic operator and this returns the remainder of the division of each vector component by (1+5) to guarantee that every entry is between zero and five. Besides, a probability p_a of the worst nests can be abandoned so that new nests can be built at a new location by random walks process and mixing, which can be performed by random permutation of the solutions according to the similarity/difference to the host egg.

Some modifications were made to MOCS in order to address the MOO problems with discrete variables (e.g., location-allocation problem, evacuation planning problem). Moreover, to improve the performance and the quality of solutions, the proposed MOCS was therefore hybridized with the Pareto Archived Evolution Strategy (PAES), which is successful in generating diverse solutions in the final Pareto optimal set (Knowles and Corne 2000). The procedure and main improved steps of the proposed MOCS algorithm can be seen in paper III (Sicuaio et al. 2022).

Some studies have modified MOCS with a focus on finding the optimal Pareto solutions (Srivastav and Agrawal 2017; Balogun et al. 2021) and others hybridized MOCS with other algorithms to improve its performance (Talib et al. 2020). Zhang et al. (2018) used a hybrid cuckoo search algorithm to solve the heating route design problem, and Jaafari et al. (2022) hybridized cuckoo search with whale optimization algorithm to model and predict landslides, and the results showed that the hybrid model with CS algorithm identified the best trade-offs among objectives, accuracy, and robustness.

Non-dominated Sorting Biogeography-based Optimization algorithm

The Non-dominated Sorting Biography-based optimization algorithm (NSBBO) is an evolutionary algorithm inspired by the standard BBO algorithm for solving multi-objective optimization (Simon 2013). Thus the general procedure of NSBBO is similar to that of BBO except for the addition of non-dominated sorting and crowding distance procedures adopted from the NSGA-II algorithm (Deb et al. 2002). BBO is among novel algorithms inspired by biogeography, which studies the geographical distribution of biological organisms.

In NSBBO, a solution is termed as habitat and has a habitat suitability index (HSI) to evaluate its quality (which is similar to fitness evaluation in NSGA-II). In the case of the minimization problem, a low-HSI habitat represents a good solution and a high-HSI is a poor solution instead (Simon 2008). Each habitat is characterized by a suitable index variable (SIVs) that corresponds with genes in the NSGA-II algorithm or decision variables of the optimization problem. A habitat with high-HSI is more likely to share (emigrate) its SIVs with nearby poor habitats, while a low HSI is more likely to accept (immigrate) shared SVIs from high-HSI habitat.

In summary, the NSBBO operates in two main operators which are migration and mutation. Migration is a probabilistic operator that improves the habitats by using the migration rate of each habitat to probabilistically share the features (SIVs) of emigrating habitat to the immigrating habitat. For habitat h_i, its immigration λ_i is used to probabilistically decide whether or not to immigrate. If the habitat is to immigrate, then the emigrating habitats h_j should be selected based on the emigration rate μ_j. Therefore, the migration operator can be defined as $H_i(SIVs) \leftarrow H_j(SIVs)$. The mutation is also a probability operator that is used to maintain the diversity among habitats. A mutation is performed by simply replacing a selected SIV of habitat with a randomly generated SIV. For a low HSI habitat, a mutation can raise the number of species to some extent, and for a high HSI habitat, a mutation may further enhance its fitness to avoid falling into a local optimum, which is similar to a mutation of other meta-heuristic algorithms (Simon 2013). The objective functions are then evaluated and solutions are sorted using the non-dominated approach.

Although the standard NSBBO and other BBO variant algorithms can efficiently solve difficult optimization problems with many-objective functions (Ma et al. 2017; Singh and Ingole 2019), there is still room for improvement. Thus, paper IV proposes an improved NSBBO to fit the addressed spatial land-use allocation problem.

First, the migration and mutation operators in standard NSBBO have a strong global exploration ability, while the local exploitation capability is weak. Note that exploration aims at finding new solutions in the most promising new regions in a search space, while exploitation means using already existing solutions and making refinement to find solutions of high quality. To maintain the balance of exploration and exploitation, a sinusoidal model was used for the migration operator instead of the linear model as proposed in the original BBO and standard NSBBO algorithm. The sinusoidal emigration and immigration rate is calculated as follows:

$$\lambda_i = \frac{I}{2}[cos(\pi \times HSI_i) + 1] \quad (8)$$

$$\mu_i = \frac{E}{2}[1 - cos(\pi * HSI_i)] \quad (9)$$

where I and E are the maximum immigration and emigration rates, respectively, $I\&E = 1$. HSI_i represents the fitness (rank) of habitat i.

Second, the challenge in optimizing a problem with multi-objective functions (e.g., 3 objectives in paper IV), is to translate those objective function values into HSI for selecting habitats to share their SIVs (e.g., migration). If the Pareto dominance of NSGA-II is applied to determine the non-dominated between habitats, the objective function values of solutions are then considered as a ranking of habitats, which will lead to the insufficient convergence of the population (An et al. 2021). To solve this, an efficient non-dominated sorting strategy (ENS) proposed by X. Zhang et al. (2015) was used to sort the solutions in the proposed NSBBO (paper IV). After selecting the best solutions from the initial population using the migration operator, new solutions are generated using crossover and mutation operators. The solutions for the next generation are then selected using the ENS procedure. The main loop is repeated until the stopping criteria are met.

BBO is among the novel population-based algorithms, but it has already received much attention from researchers in GIS applications. Kaveh and Mesgari (2019) improved the BBO algorithm using migration process adjustment to solve the location-allocation of emergency centres/ambulances. The results showed that the improved BBO has higher convergence compared to PSO and GA algorithms. Al-Fugara et al. (2020) developed three novel GIS-based models by combining Genetic Algorithm (GA), Biogeography-Based Optimization (BBO), and Simulated Annealing (SA) with Support Vector Regression (SVR) for groundwater potential mapping. The results showed that the model with the BBO algorithm performed better than the others. This shows the opportunity of using the BBO algorithm to solve other complex spatial optimization problems including the land-use allocation.

Archived Multi-Objective Optimization Simulated Annealing algorithm

The Archived Multi-Objective Optimization Simulated Annealing algorithm (AMOSA) employed in this thesis was proposed by Bandyopadhyay et al. (2008) to improve the existing multi-objective implementation of the original Simulated Annealing algorithm (Kirkpatrick, Gelatt, and Vecchi 1983), which in general do not consider Pareto dominance for accepting a new candidate solution as part of the final set. In modelling the AMOSA, the Pareto dominance approach is adopted and uses the concept of an archive to store all non-dominated solutions. The archive is limited to two parameters known as Hard Limit (HL) and Soft Limit (SL). The HL is the maximum size to achieve by termination, and it is equal to the number of non-dominated solutions required by the user; while the SL is the maximum size up to which the archive may be filled before clustering is applied. The algorithm starts with the set of solutions randomly initialized and refined in the archive by using a hill-climbing technique. The acceptance of new solutions is based on the probability determined by calculating the amount of dominance between two solutions a and b as:

$$\Delta dom_{a,b} = \prod_{i=1, fi(a) \neq fi(b)}^{M} (|f_i(a) - f_i\,(b)|/R_i) \qquad (10)$$

where $M =$ number of objectives and R_i is the range of i^{th} objectives. To change the state of the solution (generating new solutions), at a given temperature T, a new state s is selected with a probability

$$P_{qs} = \frac{1}{1+e^{\frac{-(E(q,T)-E(s,T))}{T}}} \qquad (11)$$

where q is the current state and $E(s,T)$ and $E(q,T)$ are the corresponding energy values of s and q, respectively. This equation automatically ensures that the probability value lies between 0 and 1.

The solution and decision variables were encoded and presented and tackled as discrete variables as demonstrated in Figure 5. Equations (10) and (11) were used to select and sort the non-dominated solutions in the archive. The algorithm stops when the cooling process reaches the predefined low temperature and the maximum number of generations. The pseudocode of AMOSA algorithm is shown in Figure 8.

```
Set $T_{max}$, $T_{min}$, HL, SL, TotalIter, $\alpha$, tmp=$T_{max}$.
Initialization of Archive.
c-pt = random(Archive). /* solution chosen randomly from Archive*/
while (tmp $> T_{min}$)
  for (i=0; i< TotalIter; i++)
    n-pt=perturb(c-pt).
    Checking domination status of n-pt and c-pt.
    /* Code for three different cases */
    if (c-pt dominates n-pt) /* Case 1*/
        $\Delta dom_{avg} = \frac{\left(\sum_{i=1}^{k}(\Delta dom_{i,n-pt}) + \Delta dom_{c-pt,n-pt}\right)}{(k+1)}$.
        /* k= total number of points in the Archive which dominate n-pt, $k \geq 0$. */
        Set n-pt as c-pt with probability as shown in Equation (5).
    if (n-pt and c-pt are non-dominating to each other) /* Case 2*/
        Check the domination status of n-pt and points in the Archive.
        if (n-pt is dominated by $k$ ($k \geq 1$) points in the Archive) /* Case 2(a)*/
          $\Delta dom_{avg} = \frac{\left(\sum_{i=1}^{k} \Delta dom_{i,n-pt}\right)}{k}$.
          Set n-pt as c-pt with probability as shown in Equation (5).
        if (n-pt is non-dominating w.r.t all the points in the Archive) /* Case 2(b)*/
          Set n-pt as c-pt and add n-pt to the Archive.
          if Archive-size > SL
            Cluster Archive to HL number of clusters.
        if (n-pt dominates k, ($k \geq 1$) points of the Archive) /* Case 2(c)*/
          Set n-pt as c-pt and add it to Archive.
          Remove all the k dominated points from the Archive.
    if (n-pt dominates c-pt) /* Case 3 */
        Check the domination status of n-pt and points in the Archive.
        if (n-pt is dominated by $k$ ($k \geq 1$) points in the Archive) /* Case 3(a)*/
          $\Delta dom_{min}$ = minimum of the difference of domination amounts between the n-pt
                      and the $k$ points
          prob= $\frac{1}{1+exp(-\Delta dom_{min})}$.
          Set point of the archive which corresponds to $\Delta dom_{min}$ as
          c-pt with probability=prob.
          else set n-pt as c-pt
        if (n-pt is non-dominating with respect to the points in the Archive) /* Case 3(b) */
          select the n-pt as the c-pt and add it to the Archive.
          if c-pt is in the Archive, remove it from Archive.
          else if Archive-size> SL.
            Cluster Archive to HL number of clusters.
        if (n-pt dominates k other points in the Archive ) /* Case 3(c)*/
          Set n-pt as c-pt and add it to the Archive.
          Remove all the $k$ dominated points from the Archive.
  End for
$tmp = \alpha * tmp$.
End while
if Archive-size > SL
  Cluster Archive to HL number of clusters.
```

Figure 8. Pseudocode of AMOSA algorithm. Source: Sanghamitra Bandyopadhyay et al. (2008).

Sensitivity analysis of GIS-based MOO model

Qureshi, Harrison, and Wegener (1999) stated the role of sensitivity analysis (SA) and defined it as a method that examines the stability of the model, checking the extent of variation in the output when parameters are systematically varied over a range of interests. SA also measures how the impact of uncertainties of one or many input variables can lead to uncertainties on the output variables. Research by Delgado and Sendra (2004) reviewed how the sensitivity analysis is applied to models based on GIS and MODM. This kind of analysis is conceived as the last phase in the multi-objective spatial decision-making modelling. In the context of the MODM process, the SA is of the type "what if" and some of the questions to be answered are:

- What are the most important parameters and how would the optimum solutions change as the main model parameters change?
- What are the limits of variation of the parameters to obtain the final optimal solutions?
- How stable is the model in terms of multiple simulation scenarios (i.e., number of repeatability)?

In this thesis, the SA was used to analyse the impact of parameters of each algorithm used in spatial modelling (Paper I-IV). As mentioned above, each algorithm has its particularities, and the parameters configuration is different. Hence, the parameter tuning approach, and other performance measurements (e.g., size of Pareto front, hypervolume, and repeatability) have been used in the results analysis to measure the performance of each algorithm. In addition, the first part of this thesis provides an extended SA study of four metaheuristic algorithms in which several criteria including the reliability of the model have been evaluated.

Results and discussion

The papers included in this thesis cover two different areas, each of the areas being related to one of the research objectives (see Figure 9). Spatial modelling of evacuation planning using standards and improved metaheuristic algorithms is covered in paper I, II, and III. Paper I address the first research objective of investigating the performance of four standard metaheuristic algorithms for urban evacuation planning problem of two objective functions. Paper II identifies the potential of MOABC algorithm and modifies the algorithm to improve the results of evacuation model in paper I. Paper III proposes an urban evacuation model considering three objective functions and solve the model using an improved MOCS algorithm. Paper IV proposed a multi-objective land-use allocation model using an improved NSBBO algorithm. All four papers handle spatial multi-objective decision making problems using metaheuristic algorithms in two GIS applications (disaster management and urban planning). The solutions from optimal urban evacuation planning and optimal land-use allocation can contribute to the decision-making and planning for sustainable urban development.

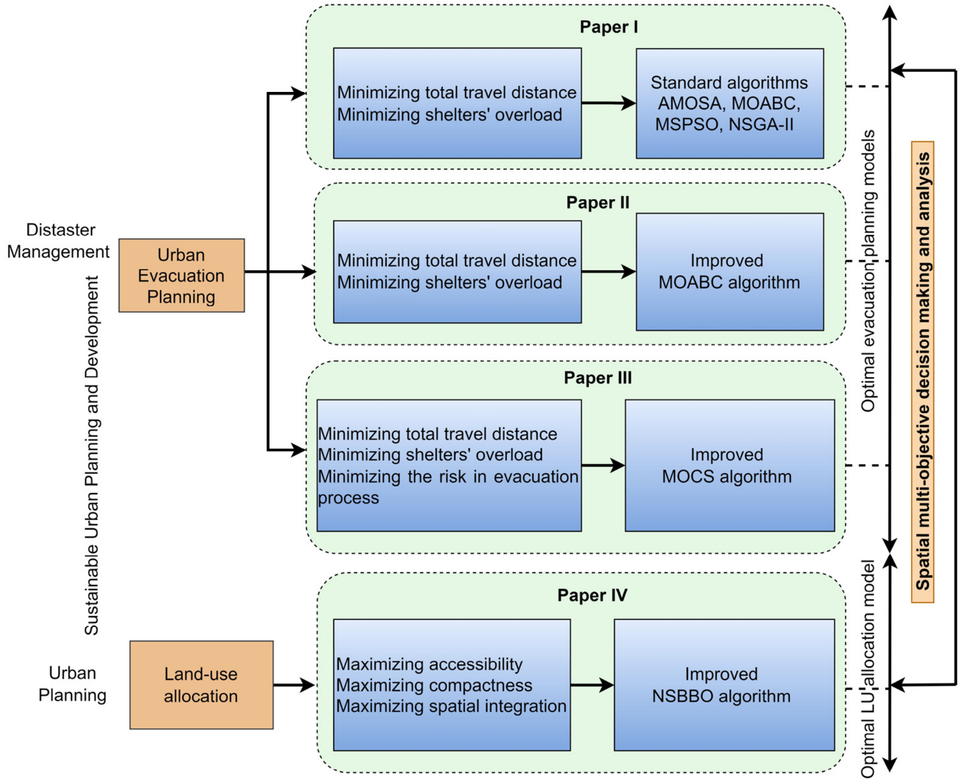

Figure 9. Schematic overview of the relationship among four papers included in this thesis.

Performance evaluation and comparison of metaheuristic algorithms

Various studies have shown that metaheuristic methods could be proper solutions to solve many real-world problems when they are well implemented (Zheng, Chen, and Ling 2015; Gunantara 2018). However, the choice of a suitable algorithm for a specific problem is still difficult for many users. Therefore, researchers need to understand how and why one metaheuristic algorithm outperforms another for tackling optimization problems. Thus, the study in a paper I explores how different metaheuristics methods perform when solving the same spatial multi-objective optimization problem. To achieve this, four standard metaheuristic methods were implemented and applied to solve the problem related to evacuation planning in Kigali, Rwanda. In this study, the spatial evacuation model was aiming to minimize two objective functions simultaneously; minimizing accumulated travel distance from high-risk zones to shelters and minimizing the overload capacity of shelters. The implemented algorithms were Archived Multi-Objective Simulated Annealing (AMOSA), Multi-Objective Artificial Bee Colony Algorithm (MOABC), Multi-Objective Standard Particle Swarm Optimization Algorithm (MSPSO), and Non-Dominated Sorting Genetic Algorithm (NSGA-II).

Several evaluation criteria and performance metrics include effectiveness (quality of optimal solutions), efficiency (convergence and execution time), and repeatability. The statistical analysis of variance method (Kruskal–Wallis test) was used to test how each algorithm achieves the best solutions and to evaluate if there are statistically significant differences between performances of the implemented algorithms. For instance, Figure 10 illustrates that AMOSA and MOABC outperformed other algorithms in terms of obtaining the minimum fitness values of two objective functions, as well as in short execution time(seconds).

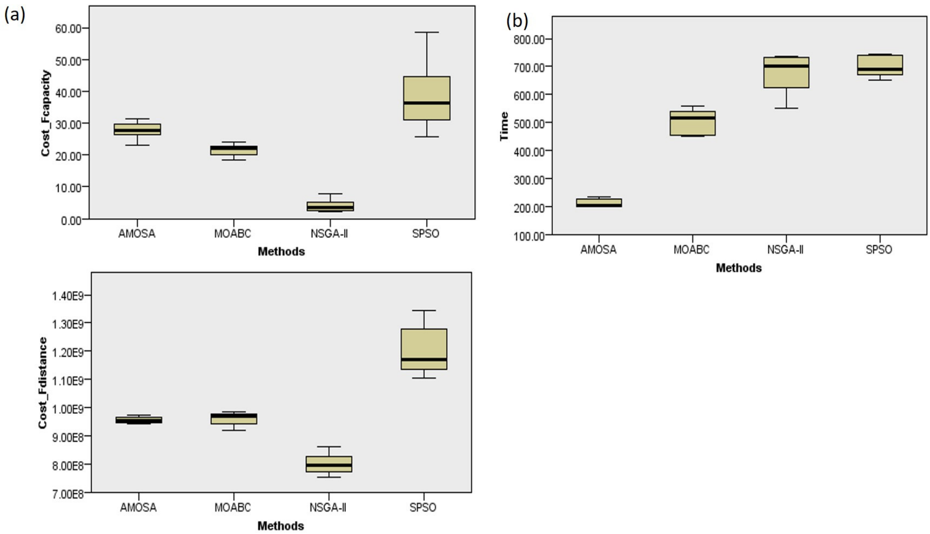

Figure 10. Box plots of comparing effectiveness and efficiency of four algorithms. (a) variation of the fitness values of overload capacity and distance function. (b) variation of the execution time of each algorithm. Modified from Paper I.

Furthermore, by evaluating the convergence speed of the four algorithms, the results show that AMOSA and NSGA-II followed by MOABC converged faster and smoother towards the final optimal solutions (see figures in Paper I). This justifies not only the competence of NSGA-II, which has been used in the literature of spatial optimization to a large extent (Mohammadi, Nastaran, and Sahebgharani 2015), but also shows the potential of the recently developed classic algorithms in solving evacuation problems (e.g., AMOSA and MOABC). To conclude, the compared metaheuristics methods and others of its type are not to find a set of "exact solutions" but a set of "good enough or close to the best solutions" in an efficient way, and therefore, more efforts could be added to improve the optimal solutions by using alternative methods. In this case, Decision-makers must be aware of this aspect, to properly assess the benefits and limitations of these techniques (Xiao and Murray 2019).

Improved MOABC algorithm for evacuation planning

After an extended investigation on the performance and application of four metaheuristics methods presented in paper I, the results showed not only that the most popular genetic algorithm (NSGA-II) can effectively solve a complex spatial decision problem, but also among the recently developed metaheuristics such as MOABC algorithm, could be an efficient tool for evacuation planning. In addition, most of the metaheuristic algorithms are originally designed to tackle general optimization problems, especially most of them are designed and tested on benchmark problems from computer science and/or engineering perspectives (Abdel-Basset, Abdel-Fatah, and Sangaiah 2018). Therefore, the use of a standard algorithm for real-world problem such as evacuation might lead to the wrong results and biased decisions. Thus, it was important to modify the MOABC to fit much better to the problem at hand. The weakness of standard MOABC was identified at local optimal search. This issue was addressed with modified neighbourhood strategies of local search, as well as improving its recombination operation by adopting a crossover operator.

The evacuation model solved by the improved MOABC, aimed at finding the optimal distribution of evacuees to safe places (as was the case in Paper I). The experimental results of the improved MOABC algorithm showed improvement from the results obtained for the multi-objective evacuation model. The impact of employed methods to improve MOABC was analysed, and the results showed a significant difference between MOABC with combined neighbourhood searching strategies (random swap, RS and random insertion, RI) together with crossover operator (Table 3). Moreover, the results of the improved MOABC outperformed the standard version of MOABC and NSGA-II algorithm in terms of optimizing two objective functions and execution time.

Table 3. Comparison of the improved MOABC against the standard MOABC and NSGA-II algorithm. The three algorithms were implemented on the same dataset and run with 500 maximum iterations.

Algorithm	Minimum fitness value of overload capacity function	Minimum fitness value of distance function	Execution time (s)
Proposed MOABC	5.8	8.72×10^{8}	161
Standard MOABC	49.0	1.18×10^{9}	163
NSGA-II	38.9	1.08×10^{9}	1971

Furthermore, it was important to assess the evolution process of the algorithm throughout iterations and track how the algorithm improves the solutions. From an operational perspective, the improved MOABC optimally allocated the minimum number of population (evacuees) as possible based on the capacity of shelters that they are assigned to. Hence, finding the closest shelter was achieved by minimizing the total travel distance at the same time as minimizing the overload capacity of the shelters. Figure 11 illustrates the variation of six selected generations together with the spatial allocation of evacuees to the assigned shelters. The minimum fitness values obtained from an optimal solution at each generation are also presented in Figure 11.

In addition, the sensitivity analysis on repeatability also displayed interesting results and proved the stability of the algorithm when solving the evacuation model. The convergence results showed how progressively the improved MOABC has optimized the distance and capacity objective functions through 500 generations.

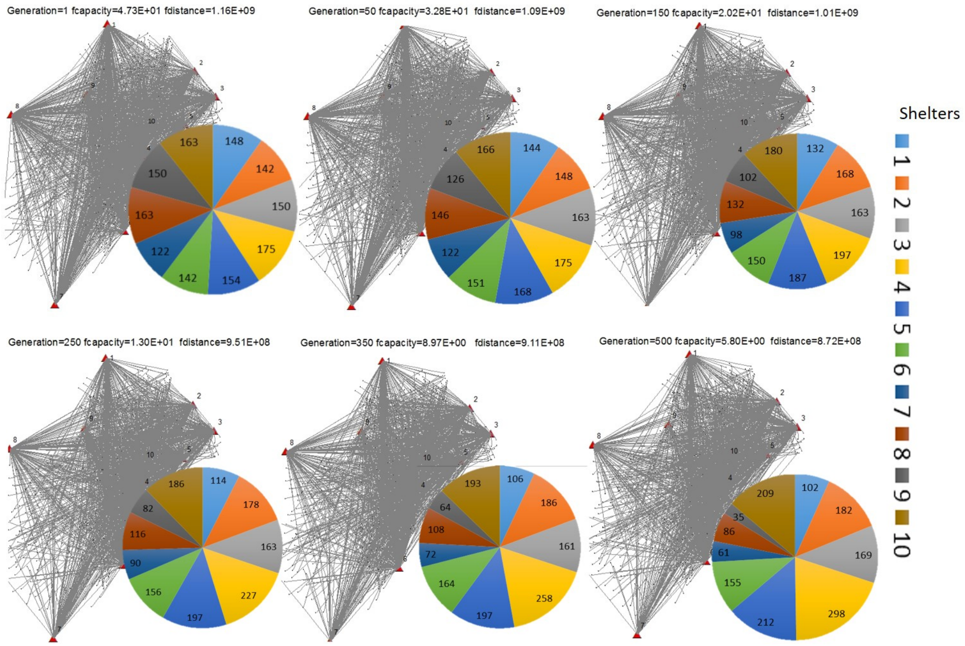

Figure 11. Variation of optimum solutions through generations. The grey lines on each graph represent the allocation of shelters. The numbers of building blocks assigned to shelters are represented on the pie chart on the right side of each graph. The minimum fitness values of capacity overload and distance function obtained at 1st, 50th, 150th, 250th, 350th generations are represented respectively. Modified form Paper II

Improved MOCS algorithm for evacuation planning

The motivation for the study in paper III was that the evacuation planning models solved in paper I and paper II involved only two conflicting spatial objectives, while there are many more factors to be considered when planning for efficient evacuation in urban areas of developing countries. For instance, the damaged roads and destroyed bridges could be a big challenge to the planners to decide on the best alternative of rescuing people from danger. In this case, a risk function was defined, tested, and adopted in the development of the evacuation model. The model consists of optimizing the distribution of people from disaster risk zones to safe areas, using the shortest and secure paths, and minimizing the shelter's overload capacity. However, a spatial decision problem with many objectives becomes even more complicated to be solved by the traditional methods. Therefore, a novel metaheuristic algorithm called multi-objective cuckoo search (MOCS) was modified and applied to fit better to the problem. The model was tested on geographical and population data of Mozambique, a Sub-

Saharan African country that is also prone to many natural disasters including hurricanes, cyclones, and floods.

The performance tracking of the improved MOCS algorithm showed that the computation time is below that of the standard MOCS algorithm. This proves that the modifications made on the main operations of MOCS have impacted the behaviour of the algorithm from a performance perspective (computation time). The application of crossover and mutation operators has raised the generation of new individuals with better solutions to take place in the next generations. Also, Lévy flights method adopted for selection, avoided the best solutions to be trapped in the local search process. Furthermore, the convergence speed was investigated to analyse how each objective function has been minimized. The mean value of the minimum fitness values in each generation was retrieved and it was found that there is a minor difference between convergences of the three objective functions.

Furthermore, the Pareto front size (number of non-dominated solutions) over generations has been analysed, it appears that when the initial parameters were set to 200 population and 500 generations, the improved MOCS obtained a smaller Pareto font size compared to that of standard MOCS. However, this is not a significant difference since the Pareto front size could change based on different parameter settings and the number of generations of an algorithm (refers to the results in paper I-II). Other important indicator is the diversity among solutions and to verify if the trade-off between objective functions meets the goal of the optimized problem. In this case, the hypervolume indicator was employed in the analysis of the results to measure the quality of Pareto front of the improved MOCS algorithm against that of the standard MOCS (Figure 12).

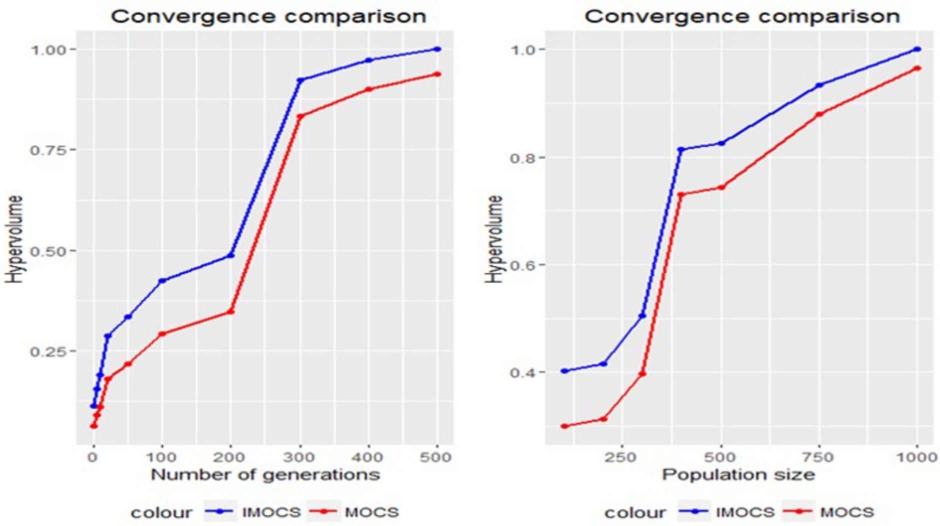

Figure 12. The hypervolume convergence analysis of optimal solutions through different number of generations (on the left) and population size (on the right). Adopted from Paper III.

Sustainable urban land-use planning approach using an improved NSBBO algorithm

Sustainable urban land-use allocation deals with the spatial arrangements of various land use to specific land units in a geospatial context. It contains social, economic, and environmental dimensions that involve different objectives (Mohammadi, Nastaran, and Sahebgharani 2016). Moreover, optimality is the key element of sustainable urban land use planning (Cao et al. 2011). These factors make sustainable land-use allocation to be regarded as a multi-objective optimization problem. Thus, paper IV of this thesis aimed to develop a multi-objective spatial optimization model for sustainable land-use allocation using an improved non-dominated sorting biography-based optimization (NSBBO) algorithm.

The goal of the developed model was to generate optimal alternatives of land-use allocations plans that lead to the balance of social integration and economic benefits in urban design areas via three spatial objectives: maximizing accessibility, maximizing compactness, and maximizing space syntax integration. This study proposed the use of an integration attribute as a new spatial component to be considered in multi-objective land-use optimization modelling. Moreover, several studies related to land use optimization modelling have often used methods that belong to evolutionary algorithms (EAs) (Rahman and Szabó 2021), since they are known to be efficient. Nevertheless, there is a need of exploring other potential algorithms that could perform even better than those EAs when they are modified and improved to fit the spatial decision problem.

In the modelling of NSBBO, parameters such as the number of generations, the size of the initial population, and the mutation probability rate play an important role in the performance and output of the algorithm. In this context, several tests have been done to study the effects of parameter changes. The results showed that the set of a high number of population and generations results in high computation time, while the obtained minimum objective values of the three objective functions are not highly affected by the changes of parameters. By analysing the optimization progress of non-dominated solutions through generations, it was observed that the algorithm converged smoothly towards the minimum value.

The contribution of the study in paper IV is twofold. First, the presented NSBBO algorithm can be used to create a set of base plans from comprehensive to detailed plans of land uses allocation. For instance, each optimal solution from a trade-off (Pareto front) can be interpreted as a prototype of a land-use plan that fulfils the concerns of specific decision-makers' interests (Figure 13). Figure 13 (a) shows the land-use map of the best solution that maximized the accessibility function. It can be observed that the NSBBO model has produced an optimal distribution of certain land uses across the residential area (e.g., mixed schools, shops, public facilities, and parks). The land-use map of best solution that maximized the spatial compactness is presented in Figure 13 (b). Land uses such as schools, open space and parks are the most compacted. Moreover, Figure 13 (c) represents the optimal land-use map of the best solution that maximized the space syntax integration function. As the space syntax integration function focused only on the allocation of commercial land use types (named neighbourhood centers), it can be seen that the cells in red colour that represent neighbourhood centers are distributed in the centre of the study area where the streets with high integration values were identified (paper IV).

Furthermore, the maximization of accessibility objective could contribute to the environmental aspect, while social equality concerns are included in the objectives of compactness and space syntax integration. Secondly, we compared the map of land-use allocation produced by the NSBBO algorithm with the existing land-use map allocation proposed in the master plan of the study area.

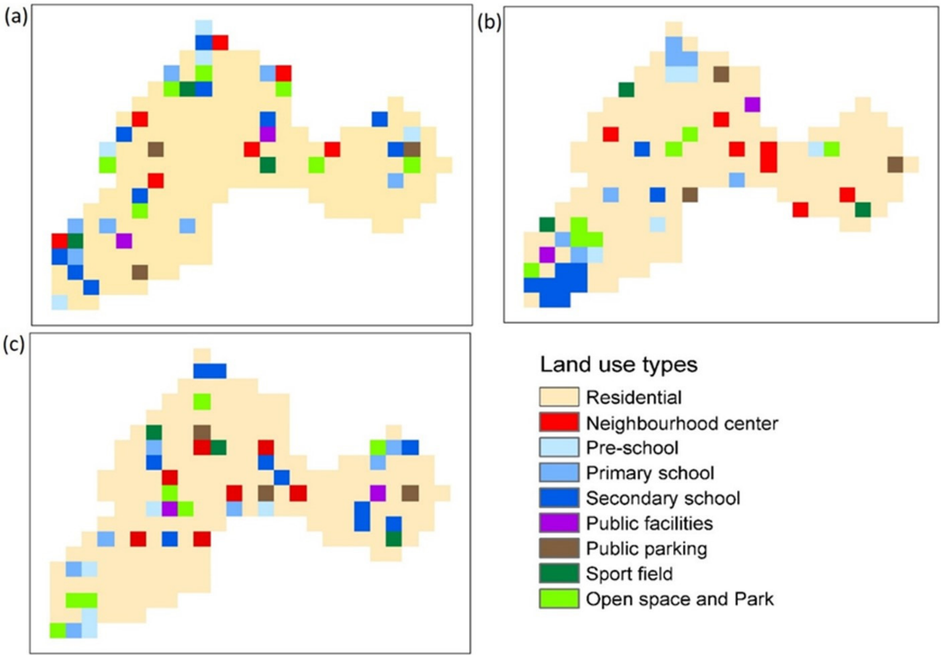

Figure 13. Correspoding spatial patterns are the best solution that maximized each objective function. (a) maximization of spatial accessibility, (b) maximization of spatial compactness, and (c) maximization of space syntax integration. Adopted from Paper III.

It was concluded that a land-use plan of NSBBO algorithm provided better compactness of some land-uses such as schools as well as an optimal distribution of shops across the residential area. This advantage could contribute to the reduction of cost and negative influences of improper decisions on urban land-use planning, particularly in developing countries.

Conclusions and Outlook

The present research demonstrated the potential use of integrated geographical information systems and multi-objective decision-making methods in solving complex spatial decision problems. The complex spatial multi-objective optimization models in disaster management and urban planning contexts were explored and developed. Furthermore, the GIS tools and metaheuristic techniques were investigated and used to solve the defined spatial optimization problems. The generation of high-quality alternatives is a key to the success of spatial multi-objective decision making. The methodological essence of metaheuristic algorithms is based on the process of evolution from initial random solutions toward a diverse set of optimal or near-optimal solutions. Because the employed metaheuristic algorithms are population-based, it is possible to design and modify algorithms to fit better to the spatial problem and to encourage the convergence of diversity and optimality. The findings showed that the employed metaheuristic algorithms are particularly appropriate for spatial multi-objective decision making.

This thesis fully benefits from a better understanding of GIS-MODM methods and their implementations to address real-world problems. However, several critical issues require further investigation. Here, three important future topics are identified. By addressing these issues, researchers and decision-makers will be equipped with more effective tools to solve spatial multi-objective decision problems.

1. Spatial optimization problems often have objectives and constraints that are difficult to translate into mathematical forms. Though metaheuristics, particularly EAs and SA algorithms, have proven to be efficient in addressing such constraints, a unified approach to constraint handling for a wide range of spatial problems would be useful. Xiao (2008) demonstrated a unified conceptual framework for geographical optimization using evolutionary algorithms that can be applied to different spatial problems. A similar study of the conceptual framework for instance using Swarm intelligence algorithms is still needed.
2. The metaheuristics algorithms, GIS tools, and visualization techniques discussed in this thesis have been separately implemented in different forms,

and efforts are needed to integrate them into a more coherent system that can be used to address spatial applications.

3. The issue of evaluating GIS-MODM methods is a very complex one since the outcome is ultimately dependent on the decision maker's preferences, expectations, and knowledge. Moreover, there are several issues related to analysing trade-offs that may have an impact on decision-making. The sensitivity analysis method using different criteria to measure the quality of the results such as hypervolume indicator, and assessing Pareto front solutions (i.e., study multiple scenarios of trade-offs), have all shown to have an impact on how we make decisions. In future work, the impact of the uncertainties on the GIS-MODM methods should be investigated.

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