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Multi-objective urban land use optimization using spatial data: A systematic review

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A R T I C L E I N F O

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A B S T R A C T

Land use optimization is a promising approach to achieve urban sustainability. Despite the increasing number of literature on land use optimization, a little investigation is made to systematically review urban land use optimization: its objectives, methodological approaches, and spatial data used etc. This creates room to review the methodological approaches to urban land use optimization. This study systematically reviews 55 articles following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol to understand important aspects of urban land use optimization. We have found that the most common objectives which were used in urban land use optimization are maximization of spatial compactness (16.67 %, n=28) and maximization of land use compatibility (13.69%, n=23), followed by maximization of land use suitability (11.90%, n=20). The findings suggest that a) one and only one land use in each cell, b) minimum and maximum area of certain land use, and c) restriction on specific land use change are the important constraints. This study also identifies that urban sustainability has been merely touched upon in urban land use optimizations. While environmental (including ecology) and economic aspects of urban sustainability were included in 46.67% and 43.33% studies respectively, the social aspect (10%, n= 3) was mostly ignored. Our findings also indicate that there is no generalized method to measure economic, environmental, and social benefits from land use planning. This study also finds that the Genetic Algorithm (GA) (32.14%, n=18) accounts for a major contribution to solve the urban land use optimization problem. Based on the findings, this study proposes some recommendations for further research and practice. The most important of them include a) framing land use optimization objective functions considering urban sustainability, b) developing a standard method to calculate values of objective functions, and c) integrating a participatory approach with mathematical optimization to derive more feasible solutions. These recommendations could be the scope of future research.

1. Introduction

1.1. Background

Land use optimization is an important tool to achieve sustainable urban land use planning, which aims to achieve long-term balanced urban development through economic prosperity, efficient resources use, environmental protection, and social equity (Cao, Huang, Wang, & Lin, 2012; Cohen, 2017; Ligmann-Zielinska, Church, & Jankowski, 2008). It is entrusted with allocating different land uses (e.g., residential land, industrial, commercial, recreational facility, open space, parks, and green land, etc.) in such a way as to derive optimal benefits. (Cao, Huang, Wang, & Lin, 2012). But, in reality, these objectives are competing and even, sometimes, conflicting (Huang & Zhang, 2014). For example, if residential development occurs in a low-lying area, it may fulfill the demand for urban housing, but it will create a problem for urban drainage. Construction of building structures may increase economic benefit, but it will deteriorate the environment and urban health. So, careful land allocation is of paramount importance in land use planning. Here comes the concept of land use optimization that allows generating alternative land use scenario from which the decision-maker choose the best option considering conflicting interest (Cao & Ye, 2013; Ligmann-Zielinska, Church, & Jankowski, 2008).

Land use optimization is a branch of spatial optimization that consists of three essentials elements. These are a) decision variables, b) objective functions, and c) constraints (Ligmann-Zielinska, 2017; Tong

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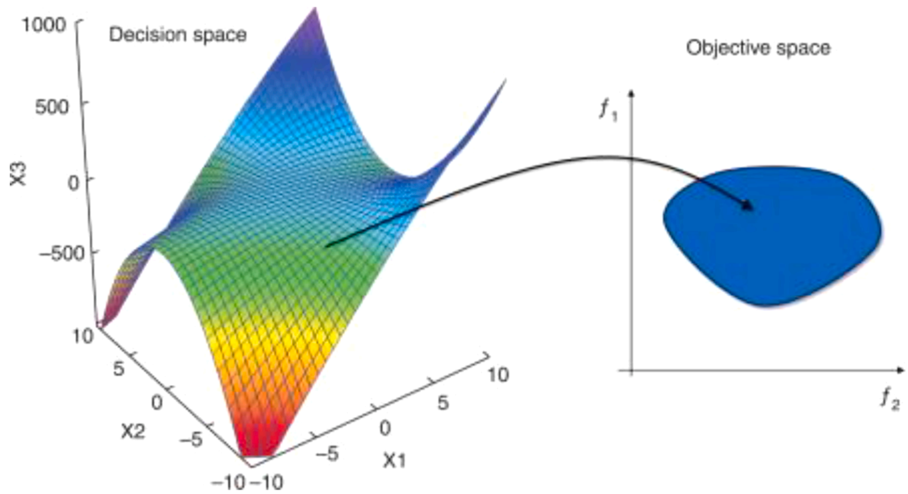

Fig. 1. Mapping between the decision variable space and the objective function space (Givi & Asadi, 2014).

& Murray, 2012). A multi-objective land use optimization problem can be formulated as follows (Deb, 2011):

$$\textit{Minimize or Maximize } f_m(x),\ m = 1, 2, \ldots\ldots\ldots M;$$

$$\text{Subject to } g_j(x) \geq 0,\ j = 1, 2 \ldots\ldots\ldots\ldots J;$$

$$h_k(x) = 0,\ k = 1, 2, \ldots\ldots\ldots\ldots K;$$

$$x_i^{(L)} \leq x_i \leq x_i^{(U)},\ i = 1, 2 \ldots\ldots\ldots\ldots n$$

Where $f_m(x)$ constitute the objective functions; $g_j(x)$ and $h_k(x)$ are the inequality and equality constraints, respectively. x_i is the spatial decision variable; $x_i^{(L)}$ and $x_i^{(U)}$ are the lower and upper bounds of the decision variable.

Decision variables in the optimization problem can be defined as quantities whose values can be changed and need to be determined to solve the optimization problem and get the solution(s) (Wang, Zhang, & Peng, 2021). The decision variables strongly influence the formulation of objective functions. An objective function simply is a function of decision variables. The objective function is either minimized or maximized to find the optimal values of decision variables. The values of decision variables are called solutions to the problem. In the context of 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. A mapping is developed between m-dimensional decision variable space and n-dimensional objective function space (Givi & Asadi, 2014). The mapping between the decision variable space and the objective function space is illustrated in Fig. 1.

In the case of the land use optimization problem, four main decision variables are considered. These four decision variables are type, size, location, and capacity (Huang, Liu, Li, Liang, & He, 2013; Mohammadi, Nastaran, & Sahebgharani, 2015). By combining these variables, any land use optimization problem tries to find the quantity (size) of specific land use (type) which needs to be allocated in a particular place (location) in order to optimize a specific objective (e.g., maximize economic benefits). Two types of constraints may be contained in the multi-objective optimization problem: a) inequality constraints, b) equality constraints, and c) lower and upper boundaries constraints. Detail discussion on constraints has been made in Section 3.2.2.

1.2. Rationale of this research

Studies on land use optimization are significantly diverse in terms of methods, objectives, and other elements (Mingjie Song and Chen, 2018b; Wang, Gao, Liu, & Song, 2010). For example, Cao et al. (2020) constructed a multi-objective land use optimization model using goal programming and a weighted-sum approach supported by a boundary-based genetic algorithm; Gao et al. (2020) developed an improved Non-dominated Genetic Algorithm-II (NSGA-II) to achieve sustainable urban land use; Zhang, Wang, Cao, He, & Shan, 2019 proposed a genetic algorithm-based multi-objective optimization (MOO) approach; Li & Ma, 2018 designed a new simulated annealing (SA) algorithm for spatial optimization of land resources. The choice of methodological approach, objective functions, constraints, and spatial scale in the data have much impact on the outcome of the study. For example, Song and D. M. Chen (2018b) performed a comparative analysis on three heuristic algorithms, namely Genetic Algorithm (GA), Simulated Annealing (SA), and Particle Swarm Optimization (PSO), to solve land use optimization problem. They considered three objectives, including a) maximizing land suitability, b) maximizing spatial compactness, and c) minimizing land conversion cost. Their result shows that the performances of the three algorithms are different on the three objectives. So, a clear understanding of their selection is very important.

A Systematic review of different aspects of land use optimization might offer ground to clearly understand and rethink the optimization process and foresee associated outcomes. By nature, it selects, identifies, and assesses related research using explicit methods to collect and analyze relevant data and aspects from different studies. It identifies the differences in approaches and associated outcomes towards a problem under investigation. It also provides an insightful synthesis of contemporary evidence related to a specific research problem (Nasir Ahmad, Mustafa, Muhammad Yusoff, & Didams, 2020). Although there is an increasing number of works in urban land use optimization, a limited number of studies investigated land use optimization from different approaches and settings. Therefore, there is a clear need for a systematic review of urban land use optimization to synthesize the core elements and to consolidate contemporary evidence of the outcome. As far as the authors are aware, there is no comprehensive review on this topic. This paper attempts to fill this gap by systematically reviewing and synthesizing contemporary research, and it is expected that this review paper will add value to future research on the topic concerned.

1.3. Objective and research questions

Against the background described in earlier sections, this paper explores the existing land use optimization to understand its elements, aspects, and context. To this end, this study will answer the following research questions. The novelty of this study is to investigate the following research questions, which were not answered in any previous study by a systematic investigation.

Table 1
Search term, sources, and the corresponding number of articles identified.

Search Term	Number of Articles found from		Search Date
	Web of Science	Scopus	
(land AND (optim* OR Allocat*)) OR (((land AND zoning) OR (spatial AND planning)) AND optim*)	1119	1150	23 July, 2020

a) Which objectives are the most important in urban land use optimization?
b) Which constraints, approaches, and methods are commonly used to construct and solve urban land use optimization problems?
c) What are the spatial data and models used in urban land use optimization?

2. Materials and methods

This study is a presentation of literature on land use optimization problems following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol (Moher et al., 2009). Although PRISMA protocol was developed exclusively for health and medical-related field, recently, it has been using in many areas, including environment, water, agriculture, land management, and sustainability research (Cohen, 2017; Higgins, Balint, Liversage, & Winters, 2018). PRISMA has some advantages, which include a) developing straightforward research questions, b) explicit inclusion and exclusion criteria, c) aiming to identify and evaluate massive relevant scientific articles, d) charting and tabulating of data, and 5) reporting and summarizing the results. This approach is also easy to use compared to other "traditional narratives." Traditional narratives in literature review follow an unstructured review approach to establish a theory on a specific research area (Steward, 2004). For example, some narrative reviews may illustrate methods and research design, and some may outline the historical development of a theory, some may concentrate on evaluating the theory, some may define the scoping of research. Traditional narratives have several limitations. They only present a broad overview of a research problem, do not have a predefined protocol, and emphasize the author's intuition and experience, and even they do not answer any specific research question (Pae, 2015). Another important limitation in a narrative review is that this type of review includes the author's biases, and they are not suitable for replication (Robinson & Lowe, 2015).

On the other hand, systematic reviews, for example, PRISMA protocol, follow a structured analysis of data and evidence collected from existing research (Pae, 2015). In the whole review process, strict criteria are defined to include and exclude the available research and to limit the author's bias. Due to the use of a well-defined protocol, it can limit bias and promote scientific evidence (Zhu, 2020). Considering the limitations of traditional narratives, we have used PRISMA protocol in our study. Based on the PRISMA protocol, the specific method used in this study is presented in the following sections.

2.1. Search strategy

We have searched the Web of Science Core Collection database and Scopus database to find the article. We have applied our search term on "Article Title" only. We have limited our search to journal articles written in English with no time limit. The search term used, and the corresponding number of articles identified have been presented in Table 1. After the search is finished, we have exported the metadata of articles as CSV file format from Scopus and an Excel file from the Web of Science database. The exported CSV file has been converted into Excel format. We have also identified 22 articles from other sources. All these

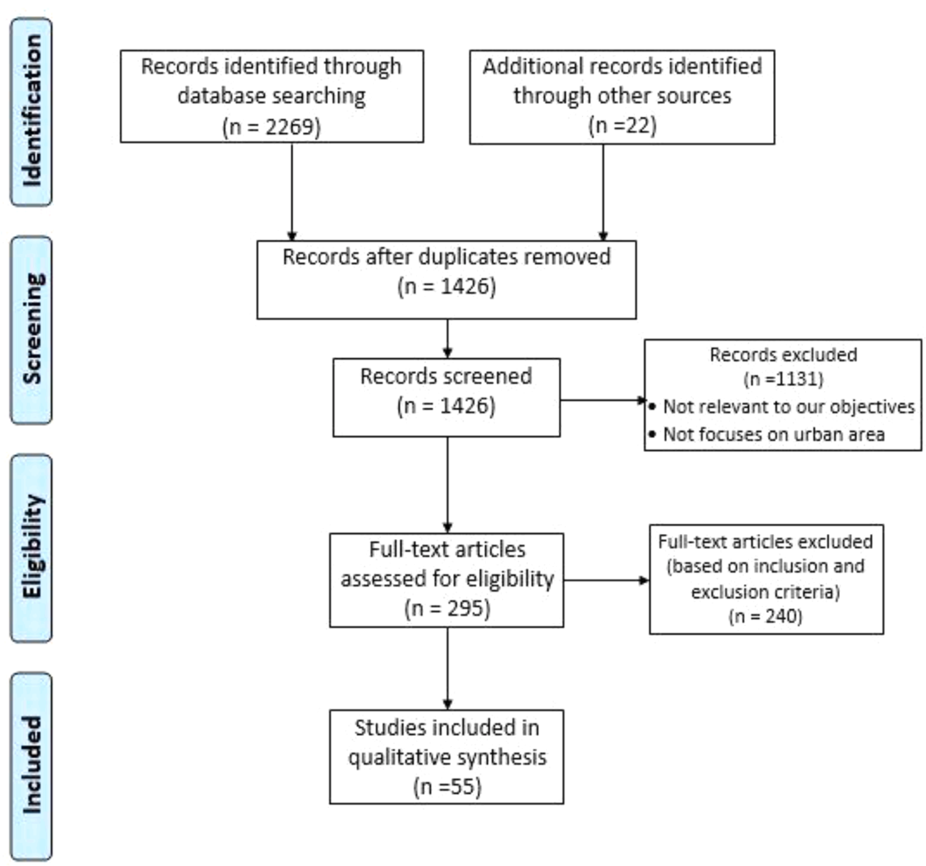

Fig. 2. PRISMA flow diagram of the literature search and final inclusion of papers Adapted from (Moher et al., 2009).

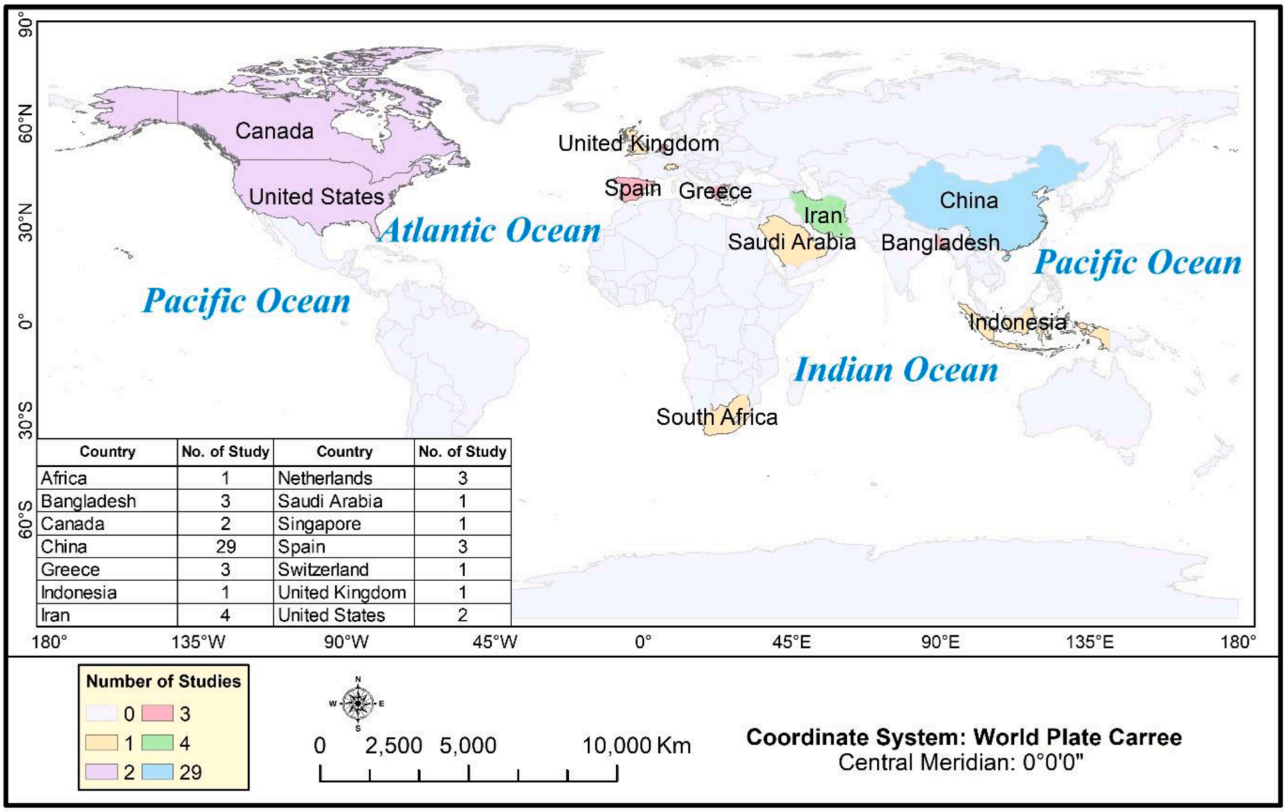

Fig. 3. Country-wise distribution of reviewed studies.

articles' data have been combined in Excel for further analysis. The systematic screening procedure, to include the full-text article for review, has been described in Section 2.3.

2.2. Eligibility criteria

According to PRISMA protocol, two categories of eligibility criteria are recommended for the inclusion and exclusion of research articles. These are study characteristics (e.g., problem, intervention and study design, etc.) and report characteristics (e.g., geographical location, years considered, language, publication status, etc.) (Moher et al., 2009). Following this guideline, we have included those studies which a) explicitly focuses on multi-objective land use optimization; b) follows the mathematical approach of optimization; c) uses spatial data; and d) produce measurable quantitative results. In the case of report characteristics, we have considered the studies which a) focused only on urban areas; b) were written in the English language; c) were published in a peer-reviewed journal article. Some land use optimization problems focused on a regional scale; we did not include those studies in our review because the objectives of regional level land use optimization are somewhat different from those of urban areas. For example, one common objective for land use optimization on a regional scale is the maximization of agricultural productivity, but it is not much relevant in the case of an urban area.

2.3. Systematic screening of the articles

The PRISMA flow diagram has been presented in Fig. 2. PRISMA protocol has proposed a four-stage systematic screening procedure for inclusion and exclusion of the articles for review. In the first stage, based on the search strategy, a total of 2291 articles have been initially selected from Web of Science, Scopus, and other sources. In the second stage, we have sorted all the articles in MS Excel and removed the duplicate records. Some 865 articles were removed, leaving 1246 articles for the next stage of screening. In the third stage, we have excluded the studies if a) they are not directly relevant to our study objective (skimming in article title and abstract), and b) they do not focus on urban areas. Thus, 1131 articles are excluded keeping 295 articles for full-text evaluation. In the fourth and final stage, we have scanned these 295 articles thoroughly and finally included 55 articles for our review based on the inclusion and exclusion criteria described in Section 2.2.

2.4. Charting and tabulating of data

We have created the article database using MS Excel. The article database includes the title of the paper, names of the authors, name of journal, country of the study, year of publication year, objectives, constraints, spatial data used, spatial data model, Approach to construct optimization problem, and Method. The list of the selected articles (n=55), along with relevant attributes, can be found in https://doi.org/10.17632/vr8w6v6yj8.1. The study location map has been created using ArcGIS 10.2 software, and all other Fig.s have been prepared in R(R Development Core Team, 2011).

3. Results and discussion

This section presents our findings of the study. Firstly, we have presented the general report characteristics (e.g., geographical location, publication year, and publication journal) then we have presented our detailed findings of study characteristics.

3.1. Report characteristics

We have compiled 55 papers, global-scale distribution of which shows a broader perspective about how urban land use optimization was emphasized in different countries in the land use planning process. Our

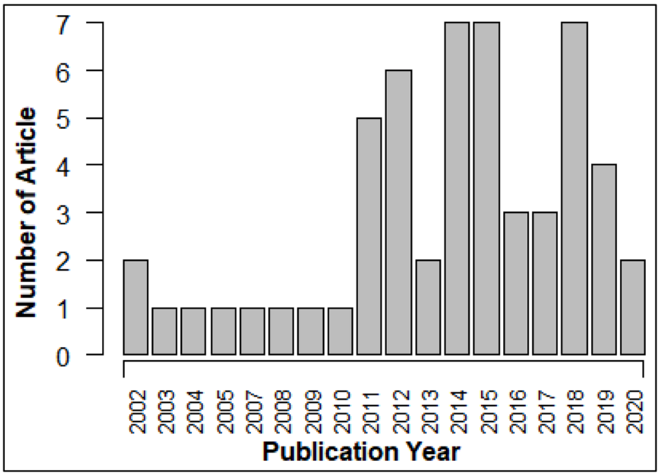

Fig. 4. Distribution of studies by publication year.

analysis (Fig. 3) shows that urban land use optimization studies were conducted in 7.61% (n=15) countries globally (Considering 197 countries in the world according to UN's recognition). Out of which, 52.73 % (n=29) studies were conducted in different cities in the Peoples Republic of China, while 7.27% (n=4) studies were conducted in Iran and only 5.45% (n=3) studies were conducted in Bangladesh, Greece, Netherlands, and Spain. It is clear from our analysis that the Peoples' Republic of China emphasized more on optimizing urban land use compared to other countries in the world. However, the geographical distribution of studies seems disproportionate since most of the studies are from China, where the representation of the western world is limited. The fact is that there are many studies of land management in the western world, and most of them focus on a regional scale rather than the urban scale. For example, García, Rosas, García-Ferrer, & Barrios, 2017 worked on sustainable land use allocation at a subregional scale in Spain, Bourque *et al.* (2019) worked on land use optimization in California to increase agricultural benefits, Uludere Aragon *et al.* (2017) focused on perennial bioenergy crop production in land allocation in the United States, Armsworth *et al.* (2020) optimized land resources allocation in the southwest United States. The studies did not focus on an urban area, and there are differences in the optimization objectives between an urban area and other areas (e.g., agricultural area). Whereas our study focuses only on the urban area and multi-objective optimization problems, so we have included those studies only, which fulfilled the eligibility criteria as discussed in Section 2.2.

Fig. 4 shows the trend of studies on urban land use optimization. Fig. 4 indicates that before 2002 there were no studies on urban land use optimization. It can be noted that, although there were many studies on land use optimization before 2002, those studies did not fulfill our inclusion criteria, and hence, we did not include those studies. This review only focuses on urban land use optimization, not other land uses (e.g., Rural land use optimization, Agricultural land use optimization, etc.). There is one interesting point that there is an increasing trend in studies on urban land use optimization since 2011.

The top 7 journals in which studies on urban land use optimization have been published are presented in Fig. 5. "International Journal of Geographical Information Science" and "Computers, Environment and Urban Systems" are two important journals in which most of the studies (n=7) were published.

3.2. Study characteristics

In section 1.4, we have set our research objective and research questions. We have set three research questions to understand urban

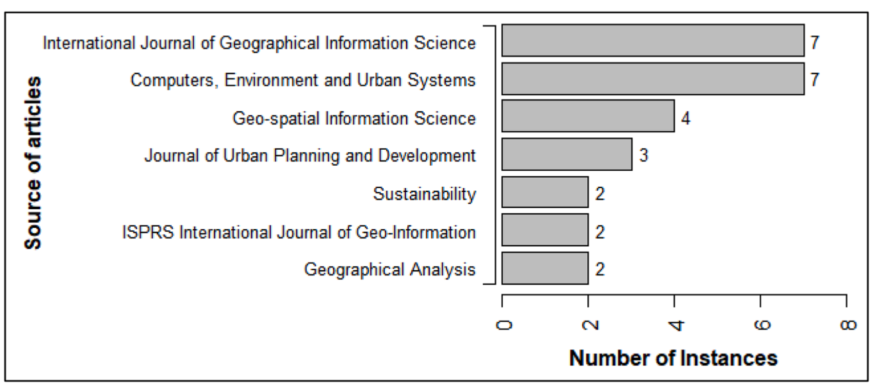

Fig. 5. Top seven Journal, which published at least two papers with a primary focus on urban land use optimization.

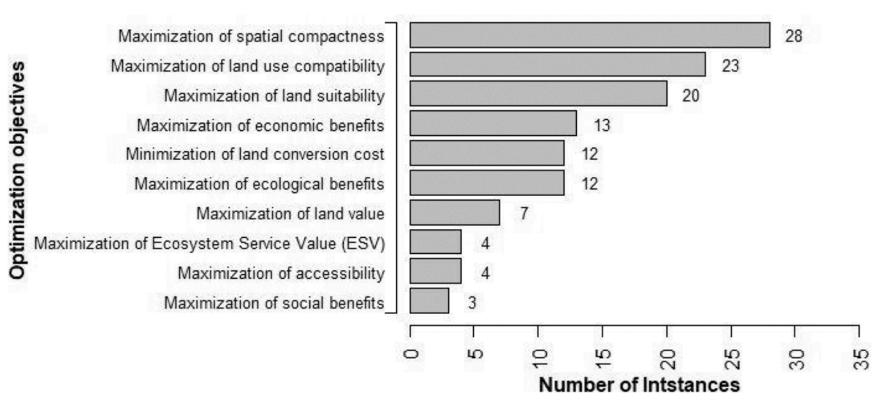

Fig. 6. Ten (10) most frequently used objectives in the urban land use optimization problem.

land use optimization. In the following sections, we have presented and discussed our study findings to answer all the research questions.

3.2.1. Objective formulation

We have identified about 43 objectives[1] from 55 Journal articles, which were used in urban land use optimization problems. These objectives are generally of two types in the case of urban land use optimization problems: a) additive objectives and b) spatial objectives. Additive objectives are calculated using the representative value or attribute of each land parcel (referred to as a cell) without considering the characteristics of land use configuration. On the other hand, spatial objectives are calculated by considering the characteristics of land-use configuration, e.g., the connectedness, contiguousness, or fragmentation of land-uses under the area of interest (Stewart, Janssen, & Van Herwijnen, 2004). The ten (10) most frequent objectives are presented in Fig. 6.

According to Fig. 6, the most frequently used objective is the *maximization of spatial compactness*. It constitutes about 16.67 % (n=28) of the total objectives. This objective has been undertaken in many studies because it is preferred that similar land uses should be in the vicinity of the same land uses to generate high general benefit from land uses. (Feixue Li et al., 2018). The benefits of spatial compactness in urban land use are well documented in the literature. These benefits include less emission from transport, promotion of walking and bicycling, short travel distance, conservation of countryside rural area, encourage public transport, low motorized mobility, equitable access to social infrastructure and services, promote public health, efficient utility services, and revitalization and regeneration of urban core, etc. (Williams, Burton, & Jenks, 2013). Mouratidis (2019) showed that residents of compact-city avail higher level of social interaction, personal satisfaction, and perceived physical health benefits; Russo & Cirella, 2018 showed that compact city development contributes to achieving urban sustainability. Therefore, maximizing spatial compactness was considered in many land use optimization problems.

Since global land is scarce and limited, city authorities are concerned about making the city compact through high-density development, reducing scattered development, and saving land. It is well-recognized that urban sprawl is an urgent problem in cities, especially in developing countries. On the other hand, compact cities play an important role in eliminating urban sprawl, alleviate pollution and promote social justice (Huang & Zhang, 2014; Feixue Li et al., 2018). It is argued that a compact city contributes much to achieve overall sustainable urban development. Many governments have formulated various policies towards achieving sustainable urban development through compact cities. Thus, consideration of maximizing spatial compactness in many studies reflects global concern about sustainable urban land use planning.

Fig. 6 indicates that the second important objective used in urban land use optimization is the *maximization of land use compatibility* followed by *maximization of land use suitability,* which accounts for 13.69% (n=23) and 11.90% (n=20) of the total objectives, respectively. Land use compatibility can be defined as the situation in which current land use or activity can co-exist with neighboring land use or activity without creating any adverse effect. Land use compatibility has been addressed in many land use optimization problems due to several reasons. First, land use compatibility contributes to attaining the highest and best use of land. The best use of land helps to create economic vitality, sound community, and promote social interaction. Secondly, compatible land uses reduce the physical, social, and economic conflicts that arise due to incompatible land uses. Third, it has significance in achieving social interactions, a pleasant and healthier environment, increasing urban livability through human-environment interaction (Kai Cao et al., 2020; Handayanto, Tripathi, Kim, & Guha, 2017; Mingjie Song and Chen, 2018b). Our findings on land use compatibility are also supported by many other studies. For example, Pahlavani, Sheikhian, & Bigdeli, 2020 evaluated residential land use compatibilities using the density-based model to understand to what extent other non-residential land uses are compatible with residential land uses; Kiani Sadr, Nassiri, Hosseini, Monavari, & Gharagozlou, 2014 assessed the impact of land use compatibility on noise pollution and found that incompatible land uses leads to noise pollution; Libby & Sharp, 2003 worked on policy issues to ensure land use compatibility in rural-urban fringe; Cohn et al. (2005) studied the impact of land use compatibility on highway noise.

The third important objective is the maximization of land use suitability (LUS) which has also been used in many land use optimization problems. LUS is defined as the degree of fitness of a certain type of land use to be allocated in a specific land parcel considering preferences, requirements, or predictors of some activities. LUS has been considered in many land use optimization problems because it informs decision-makers about the social, economic, and environmental consequences of particular land use choices within land use planning. Due to the continuous urban sprawling, it creates the burden on the urban environment beyond the capacity of the city, which leads to serious conflicts among different competing urban land uses, and creates serious environmental problems, including fragmentation of natural resources, deficiency of land resources, and air pollution (Huang, Li, & Zhang, 2019). It is argued that part of these issues arise due to the lack of suitability among different land uses within the urban area (Akbari, Neamatollahi, & Neamatollahi, 2019). The significance of land use suitability in land use optimization is also justified by other research findings. Bagheri, Sulaiman, & Vaghefi, 2012 urged to evaluate the land suitability in a coastal area of Malaysia to provide a suitable room for the coastal ecosystem; R. Liu, Zhang, Zhang, & Borthwick, 2014 developed an Urban Development Land-use Suitability Mapping (UDLSM) approach to mapping urban development land-use suitability in Beijing; Parry, Ganaie, & Sultan Bhat, 2018 attempted to find suitable locations for urban amenities and other services based on GIS-based land suitability analysis using AHP model.

Some other objectives used frequently in urban land use optimization are Maximization of economic benefits (7.74%, n=13), Maximization of ecological benefits (7.14%, n=12), Minimization of land conversion cost (7.14%, n=12), Maximization of land value (4.17%, n=7), Maximization of accessibility (2.38%, n=4), and Maximization of Ecosystem Service Value (ESV) (2.38%, n=4). Maximization of ecological benefits and maximization of Ecosystem Service Value (ESV) are similar to each other. Both the objectives were addressed in many land use optimization problems since they provide multiple services which have significance to the health, well-being, livelihood, and survival of humans. Due to urbanization worldwide, human-ecology interaction has been a major issue of environmental concern. The impact of land use changes, resulted from human-ecology interaction and urbanization, on ecosystem services is well documented. For example, Su, Li, Hu, Xiao, & Zhang, 2014 assessed the ESV changes of Shanghai, China, from 1994 to 2006 and found that ESV had decreased significantly due to land use changes caused by urbanization; Estoque & Murayama, 2013 investigated the changes in ESV of a city of Philippines and noticed that there is a substantial decrease in annual ESV due to land use changes caused by population growth and urban expansion.

Maximization of economic benefits has been undertaken in many land use optimization problems since differences in geographical locations, different land uses have a different economic benefit, and even the same land use in a different location might have a different economic benefit. Economic benefit from land use has also been considered from an urban sustainability point of view. Maximizing total economic benefit from land use is not enough for urban sustainability; equitable spatial distribution is also necessary to reduce social conflict. Land use optimization plays an important role in maximizing economic benefit while ensuring equitable distribution of economic production and social

[1] This number represents unique objectives. Some objectives were used in multiple studies, thus a total of 168 objectives including duplication were identified from 55 Journal articles.

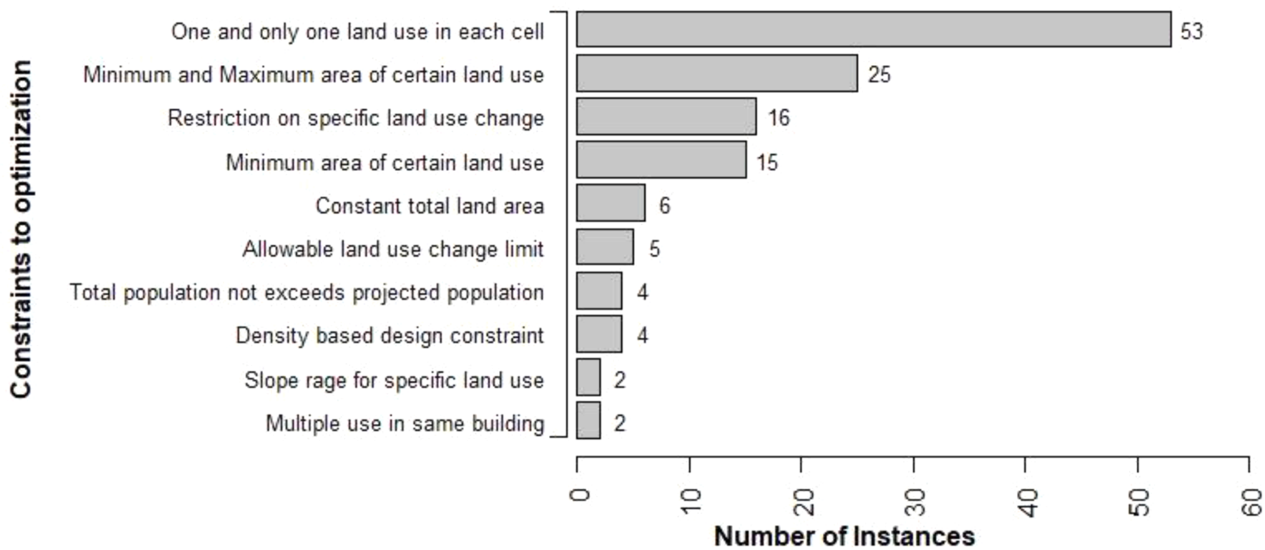

Fig. 7. Ten most frequently used constraints to the optimization and corresponding number of instances in the literature.

justice in terms of economic benefits from land use allocation. Various studies have emphasized this issue of equitable distribution of economic benefits from land use. For example, in Kerala, India, the social conflict has been reduced through equitable distribution of economic resources and land use rather than only maximizing economic benefits (Basiago, 1998).

The objective "minimizing land conversion costs" has been included in many land use optimization problems because it will result in decreasing the development cost and, in turn, will improve overall societal and economic benefits. Accessibility indicates how accessible are the urban services. It is measured in terms of the distance between the two land uses types under concern; the smaller the distance between two land use types, the more is the accessibility between them. Maximization of accessibility has been considered in land use optimization because it contributes to urban sustainability, enhances the overall quality of urban life, and improves urban livability. Studies suggest that a higher level of accessibility within the city can contribute to decreasing up to 80% of the CO_2 emission motorized transportation (Cao, Huang, Wang, & Lin, 2012). Accessibility issue in urban land use planning has also been emphasized in many studies, including Duranton and Guerra (2016) and Mora, Gilart-Iglesias, Pérez-Del Hoyo, & Andújar-Montoya, 2017.

It may be noted that the maximization of social and environmental benefits was not frequently used in urban land use optimization problems. One reason for this may be many researchers argued that social benefits could be collectively achieved through compatibility, compactness, and accessibility, etc. (Cao, Huang, Wang, & Lin, 2012; Y. Liu, Zhang, Zhang, & Borthwick, 2014; Zhang et al., 2016), and environmental benefits can be achieved through ecological and ecosystem service value, etc. (Feixue Li et al., 2018; Zhang et al., 2016). Therefore, consideration of environmental benefits was not directly visible in the urban land use optimization problem.

In connection with urban sustainability dimensions, our findings indicate that less attention was drawn to incorporate sustainability dimensions in urban land use optimization; only two studies focused on urban sustainability (Cao, Huang, Wang, & Lin, 2012; Yuan, Liu, He, & Liu, 2014). Overall, environmental (including ecology) and economic aspects were included in 46.67% and 43.33% of studies, respectively, but the social aspect (10%, n= 3) was mostly ignored. Our findings also suggest that there is a lack of using common proxy variables and standard methods to evaluate economic, environmental, and social benefits from land use optimization. Some researchers used GDP to measure economic benefit (Li & Parrott, 2016), while others used land rent theory to calculate economic benefit (Ma & Zhao, 2015). Some researchers considered carbon storage as a proxy variable to measure environmental benefit (Yuan, Liu, He, & Liu, 2014), where some researchers considered ecological suitability (Cao & Ye, 2013). Similarly, there is no established method to calculate social benefits from land use. So, there is a huge research scope to work on developing standard methods to measure social, environmental, and economic benefits from land use optimization.

3.2.2. Constraints

There are three types of constraints that are used in multi-objective optimization problems. These constraints are a) inequality constraints, b) equality constraints, and c) lower and upper boundaries constraints. In any optimization problem, decision variables are used to define the constraints. As mentioned in Section 1.1, there are four main decision variables in land use optimization problems. In which land use types include residential, commercial, water bodies, agricultural, recreational, and green space, etc., land use size means the quantity of area of particular land use to be allocated, land use location defines where the specific land use to be allocated, and capacity is the attribute attached to the land use or grid cell, e.g., the slope of the land or population density in a particular area. From the literature, we have identified about 15 unique constraints, excluding repetition. The ten (10) constraints are presented in Fig. 7.

From Fig. 7, it is evident that the constraint "one and only one land use in each cell" was used more frequently (n=53) in urban land use optimization problem followed by "minimum and maximum area of certain land use" (n=25) and "restriction on specific land use change" (n=16). The first constraint indicates that only one land use type can be allocated in one land unit. But the practical scenario is seen to be different. In many cities, there are buildings with multiple uses on different floors of the same building. Due to computational complexities, most of the authors did not consider multiple uses in the same building while optimizing land use allocation. We have identified only two studies by Haque & Asami, 2014 and Sharmin, Haque, & Islam, 2019 in which multiple uses in the same building have been allowed for optimizing land use allocation. The second most frequently used constraint is the minimum and maximum area of certain land use. The minimum and maximum limits of specific land use are defined to ensure balanced development and specific requirements. This range of limits totally depends on the high-level government, stakeholder's opinion, and land use

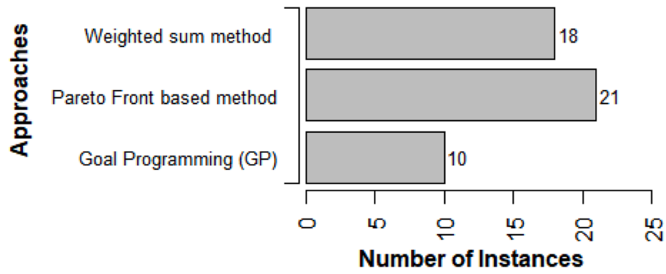

Fig. 8. Approaches to the construction of Urban land use optimization.

policy of the respective city. For example, the land use policy of China requires that the minimum area of arable land should not be less than 10 $\times$ 10^9 mu to ensure food security (Y. Liu, Zhang, Zhang, & Borthwick, 2014). Restriction of specific land use changes has also been used as a constraint in many studies to preserve certain land use categories. This restriction depends on the city's land use policy, need, and availability of specific land use types. For example, local regulations and national laws of Wuhan, China requires that a) in preservation areas, agricultural land cannot be converted to urban land, b) water bodies should be kept intact, c) urban land cannot be converted to agricultural land and d) land with a slope less than 25° cannot be converted to arable land (Yuan, Liu, He, & Liu, 2014). Constant total land use has been used as a constraint in some studies to confirm that total land area cannot be increased or decreased while optimizing land use allocation. This constraint has implications regarding the urbanization and expansion of cities. This constraint strictly prohibits cities from physical expansion and conversion of agricultural land around the cities. Authors considered this constraint in cities where there is no need or scope for further expansion of cities. For example, Zhang et al. (2016) used this constraint in their studies conducted in Changsha city of China to ensure that the city will not be allowed for further expansion. Allowable change limit of land use has been defined in some studies to allow increase or decrease of existing land uses up to a certain limit for land use. This constraint has implications in optimizing land use allocation. It is a general tendency for the quantity of land uses which produce higher economic benefits to be increased. For example, in general, commercial land produces higher economic benefits, whereas urban greenspace generates lower economic benefits. Under this situation, if no range is defined, the optimization system will try to increase commercial land use and decrease urban green space as much as possible. But this will not be a feasible solution. So, the allowable change limit is defined to control the maximum and minimum area of land use. For example, Sharmin, Haque, & Islam, 2019 set 25% allowable land use change limit in their study to generate alternative land use allocation for a small mixed-use area of Dhaka city in Bangladesh. In some studies, the number of total populations has been kept constant for the efficient management of the city and to reduce the burden on existing utilities. Because if the number of populations would have been allowed to increase, it would create a burden on the utilities, transport and other urban services leading to mismanagement of city. Slope range was also used in some studies as constraint to specify the land use types in specific land in terms of slope. For example, due to the local and national regulations, it was decided that no land of Wuhan, China can be converted to arable land if it has slope less than 25° (Yuan, Liu, He, & Liu, 2014).

3.2.3. *Construction of optimization problem*

Construction methods of multi-objective optimization problems are classified into two categories: Scalarization and Pareto front-based method (Cao, Zhang, & Wang, 2019). The most common methods under the scalarization technique are a) the Weighted sum method, b) Goal programming, and c) ε-constraint method. We have identified three types of construction methods that are used in urban land use optimization and have been presented in Fig. 8. The Fig. shows that about 42.86% of studies used the Pareto front-based (n=21) method to construct urban land use optimization problems, followed by the Weighted sum method (36.73%, n=18) and Goal programming (20.41%, n=10). These methods are shortly described in the following sections.

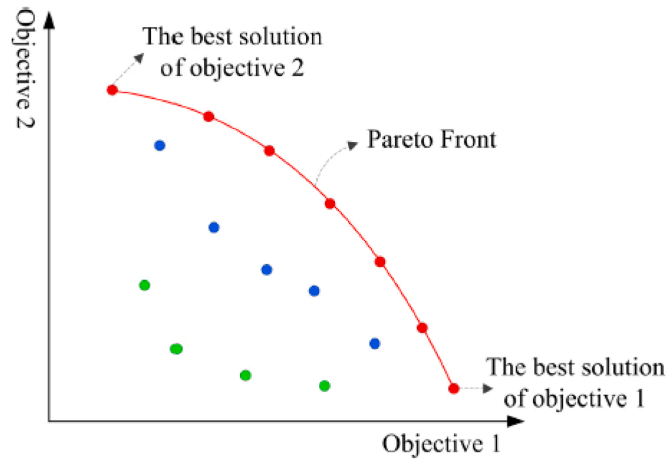

Fig. 9. Illustration of Pareto optimal front and solutions (Yang, Zhu, Shao, & Chi, 2018).

3.2.3.1. Pareto front based method. The Pareto approach attempts to find a set of non-dominated solutions. According to this concept, a solution is said to be Pareto optimal when no further improvement is possible in any objective function without degrading at least one of the other objective function(s) (Deb, 2011). Fig. 9 illustrates that the solutions on the Pareto front line exhibit different combinations of tradeoffs among the multiple conflict objectives.

Our findings show that many studies have applied the Pareto front-based method to solve land use optimization problems because this method can satisfy the demand of multiple stakeholders while keeping everyone's objective optimized. Despite having many positive sides, Pareto-optimality may show inefficient tradeoffs in practical problems, and even sometimes, it may be impossible to find the Pareto front if the optimization problem is associated with a large number of decision variables. In the face of this problem, a heuristic algorithm such as particle swarm optimization and genetic algorithms may be efficient to find the Pareto front.

3.2.3.2. Weighted sum method. According to the weighted sum method, all objective functions are combined into one scalar objective function assigning specific weight to each objective. Then this scalar optimization problem is solved to find the non-dominated solutions. This method can be expressed by Eq. (1).

$$min \sum_{i=1}^{k} w_i f_i(x) \tag{1}$$

Subject to $x \in F,\ \sum_{i=1}^{k} w_i = 1,\ where\ w_i \geq 0$

Nonnegative weights are assigned to each objective function. Since the weighted sum method can generate effective and efficient solutions, this method has been applied in many urban land use optimization problems, including Zhang and Wang (2019), Song and D. M. Chen (2018b), Feixue Li *et al.* (2018), Handayanto, Tripathi, Kim, & Guha, 2017, and Yang, Sun, Peng, Shao, & Chi, 2015. Although the weighted sum approach is very popular and simple, it has some inherent problems. First, the outcome of the final solution largely depends upon the selection of weights given to each objective function. So, careful selection weight is necessary; otherwise, the outcome may not end up with a desirable result. Second, in a weighted-sum approach, multiple

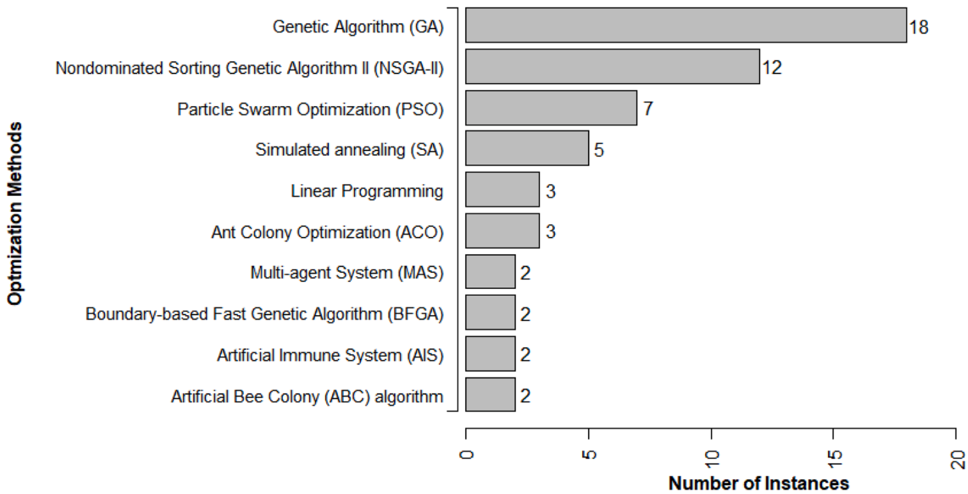

Fig. 10. Methods to solve the urban land use optimization problem.

objectives are converted to a single objective, and, in most cases, a single-objective algorithm finds a solution satisfying the first-order optimality criterion; the additional test may be required to obtain the optimal solution (Deb, 2011). Third, there are many multi-objective optimization problems that are non-convex, but the weighted sum method does not work with non-convex problems. Fourth, sometimes multiple solutions generated by the Pareto front may be weakly dominated by each other; in this case, the weighted-sum approach may fail to identify some true Pareto front solutions.

3.2.3.3. Goal programming. Goal programming is considered as an extension of linear programming where the goal for each objective function is set to be achieved. The commonly used formula to formulate the multi-objective optimization problem using goal programming with reference points can be expressed as follows (Li & Parrott, 2016):

$$\mathrm{MinF} = \sum_{q=1}^{Q} \left[\frac{f_q(x) - I_q}{\lambda_q - I_q} \right]^p \tag{2}$$

Where F is the overall objective function, Q is the number of objectives, q is the index of objectives, $f_q(x)$ is the objective function with index q, I_q is the possible ideal value of the objective $f_q(x)$, λ_q is the worst value of the objective $f_q(x)$, p is a penalty coefficient for the objective violation increase, value for p is 2 to be considered to be appropriate (Stewart, 1991). The goal programming approach has been applied in many optimization problems, including urban land use optimization problems because this method is very suitable to produce non-dominated solutions considering stakeholder preferences.

3.2.3.4. ε-constraint method. Besides the weighted sum method, the ε-constraint method is considered as the best approach to solve multi-objective optimization problems. In this approach, having p objective functions, only one objective is kept as it is, and other p-1 objectives are transformed into constraints. This is known as the ε-constraint problem. Then the ε-constraint problems are integrated with heuristics algorithms to solve the optimization problems (Chiandussi, Codegone, Ferrero, & Varesio, 2012). Thus, the problem:

$$\min_{x \epsilon X} \left(f_1(x), \ldots\ldots.f_p(x)\right)$$

Can be substituted by the ε-constraint problem as follows:

$$\min_{x \epsilon X} f_j(x)$$

Where, $f_k(x) \le \varepsilon_k \; k = 1, \ldots\ldots\ldots p, \; k \ne j$

Although we did not identify the application of the ε-constraint method in our cases, nevertheless, many optimization problems were solved by this method (Copado-Méndez, Pozo, Guillén-Gosálbez, & Jiménez, 2016).

3.2.4. Methods to solve the optimization problem

Different methods are used to solve land use optimization problems. The decision variables play an important role in determining the solving approach to multi-objective optimization problems. If the decision variables are discrete, then an exact approach (e.g., Linear Programming, Integer Programming) is preferred; if the decision variables are continuous, then the heuristic approach is the most preferred approach. If the optimization problem contains both discrete and continuous decision variables, mixed-integer methods are used to solve the problem (Panwar, Jha, & Srivastava, 2018; Pappas et al., 2021). In the case of the exact approach, linear programming can only be used if the decision variables, objective functions, and constraints are all linear (Wang & Fang, 2018). The graphical method can be used to solve linear programming problems if there are only two variables. If any one of them is not linear, then linear programming cannot be used to solve the optimization problem. In our case, there are only three studies in which the decision variables, objective function, and constraints are linear. These studies used the linear programming method to solve land use optimization problems. In other cases, the decision variables are non-linear, and the objective functions are continuous, so heuristic approaches were used to solve the optimization problem. Fig. 10 describes the ten (10) most frequently used optimization techniques in urban land use optimization problems. Our findings suggest that, the most popular technique is the Genetic Algorithm (GA) (n=18), followed by Nondominated Sorting Genetic Algorithm II (NSGA-II) (n=12), Particle Swarm Optimization (PSO)(n=7), and Simulated Annealing (SA)(n=5).

We have identified two categories of solving strategies towards land use optimization problems: exact and heuristic methods. Exact methods evaluate all feasible solutions and find a set of unique non-dominated solutions. The best solution(s) are guaranteed by exact methods (Ligmann-Zielinska, Church, & Jankowski, 2008; Tong & Murray, 2012). Some popular exact methods are Enumeration, Linear Programming, Integer Programming with Branch & Bound method, and Dynamic Programming (Rath & Gutjahr, 2014). As shown in Fig. 10, only linear programming was used in urban land use optimization problems (n=3). Linear programming technique optimizes linear objective function subject to some linear equality and inequality constraints. Fig. 10 depicts that the exact approach towards urban land use optimization is not common practice by the researchers. The limited use of exact methods in solving spatial optimization problems is primarily due to the location component, which makes land use optimization different from other optimization problems. Land use optimization is not a simple allocation

Table 2
Reason behind using different optimization methods by different authors.

Name of Methods	The reason behind using the methods
Genetic Algorithm (GA)	Robustness and efficiency (Haque & Asami, 2014, Haque & Asami, 2011; Huang & Zhang, 2014; Li & Parrott, 2016; Porta et al., 2013; Mingjie Song and Chen, 2018b; Zhang, Wang, Cao, He, & Shan, 2019); ability to search in complex, large and poorly-understood search spaces (Huang & Zhang, 2014; Li & Parrott, 2016; Zhang, Wang, Cao, He, & Shan, 2019); Natural selection towards global optimization (Cao & Ye, 2013; Gong, Liu, & Chen, 2012; Li & Ma, 2018; Y. Liu, Zhang, Zhang, & Borthwick, 2014; Zhang, Wang, Cao, He, & Shan, 2019; Zhang & Huang, 2015)
Nondominated Sorting Genetic Algorithm II (NSGA-II)	Derivation of Non-dominated solutions (Karakostas, 2017; Lubida, Veysipanah, Pilesjo, & Mansourian, 2019; Mohammadi, Nastaran, & Sahebgharani, 2015; Schwaab et al., 2018; Sharmin, Haque, & Islam, 2019; Shaygan, Alimohammadi, Mansourian, Govara, & Kalami, 2014; Mingjie Song and Chen, 2018a, 2018b); intelligent ranking of the Pareto solutions (Lubida, Veysipanah, Pilesjo, & Mansourian, 2019; Sharmin, Haque, & Islam, 2019; Mingjie Song and Chen, 2018b); Diversity preservation in the solutions (Kai Cao et al., 2011; Karakostas, 2015; Lubida, Veysipanah, Pilesjo, & Mansourian, 2019; Wang, Zhang, & Wang, 2019);
Particle Swarm Optimization (PSO)	Less computational time (Handayanto, Tripathi, Kim, & Guha, 2017); To ease Continuous optimization problem (Handayanto, Tripathi, Kim, & Guha, 2017; Mingjie Song and Chen, 2018b); Rapid convergence (Feixue Li et al., 2018; Li & Parrott, 2016; Yaolin Liu, Li, Shi, Huang, & Liu, 2012; Sahebgharani, 2016); flexibility and simplicity of operators (Feixue Li et al., 2018; Yaolin Liu, Li, Shi, Huang, & Liu, 2012; Yang, Sun, Peng, Shao, & Chi, 2015); improved adaptability of search-space (Feixue Li et al., 2018; Yaolin Liu, Li, Shi, Huang, & Liu, 2012);
Simulated annealing (SA)	Rapid convergence (Mingjie Song and Chen, 2018b); Improved performance (Mingjie Song and Chen, 2018b); can control solution acceptance probability (Santé-Riveira, Boullón-Magán, Crecente-Maseda, & Miranda-Barrós, 2008); can derive the ideal alternative solution (Caparros-Midwood, Barr, & Dawson, 2015; Li & Ma, 2018); to ease computational complexity (Yl Liu, Li, Shi, Huang, & Liu, 2012)
Linear Programming	guarantee an optimal solution (Yl Liu, Li, Shi, Huang, & Liu, 2012)
Ant Colony Optimization (ACO)	Better efficiency and effectiveness (Li & Parrott, 2016); minimum search path cost (X. Liu, Li, Shi, Huang, & Liu, 2012)
Multi-agent System (MAS)	To integrate local simulation to global optimization (Yuan, Liu, He, & Liu, 2014; Zhang et al., 2016)
BFGA	Efficient to solve large problems (Cao, Huang, Wang, & Lin, 2012; Kai Cao et al., 2020)
AIS	Specially developed for multi-objective optimization problem (Ma & Zhao, 2015); better performance in spatial data (Huang, Liu, Li, Liang, & He, 2013)
Artificial Bee Colony (ABC)	low computational cost (Yang, Sun, Peng, Shao, & Chi, 2015); to increase genetic diversity (Yang, Zhu, Shao, & Chi, 2018)

regarding how much land units would be allocated to each category; rather, it also entails where to allocate. Due to this property of location-allocation, land use optimization becomes more complex compared to other optimization problems. This complexity disfavor land use optimization problems to be solved by exact methods.

Modelling land use optimization problems is also complex due to geographic and topological relationships and properties of land parcels such as distance, adjacency, connectivity, containment, and shape (Tong & Murray, 2012). Adjacency refers to what extent two land units are neighbors, whereas connectivity indicates the ability to reach one location from another location in terms of impedance. Containment signifies whether one land unit is completely within another land unit. We have identified several reasons why exact methods are seen as limited in case of land use optimization problems. Many researchers argued that exact methods are seen to be efficient in case of single objective or multiple objectives having no conflicts (Mingjie Song and Chen, 2018b). But in the real world, land use optimization problems consist of multiple objectives having conflicting interests among the stakeholders. Another drawback of the exact method is that they produce only a single optimum solution. But in most cases, the single best solution may not be the feasible solution for the decision-maker because multiple stakeholders with conflicting interests are involved in land use decisions (Li & Ma, 2018; Mingjie Song and Chen, 2018a). The exact method shows good performance when optimization problems are simple. But land use optimization problems are complex due to it's spatial component. So exact methods are infeasible in solving land use optimization problems. Exact methods are suitable when there is a limited number of land units to be allocated. But if the number of land units is large, then it becomes very difficult for an exact method to generate a feasible solution. For example, an exact method like integer programming become infeasible if there are more than 2000 or 3000 land units need to be allocated (Stewart, Janssen, & Van Herwijnen, 2004). Although exact methods explicitly guarantee an optimal solution but can be much slower when there exist multiple conflicting objectives. Besides, exact methods find it very difficult to solve continuous optimization problems since the feasible solution region is non-convex (Aerts, Eisinger, Heuvelink, & Stewart, 2003). Due to the above reasons, exact methods seem to be limited in land use optimization problems.

In contrast to exact methods, the heuristic approach utilizes the rule of thumb or best practice to produce a set of near-optimal solutions. Our findings illustrate that the most frequently used heuristic to solve urban land use optimization problems are GA (32.14%), NSGA-II (21.42%), PSO (12.50%), and SA (8.93%). In GA, a set of candidate solutions or populations are generated randomly in an iterative process. The set of populations in each iteration is called generation; the fitness value of the populations is evaluated in each generation, and the best-fitted values are selected for the next generation, and this process continues until the best solutions are found. Detailed procedures of GA can be found in many kinds of literature (Nandi & Deb, 2016). Table 2 summarizes the reasons behind using different optimization methods by respective authors. We have identified three main reasons for which GA was used in so many land use optimization problems. First, GA is robust and efficient in handling varieties of multi-objective optimization problems to find the global optimum. Second, GA has the ability to search in complex, large, and poorly understood search spaces to find the fittest solution. Third, it follows a natural selection procedure towards global optimization. This is an important criterion for choosing GA in many studies because land use allocation is an outcome of many competing factors and interests. Despite the many advantages of GA, it has two challenges in land use optimization problems. Firstly, land use optimization is a spatial optimization problem, and the land use is represented by a raster cell where the decision variable is represented by each cell, making millions of decision variables in the whole optimization process. It makes very difficult to find the optimum solution. Secondly, genes used in the land use optimization process are non-computable because these genes are character and only used to mark the land use type. So, a common type of crossover is not applicable in this case, although crossover is the main operator in the selection process. Therefore, this is a challenging task to design crossover in traditional GA to optimize land use.

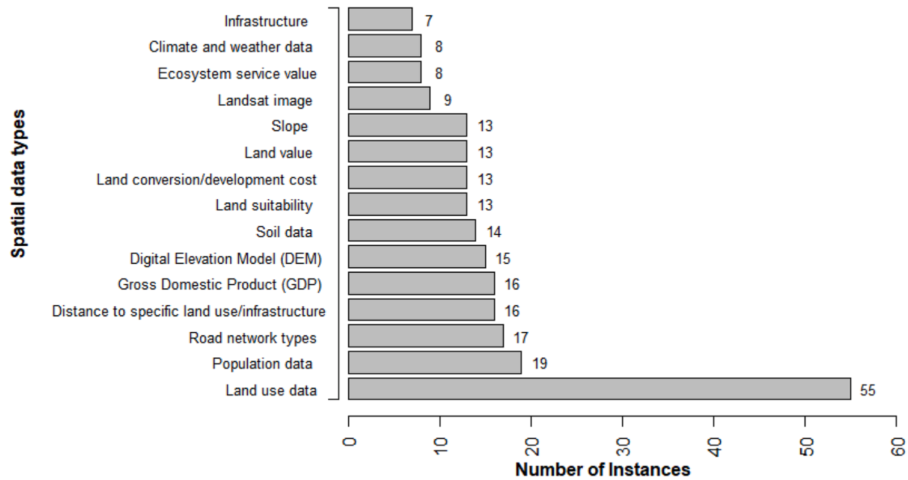

Fig. 11. Common Spatial data used in urban land use optimization

The second most frequently used method to solve urban land use optimization is NSGA-II. In contrast to GA, NSGA-II follows an elitist principle to select the best fittest population. A set of non-dominated solutions are selected in such a way that no further improvement is possible without losing the value of any objective. As it is seen from Table 2, there are several reasons for using NSGA-II by many authors. Derivation of non-dominated solutions is the most important among them. Table 2 also suggests that NSGA-II can preserve the diversity among solutions and can intelligently rank the non-dominated solutions to ease the decision-maker to select the best option. Successful application of NSGA-II in urban land use optimization is frequent and can be found in many kinds of literature (Gao et al., 2020; Mohammadi, Nastaran, & Sahebgharani, 2015; Shaygan, Alimohammadi, Mansourian, Govara, & Kalami, 2014). However, NSGA-II also has some limitations. Sometimes NSGA-II fails to find well-diversified non-dominated solutions because it may lose its selection pressure while evaluating fitness function. This happens due to the generation of the higher portion of the initial population from non-dominated solutions (He & Yen, 2016). In addition, if there are higher distances among parent solutions, they are likely to produce offspring far beyond the true solutions.

PSO has been applied in many studies to solve land use optimization problems (Feixue Li et al., 2018; Masoomi, Mesgari, & Hamrah, 2013). Table 2 indicates the reasons behind the use of PSO in many studies. PSO can perform complex problem with less computational cost and time. Some authors used PSO due to its rapid convergence and improved adaptability of search space. PSO has the advantage due to its flexibility and simplicity of its operators. Although PSO showed a better performance compared to GA, it results in lower accuracy. If a small initial weight is used, this problem may be solved, but it may also cause to lower particle's searching distance. SA is another popular heuristic algorithm for land use optimization. When it becomes important to find approximate global optima compared to precise local optima, SA is a preferable alternative to other search techniques (Goffe, Ferrier, & Rogers, 1994; Suppapitnarm, Seffen, Parks, & Clarkson, 2000). Table 2 indicates that the most important characteristic of SA for which it has been used by many authors is its ability to control the acceptance probability of the solutions. In SA, each solution is attributed to temperature. The temperature between the two nearest solutions decides the acceptance probability. This strategy helps to find the fittest solutions from a large search space. Eventually, due to this property, SA eases the computational complexity of problems having multiple objectives and large search space.

3.2.5. Spatial Data in urban land use optimization

3.2.5.1. Spatial data type. Spatial data is an essential element in land use planning. Preparation of a good land use plan requires as much data and information (Rahman & Szabó, 2020). Most importantly, these data include transportation and road network, travel behavior and pattern, physical feature, population density, socio-economic condition, soil characteristics, land cover, water, and environment, etc. The availability of spatial data, data structure, accuracy, level of detail greatly affects the solution strategies and final output.

We have identified fifteen (15) types of major spatial data used in the urban land use optimization process. The spatial data includes the statistical data, which were converted to spatial data adding the corresponding location component. The spatial data used in the urban land use optimization process have been summarized in Fig. 11. The spatial data has been represented as point, line, and area features. Needless to say, the land use data is the prime data that was used in every study.

Many studies have classified land use data differently. Different city authorities and researchers classified land use differently, considering study purposes. For example, Cao, Zhang, & Wang, 2019 used six categories of land use, including agriculture, forest, grassland, water bodies, built-up land, and unused land, whereas Handayanto, Tripathi, Kim, & Guha, 2017 used ten (10) types of land use including commercial buildings, industrial buildings, elementary schools, middle schools, colleges, medical facilities, sports areas, parks, low-density residential areas, and high-density residential areas. To prepare land use map, mainly satellite images and existing secondary sources were used in many studies. Population data was also frequently used in urban land use optimization. Two applications of population data were mostly observed in land use optimization: demand calculation and maximum or minimum limit for which any objective to be optimized. In most of the cases, Population data was seen to be measured as population density. Another important spatial data that was used frequently is the road network. The road network data was mainly used to measure spatial access to different urban facilities. Gross domestic product (GDP) and land value were also used in many land use optimization studies, which focus on the maximization of economic benefits and landowner's gain. GDP was presented as per unit of area or block. Digital Elevation Model (DEM) and Slope were mainly used to calculate land suitability and agricultural productivity (Feixue Li et al., 2018; W Zheng, Ke, Xiao, & Zhou, 2019). Ecosystem Service Value (ESV), Climate and Weather data were used to measure the environmental benefits (Zhang et al., 2016, 2019; Weiwei Zheng, Ke, Xiao, & Zhou, 2019).

3.2.5.2. Spatial data model. The selection of spatial data model, either vector or raster, can affect the construction of the overall model and results. Fig. 12 shows the type of popular spatial data models in spatial optimization. Fig. 12 shows that about 80% (n=44) of studies used the raster data model while only six studies used the vector model.

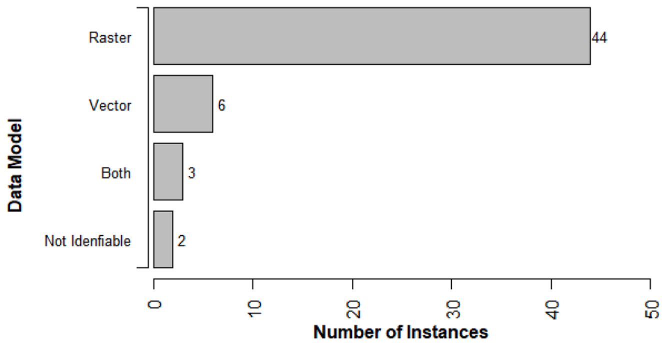

Fig. 12. Spatial data model used to design urban land use optimization problem

However, in the two studies, it was not clearly mentioned the data model used.

There are advantages and disadvantages both in raster and vector data structure in the land use optimization model. Land use optimization problems can be easily formed using raster-based representation. The most revealed advantage of a raster data model is that the land uses can be easily encoded, and the representation of spatial relationships is very straightforward. Raster-based model is preferable and can be found in many studies, including Gao *et al.* (2020), Zhang, Wang, Cao, He, & Shan, 2019, Yang, Zhu, Shao, & Chi, 2018, Li & Ma, 2018, and Feixue Li *et al.* (2018). However, the raster model sometimes may become impractical because it may lead to multiple land use categories allocated to a single land category and a single land use plot to multiple categories. In addition, raster-based representation requires more units and space compared to vector-based representation for a similar feature. Land use optimization problems using raster data also take unrealistically higher computation time.

In contrast to the raster-based model, the vector-based model is more intuitive and matches real-world land use planning. Since, in the vector data model, spatial features are represented by coordinates through points, lines, and polygons; real-world spatial entities are best represented with less deviation. Thus, the accuracy and computational efficiency can be improved by using the vector data model in land use optimization. As compared to the raster data model, in vector format, the number of spatial units can also be decreased. The use of vector-based urban land use optimization can be found in Cao *et al.* (2020), and Handayanto, Tripathi, Kim, & Guha, 2017. In the vector-based model, there are also some problems. For instance, the spatial relationship is somewhat difficult and sophisticated. Another problem with using vector format is related to spatial units. In a vector model, a large area may not be subdivided into smaller spatial units since it will create computational complexities.

4. Knowledge gaps and future scope of research

In this study, we have systematically reviewed 55 articles that concentrate on urban land use optimization. This provides plausible ground to identify the knowledge gaps in urban land use optimization. Firstly, although there exists diversification in optimization objectives, sustainability was not the main focus in urban land use optimization, although sustainable land use is an important consideration in urban land use planning. We have identified only two studies (Cao, Huang, Wang, & Lin, 2012; Yuan, Liu, He, & Liu, 2014) that focused on sustainability, including all three aspects; other studies considered only one or two aspects of sustainability. It may be noted that only 10% (n=3) of studies included social aspects of sustainability. To fill this knowledge gap, future research could focus on sustainable urban land use. Secondly, although sustainability dimensions have been considered partially in many studies, there is a lack of consensus in using proxy variables to calculate the benefits of sustainability dimensions. For example, environmental benefits from land uses have been calculated by using carbon storage as a proxy variable (Yuan, Liu, He, & Liu, 2014), valuing natural resources and ecology (Cao, Huang, Wang, & Lin, 2012), quantifying ecological suitability (Cao & Ye, 2013), etc. So, there is a clear research gap in using proxy variables and framing a common approach towards evaluating sustainability dimensions in relation to land use optimization. Third, from our reviewed articles (n=55), we did not find any established method to calculate social benefits. Researchers used the different concepts to measure social benefits without similarity. For example, Zhang *et al.* (2016) used social security service value as the indicator of social benefits, Yuan, Liu, He, & Liu, 2014 used spatial compactness, and Cao, Huang, Wang, & Lin, 2012 used accessibility, compatibility, and compactness as indicators of social benefits. This gap may be fulfilled by conducting research on developing methods to measure social benefits from land use. Fourth, most of the studies have a constraint that "one and only land use" should be allocated in each plot, which might not be practical in many cities having mixed uses in the same building. We have identified only two studies (Haque & Asami, 2014; Sharmin, Haque, & Islam, 2019) that allow multiple land uses (more than one use in one building) in the same plot. This necessitates to development of efficient strategies to incorporate multiple land uses in the building while developing an optimization model. Fifth, based on our understanding from the reviewed papers, we have identified that urban land use optimization has been constructed mathematically. This approach results in a quantitative allocation of land use considering multiple conflicting objectives and do not integrate qualitative value as desired by the local public. For example, the value of conservation of wetland and green space may not only be evaluated quantitatively. At the same time, land use decision is strongly influenced by stakeholders opinions, but hardly any method can incorporate stakeholders opinion to construct optimization problem. Owing to this limitation, only quantitative optimization is insufficient to meet the public agreement. This makes the clear need for developing an approach to incorporate stakeholders' opinions integrated with the mathematical optimization process. This knowledge gap may be filled up by doing further research on coupling public participation with land use optimization.

5. Recommendations

Based on the findings from our study, we are proposing the following recommendations to be incorporated urban land use optimization. We strongly argue that these new ideas will improve the existing approach to land use optimization.

Selection of objectives: In the past decades, land use optimization has been investigated towards achieving various objectives (Cao, Zhang, & Wang, 2019; Haque & Asami, 2011; Karakostas, 2015), and these objectives are diverse and contextual. Fig. 6 indicates that some objectives show clear importance over others in land use optimization problems. Maximization of spatial compactness and maximization of land use compatibility have great significance in land use planning and urban sustainability. So, we recommend considering these two objectives with other location-specific objectives in future land use optimization. Our findings suggest that sustainability dimensions have been poorly addressed in urban land use optimization problems. Hence, we recommend that objective functions should be framed considering three core pillars of sustainability. There may be many sub-objectives within core sustainability dimensions. For example, optimizing urban green space (Kai Cao et al., 2020), minimizing pollution (Huang & Zhang, 2014), optimizing ecosystem service value (Weiwei Zheng, Ke, Xiao, & Zhou, 2019) fall within the objective function of the environmental domain. Even, there may be conflicting objectives as discussed in section 1. So, before the selection of sub-objectives stakeholder consultation workshop should be arranged to understand the trade-offs among different objectives.

Calculating value (benefit) of objective functions: Our discussion in section 3.2.1 illustrates that there is no common agreement to calculate the economic, environmental, and social benefits from land use optimization. This creates a definite problem to measure the degree to which a particular city has attained or to be attained the progress towards sustainability. So, more work is needed to define proxy variables and to develop standard methods to measure social, environmental, and economic benefits from land use. Based on our findings and understanding, we recommend that land use compatibility, land use suitability, spatial compactness, and spatial access to basic services and urban facilities could be a measure of social benefits; four groups of ecosystem services (e.g., provisioning services, supporting services, regulating services and cultural services) could be a measure of environmental benefits; and GDP and land development cost could be the measure of economic benefits from land use. Our justification for proposing the above measures of social benefit is that social benefit from land use indicates equal access to basic services and urban facilities, where land use compatibility, suitability, spatial compactness, and spatial access are the important measures to social equity (Bryan et al., 2015).

Defining constraints: Existing urban development policy, stakeholder groups, government regulations, and future expectations affect the selection of constraints (Niu et al., 2013; Shi, Zhan, Yuan, Wu, & Li, 2015; M Song and Chen, 2018; Xia, Liu, Liu, He, & Hong, 2014). For example, K Cao et al. (2020) considered green space as a conservation area in their study and set residential area to be 50% of the total area. Similarly, conservation of wetland or minimum green space as constraints could be different in different cities. Some cities may impose conversion of agricultural land (Deelstra & Girardet, 2000) while others may not; some cities may want to increase residential area (Cook, Hall, & Larson, 2012) while others may want to increase commercial area. So, the selection of constraints is completely area-specific. Based on the findings, our suggestion is to study government regulation, urban development policy and to conduct stakeholder workshop to select appropriate constraints. We have also identified that most of the studies considered only single use in one land unit due to computational complexities. But the practical scenario is different; in the same building, there may be different uses on different floors. But this issue was not considered. Hence, we recommend considering multiple uses in the same building in future studies.

Constructing optimization problem: Our discussion in section 3.2.3 suggests that each method to construct an optimization problem has its advantages and disadvantages. For example, although Pareto-optimality may show inefficient trade-offs in the case of a large number of decision variables (Mingjie Song and Chen, 2018a). Another problem with the Pareto front may be the generation of an infinite number of solutions from which true solutions need to be discovered(Gao et al., 2020). To resolve the problem, mathematical optimization techniques having local convergence properties may be integrated with evolutionary multi-objective optimization. On the other hand, the weighted sum approach largely depends upon the selection of weight (Shaygan, Alimohammadi, Mansourian, Govara, & Kalami, 2014). Wrong selection of weight of objective function may result in impractical solutions. To remove this problem, the selection of weight of objective function through stakeholder consultation and public participation. After resolving the above two problems, we believe that a combination of Pareto-optimality and weighted may improve the identification of true solutions.

Solving optimization problem: As discussed in section 3.2.4, some algorithms may work better in a certain setting, but the same algorithm may show poor performance in another setting (Yaolin Liu, Li, Shi, Huang, & Liu, 2012). So, it is not possible to tell which algorithm will produce the best result without investigating the problem setting under consideration. Based the table 2 and analysis of the findings, we recommend that GA can be used if the search space is large, complex, and is poorly-understood search spaces; NSGA-II can be used in a situation where multiple non-dominated solutions are required by decision-makers rather than single best solution; PSO can be used if computational time is considered as important selection factor; SA can be used if rapid convergence is a prime factor and if the optimizer intends to control the solution acceptance probability. However, we have identified that GA and NSGA-II perform well in spatial objectives (Annepu, Subbaiah, & Kandukuri, 2012; K Cao et al., 2020,), whereas SA and PSO perform well in additive objectives (F Li et al., 2018; Li & Ma, 2018; Mingjie Song and Chen, 2018b). Based on these findings, we recommend that GA and NSGA-II may be used where the number of spatial objectives is greater than additive objectives, and in alternative cases, SA and PSO can be used preferably. If the number of spatial and additive objectives are equal, then both groups can be tested to select the algorithm that produces a good result.

Using spatial data model: Although the raster data model is most frequent, there is a limited discussion to define the neighborhood within the raster data model. Definition of neighborhood plays an important role in calculating the objective function (Yuan, Liu, He, & Liu, 2014). Based on the literature, we have identified two types of neighborhoods: a) Moore neighborhood and b) Von Neumann neighborhood as shown inFig. 13.

In a two-dimensional raster data model, the Moore neighborhood is defined as a central cell surrounded by the neighboring eight cells, where the Von Neumann neighborhood is composed of a central grid cell surrounded by four adjacent cells (Karakostas, 2017, 2016). Moore neighborhood takes higher computational time but produces a more accurate result. On the other hand, using the Von Neumann neighborhood is straightforward but produces a less accurate result in some cases (Karakostas, 2015). We recommend that in the land use optimization problem, the Moore neighborhood should be used because, in the Moore neighborhood, the central cell is influenced by adjacent eight cells compared to four cells in the Von Neumann neighborhood. So, the use of the Moore neighborhood will produce a more rational value of the objective function.

6. Limitations and implications of this research

Our study has added fruitful insights into urban land use optimization. Nevertheless, it has some limitations. Our review is based on the peer-reviewed articles published in the English language only. It can be mentioned that most of the studies were conducted in China, but we did not include any article published in the Chinese language. This is likely that articles published in other languages might contain valuable information. Another limitation is that we have only included articles that focused on urban land use optimization; surely, there are many articles that focused on rural land use optimization, agricultural land use optimization, which might be a valuable source of insights. We recommend that future studies can be conducted, including those variations, to understand the differences. We also did not compare the performance of different methods because for performance evaluation; it is required to apply different methods on the same study area with the same dataset, which requires a separate study. We have just mentioned different methods relating to land use optimization (e.g., how to calculate different objectives, how to construct the problem, and solution methods) along with some brief discussion. Elaboration of those methods might be helpful for the readers to understand the detailed procedure, but we did not elaborate on those methods because this was not the scope of our study.

Despite the limitations above, this study has some academic and empirical implications. To the best of our knowledge, this review is the first of its kind considering the most important aspects of urban land use optimization. This paper offers some recommendations on selecting objective functions, calculating the value of objective functions, defining constraints, constructing and solving the optimization problem, and spatial data model. The future researcher may find indicative guidance from those suggestions. This will also help policymakers to decide realistic objective functions to address urban sustainability.

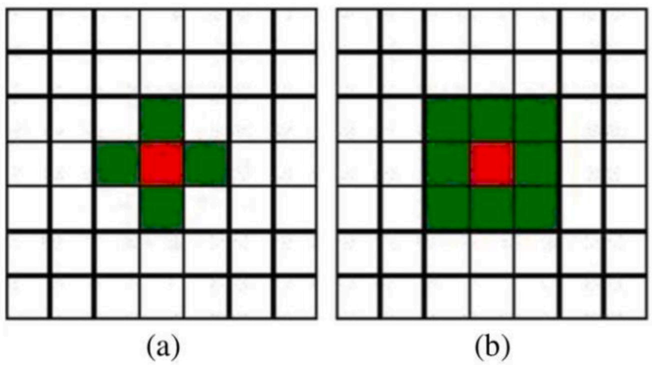

Fig. 13. (a) Von Neumann neighborhood. (b) Moore neighborhood.

7. Conclusion

Based on our findings, this study concludes that the most common objectives in urban land use optimization are maximization of spatial compactness, maximization of land use compatibility followed by maximization of land use suitability, while frequently used constraints are a) one and only one land use in each cell, b) minimum and maximum area of particular land use, and c) restriction on specific land use change. This study also clarifies that sustainability in urban land use optimization is merely touched upon while no generalized method was established to measure economic, social, and environmental benefits from land use planning. This study also finds that Pareto based method is more popular to construct urban land use optimization problems while the Genetic Algorithm (GA) accounts for the major contribution to solve the optimization problem. This study also recognizes that spatial data is an indispensable part of formulating urban land use optimization problems where the raster data model is preferable to design urban land use optimization problems. Based on the findings of the study, we have proposed some recommendations for further studies. Most importantly, future studies should focus on urban sustainability while formulating objective functions, and a common method should be developed to measure the values of objective functions. We also recommended that the participatory approach should be integrated with mathematical optimization to derive acceptable solutions in land use allocation. We think that our proposed recommendations can remove the existing shortcomings and improve the overall approach towards land use optimization and help to achieve urban sustainability. According to the best of our knowledge, this study is the first of its kind. No previous study comprehensively discussed and synthesized the different aspects of land use optimization. In this review, different aspects of land use allocation have been explored, and future research direction has been indicated based on our findings. Thus, we strongly believe that this research is a novel work and has fulfilled the previous research gap on this topic. So, researchers in this field are expected to get benefit from this review paper by understanding the overall idea of urban land use optimization, its current state, and future research scope.

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The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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