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Development of Multi-scale/Multi-objective Spatial Optimization Model Based on Genetic Algorithms

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Abstract

Development of Multi-scale/Multi-objective Spatial Optimization Model Based on Genetic Algorithms

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The meeting of heterogeneous goals while staying within the constraints of spatial planning is a nonlinear problem that cannot be solved by linear methodologies. Instead, this problem can be solved using multi-objective optimization algorithms such as genetic algorithms (GA), simulated annealing (SA), ant colony optimization (ACO), etc., and research related to this field has been increasing rapidly. GA, in particular, are the most frequently applied spatial optimization algorithms and are known to search for a good solution within a reasonable time period by maintaining a balance between exploration and exploitation. However, despite its good performance and applicability, it has not adequately addressed recent urgent issues such as climate change adaptation, disaster management, and green infrastructure planning. It is criticized for concentrating on only the allocation of specific land use such as urban and protected areas, or on the site selection of a specific facility.

Therefore, in this study, a series of spatial optimizations are proposed to address recent urgent issues such as climate change, disaster management, and urban greening by supplementing quantitative assessment methodologies to the spatial planning process based on GA and Non-dominated Sorting Genetic Algorithm II (NSGA II). This optimization model needs to be understood as a tool for providing a draft plan that quantitatively meets the essential requirements so that the stakeholders can collaborate smoothly in the planning process. Three types of spatial planning optimization models are classified according to urgent issues. Spatial resolution, planning objectives, and constraints were also configured differently according to relevant issues. Each spatial planning optimization model was arranged in the order of increasing spatial resolution.

In the first chapter, the optimization model was proposed to simulate land use scenarios to adapt to climate change on a provincial scale. As climate change is an ongoing phenomenon, many recent studies have focused on adaptation to climate change from a spatial perspective. However, little is known about how changing the spatial composition of land use could improve resilience to climate change. Consideration of climate change impacts when spatially allocating land use could be a useful and fundamental long-term adaptation strategy, particularly for regional planning. Here climate adaptation scenarios were identified on the basis of existing extents of three land use classes using Multi-objective Genetic Algorithms (MOGA) for a 9,982 km^2 region with 3.5 million inhabitants in South Korea. Five objectives were selected for adaptation based on predicted climate change impacts and regional economic conditions: minimization of disaster damage;

and existing land use conversion; maximization of rice yield; protection of high-species-richness areas; and economic value. The 17 Pareto land use scenarios were generated by six weighted combinations of the adaptation objectives. Most scenarios, although varying in magnitude, showed better performance than the current spatial land use composition for all adaptation objectives, suggesting that some alteration of current land use patterns could increase overall climate resilience. Given the flexible structure of the optimization model, it is expected that regional stakeholders would efficiently generate other scenarios by adjusting the model parameters (weighting combinations) or replacing the input data (impact maps) and selecting a scenario depending on their preference or a number of problem-related factors.

In the second chapter, the optimization model was proposed to simulate land use scenarios for managing disaster damage due to climate change on local scale. Extreme landslides triggered by rainfall in hilly regions frequently lead to serious damage, including casualties and property loss. The frequency of landslides may increase under climate change, because of the increased variability of precipitation. Developing urban areas outside landslide risk zones is the most effective method of reducing or preventing damage; planning in real life is, however, a complex and nonlinear problem. For such multi-objective problems, GA may be the most appropriate optimization tool. Therefore, comprehensive land use allocation plans were suggested using the NSGA II to overcome multi-objective problems, including the minimization of landslide risk, minimization of change, and maximization of compactness. The study area is Pyeongchang-gun, the host city of the 2018 Winter Olympics in Korea, where high development pressure has resulted in an urban sprawl into the hazard zone that experienced a large-scale landslide in 2006. We obtained 100 Pareto plans that are better than the actual land use data for at least one objective, with five plans that explain the trade-offs between meeting the first and the second objectives mentioned above. The results can be used by decision makers for better urban planning and for climate change-related spatial adaptation.

In the third chapter, the optimization model was proposed to simulate urban greening plans on a neighborhood scale. Green space is fundamental to the good quality of life of residents, and therefore urban planning or improvement projects often include strategies directly or indirectly related to greening. Although green spaces generate positive effects such as cooling and reduction of rainwater runoff, and are an ecological corridor, few studies have examined the comprehensive multiple effects of greening in the urban planning context. To fill this gap in this field's literature, this study seeks to identify a planning model that determines the location and type of green cover based on its multiple effects (e.g., cooling and enhancement of ecological connectivity) and the implementation cost using NSGA II. The 30 Pareto-optimal plans were obtained by applying our model to a hypothetical landscape on a neighborhood scale. The results showed a synergistic relationship between cooling and enhancement of connectivity, as well as a trade-off relationship between greenery effects and implementation cost. It also defined critical lots for urban greening that are commonly selected in various plans. This model is expected to contribute to the improvement of existing planning processes by repeating the positive feedback loop: from plan

modification to quantitative evaluation and selection of better plans. These optimal plans can also be considered as options for “co-design” by related stakeholders.

▣ *Keywords: Climate change adaptation, Landslide damage, Non-dominated sorting genetic algorithms II, Urban greening*

▣ *Student number: 2015-31321*

Publications

Please note that Chapters 1-3 of this dissertation proposal were written as stand-alone papers (see below), and therefore there is some repetition in the methods and results.

CHAPTER 1

Yoon, E.J. et al., 2019. Modelling Spatial Climate Change Land use Adaptation with Multi-Objective Genetic Algorithms to Improve Resilience for Rice Yield and Species Richness and to Mitigate Disaster Risk. Environmental Research Letters. (*In press*)

CHAPTER 2

Yoon, E.J. et al., 2017. Multi-Objective Land-Use Allocation Considering Landslide Risk under Climate Change: Case Study in Pyeongchang-gun, Korea. Sustainability 9, pp.1-14.

CHAPTER 3

Yoon, E.J. et al., 2019. Multi-Objective Planning Model for Urban Greening based on Optimization Algorithms. Urban Forestry & Urban Greening. *(In press*)

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1. INTRODUCTION

Spatial planning is about how and where to distribute specific land uses and it provides an outline for realizing different levels of strategy on real space. However, a number of constraints and interests are involved in changing actual space (Neemaand Ohgai, 2010; Gong et al., 2012; Haque and Asami, 2014). Therefore, when allocating a use to a specific location, it is necessary to comprehensively consider and achieve various purposes, and this can be expressed as sustainability of space when it covers the environment, society, and economy aspects (Jung et al., 2016). Although the necessity of sustainability has been consistently pointed out since sustainability was first advocated in 1972, failures of sustainability in actual spatial planning have also been reported (Chen et al., 2014). There has been a lot of research on the derivation and synthesis of indicators and strategies related to the environment, society, and economy. However, there is insufficient methodology to spatialize this (Bae, 2017).

According to the Geographical Information System (GIS) technique, spatially distributed habitat quality and productivity, the possibility of disasters etc. can be considered from a spatial perspective (Kim et al., 2012; Eum, 2016; Lee, 2011). However, the process of drawing boundaries for each land use is still based on the qualitative methodology, i.e., judgment of planners (Yoon et al., 2018a). This qualitative methodology has the advantage of utilizing comprehensively accumulated knowledge of experts, which is difficult to quantify. However, this is not sufficient to encourage cooperation among various stakeholders because it is difficult to objectively determine whether the spatial plan is sufficient to solve the problem at hand or if it is the best possible scenario (Zhang and Chi, 2018; Mo et al., 2013). Furthermore, it is anticipated that the problem will be exacerbated by climate change impacts.

The meeting of heterogeneous goals while staying within the constraints of spatial planning is a nonlinear problem and cannot be solved by the existing linear methodology. Therefore, the problem is solved by using multi-objective optimization algorithms, and research related to this field has been increasing rapidly (Yoon and Lee, 2017). There are many kinds of algorithms—GA, NSGA II, ACO, SA, Tabu Search (TS), and greedy algorithm—but GA have the longest history and are still the most frequently applied in spatial optimization (Matthews et al., 2000; Stewart et al., 2004; Zhang and Huang, 2015). By combining exploration and exploitation, it is known to search a good solution within a reasonable time period (Datta et al., 2008). Although the planning model built on the basis of such an optimization algorithm shows good performance and applicability, it has not adequately addressed recent urgent issues such as climate change adaptation and green infrastructure planning. There is a criticism that it is concentrated on the allocation of single land use or the site selection of a specific facility.

Therefore, in this study, series of spatial optimizations were proposed to solve issues such as climate change, disaster management, and urban greening improvement by supplementing quantitative assessment methodologies to the existing spatial planning process based on optimization algorithms such as GA and NSGA II. In addition, the optimization model needs to be understood as a tool for providing a draft plan that quantitatively meets the essential requirements so that the stakeholders can collaborate in the planning process smoothly, rather than replacing the existing space planning process. Three types of spatial planning optimization models are classified according to urgent issues. Spatial resolution, planning objectives, and constraints were also configured differently according to relevant issues. Each spatial planning optimization model was arranged in the order of increasing spatial resolution.

2. CHPATER 1: Modelling Spatial Climate Change Land use Adaptation with Multi-Objective Genetic Algorithms to Improve Resilience for Rice Yield and Species Richness and to Mitigate Disaster Risk

2.1. Introduction

Ongoing climate change has increased the frequency and severity of droughts, flooding, and urban heat islands (UHIs) (IPCC 2014). In recent decades, this has resulted in increased damage and casualties from weather-related disasters, decreased agricultural production, degraded or destroyed ecosystems, and other effects (Galán-Martín et al 2017, Klijn et al 2012, Lehmann et al 2013, Polasky et al 2008, Scarano 2017). Various studies have attempted to identify which areas will be most exposed to climate change impacts and at what intensities (Chavas et al 2009, Kim et al 2014, Thorne et al 2017a), but further discussion of climate change adaptions from the perspective of land use is needed (Klein et al 2013). Although land use decisions have long-term consequences and can be very climate-sensitive (Hallegatte 2009), relatively little is known about best managent practices from a spatial perspective relative to climate change (Campbell 2006, Hurlimann and March 2012).

At multiple scales, allocating land use categories to appropriate areas with consideration of climate change impacts is an aggressive and important adaptation strategy (Hurlimann and March 2012, Wilson 2006). This can be a pre-emptive measure because most climate adaptation measures for water stability, agriculture, and forestry are implemented through land use or land management. For land use planning, the integration of various adaptation strategies critical because related climate change impacts may spatially overlap. Furthermore, trade-offs between adaptation strategies can occur due to competing objectives and other conditions (Galán-Martín et al 2017, Kennedy et al 2016). For example, enhancing climate adaptation in one sector may weaken resilience in other sectors (Thorne et al 2017b). This raises the challenge of incorporating these complex relationships, in addition to existing considerations, into long-term land-use planning. Many studies have shown that these multi-dimensional problems are difficult to solve with existing planning models (Cao et al 2012, Porta et al 2013). Thus, innovative methodologies are needed to generate adaptation options with more robust and flexible characteristics under conditions of increasing uncertainty (Hallegatte 2009).

The multi-objective genetic algorithm (MOGA) is a popular optimization algorithm for addressing multi-objective problems in land management (Eikelboom et al 2015, Matthews et al 2000, Stewart et al 2004). It does not produce a single optimal (definitive) result, but is rather a scenario generator that detects a series of suitable solutions for multiple objectives by exploring possible combinations within a reasonable time (Li et al 2009). Studies using this optimization approach have examined realigning land use to respond to a single climate impact (Reichold et al 2010, Yoon et al 2017, Zhang and Huang 2015, Zhang and Huang 2014) or repositioning a single land use (Caparros-Midwood et al 2016, Li et al 2009, Mehri et al 2014, Neema and Ohgai 2010, Reichold et al 2010). However, land use conversions in specific areas may lead to other conversions to maintain the current land use proportions, or produce changes in regional resilience. Thus, it is important to incorporate multiple land uses and climate-induced events into one computational process. Repeated optimization modelling provides a range of land use scenarios for stakeholder engagement and is a well-known pathway to managing uncertain climate change scenarios (IPCC 2014).

In this study, we addressed the gap between climate change impacts and spatial adaptation by identifying a range of spatially distributed regional scenarios that balance land use and climate adaptation using MOGA. In this methodology, several objectives and constraints that should be achieved for adaptive and sustainable land use scenarios were selected taking into account current and future condition of study area. There is much more involved in actual land use, but it is important to describe land use scenarios satisfying prerequisites encompassing various sectors. Recent studies have suggested spatial adaptation strategies as a practical tool, but they have mainly focused on agricultural sector and related land use (Eikelboom and Janssen 2012; 2017, Dunnett et al 2018). However here, we established five objectives related to multi land use and multi sector of climate change impacts as a priority consideration for the entire region. Through this, co-benefit and trade-offs between sectors can be implicit in optimized land use scenarios, thus its effectiveness can be better even if the performance is lower than deriving the best one in single sector. When these are satisfied, model outputs could be served as a draft for co-design with stakeholders with different interests, or support decision-making of land use change strategies (Ligmann-Zielinska et al 2018).

2.2. Study area

South Chungcheong Province is located in central South Korea, including the cities of Sejong and Daejeon as well as important agricultural areas with relatively flat terrain and warm climatic conditions. The average altitude of the area is about 100 m. The annual average temperature is 11.9 °C and annual precipitation is 1100–1300 mm. In 2017, there were 3.5 million inhabitants. Sejong (population ~30,000) is growing rapidly since its designation as the nation's administrative capital. Daejeon (population ~1.5 million) is surrounded by a green belt intended to prevent urban expansion. The province is ecologically important because it covers the junctions of mountain ranges such as the Noryeong, Gaya, and Charyeong, semi-natural areas such as farmland, and rivers and oceans. Such heterogeneous landscape can support high species diversity (Choe et al 2018). In addition, this province includes major rice fields, accounting for 18% of total rice production in South Korea (http://kosis.kr). Urban, agricultural, and natural land comprise 305 km2, 3589 km2, and 5526 km2, respectively, while water covers 562 km2. Climate change adaptation plans for this region have been underway since 2016 (http://www.aurum.re.kr/), but strategic spatial planning has not been included due to a lack of relevant methodologies (Yoon et al 2018).

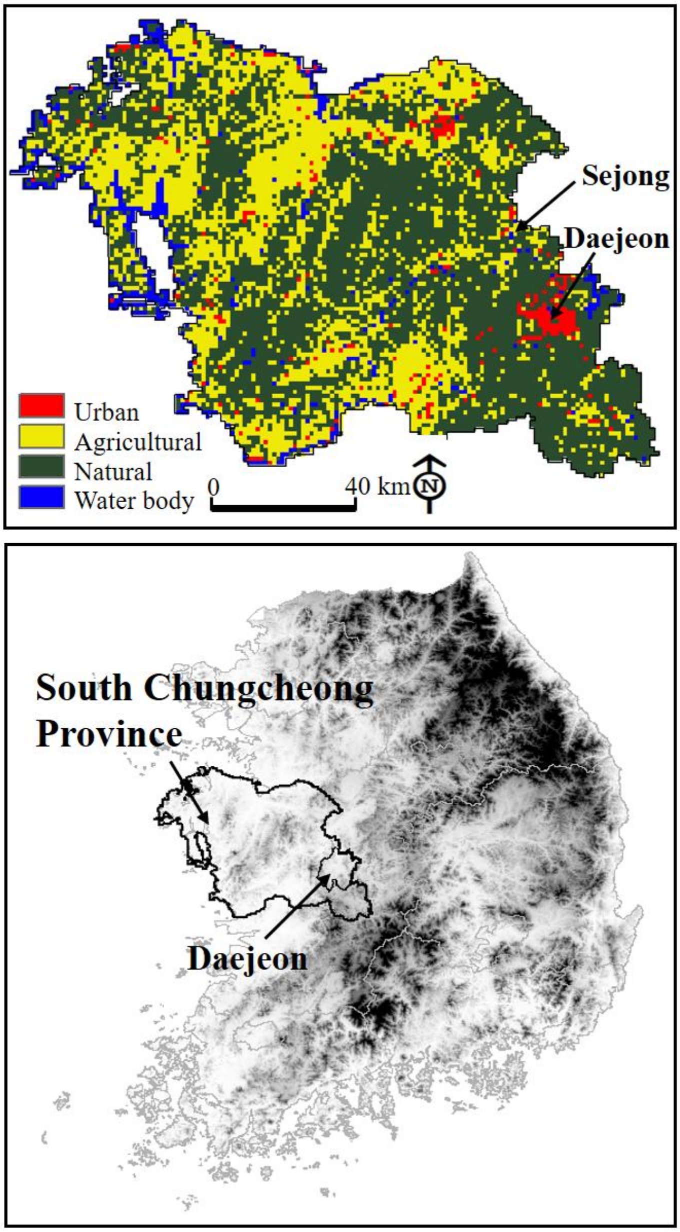

Figure 1. Study area in South Korea

2.3. Methodology

We produced land use scenarios for climate adaptation in the form of a 1 km raster projected to the 2050s. Each scenario consisted of three land use types: urban, agricultural, and natural (Yoon et al 2017). We then reallocated the current spatial extent of each of land use type based on these projections and compared the results against current spatial distributions with regard to climate adaptation, economic impact, and conversion amount.

2.3.1. Climate change impact and optimization objectives

We set five objectives for adaptation based on predicted climate change impacts and economic conditions in the region. Three of these considered the direct impacts of regional climate change on land use, inconsistencies with the current land use patterns, and landslides, which may occur more frequently than in the past: ‘minimization of disaster damage’; ‘maximization of rice yield’; and ‘maximization of species richness’. We used predictive maps of landslide probability, potential rice yield, and the potential habitats of 30 plant species under the representative concentration pathway 8.5 (RCP8.5) climate projections in the 2050s (2046–2055) (Figure 2 A-C; Supplemental Table 1; http://motive.kei.re.kr/). RCP8.5 was selected because it is the current actual emission trend, and because it can make climate change problems the most apparent (Riahi et al 2011). And it was downscaled from the Global Climate Model (HadGEM2-AO) administered by the Korea Meteorological Administration.

The other two non-climate-based objectives were 'maximization of economic value' and 'minimization of land use conversion'. We considered the latter important due to the high costs of such conversions (Cao et al 2011). We used economic productivity maps for urban, agricultural, and natural areas created using statistics from 2015–2016 (Figure 2 D-F; Supplemental Table 1). The five objectives were intended to be linked to long-term sustainability by maintaining a balance between social (safety from disaster), economic (land productivity and yield), and environmental (species richness) values.

Minimization of disaster damage: Landslides are a major risk in South Korea that can be amplified by more extreme weather events (Kim et al 2014). Since this region lacks a response system to landslides due to lack of experience, damage could be amplified when it occurs in future. We calculated disaster damage as the predicted economic losses ($) based on landslide probability, estimated by ensemble model (Supplemental Table 1), and monetary values of land use types in the 2050s. We assumed that maximum economic loss equaled the monetary value of land if landslide probability was 100%, reduced in proportion to reducing landslide probability (Figure 2A; Supplemental Equation 1).

Maximization of rice yield: Given regional variance in crop yield and limited South Korean areas for crop production, food security issues are an important consideration (Chavas et al 2009, Godfray et al 2010). Moreover, this region is responsible for a significant portion of main farming system in nation, rice yield. Thus it is important to secure agricultural areas that are projected to remain highly productive. In this objective, rice yield indicated the maximum amount (kg) of rice that could potentially be harvested from land use scenarios in one year in the 2050s. Potential rice yield was estimated by DSSAT (Supplemental Table 1) and we assumed only the potential rice yield of grids overlapping with allocated agricultural areas (Figure 2B; Supplemental Equation 2).

Maximization of species richness: Even without increasing the extent of natural areas, total biodiversity can be increased when natural areas contain habitats more suitable for a wider range of species (Ceballos and Ehrlich 2006). Although this region has potential to support diverse species due to junctions of heterogeneous landscapes, the current land use patterns are inconsistent with projected future species richness patterns (Figure 2C). In this objective, possible target species were estimated by MigClim (Supplemental Table 1), and species richness indicated the sum of target species that could be conserved by gridded land use scenarios in the 2050s. We assumed that conserved grids overlapped with allocated natural areas (Figure 2C; Supplemental Equation 3).

Maximization of economic value: Economic value, as indicated by total economic productivity ($), was derived from current land use using three assumptions. First, three land use types (urban, agricultural, and natural), could be mixed within a 1 km grid. Second, the current economic productivity of land uses varies depending on area, location, and economic factors such as transaction prices, added value, and rice and timber yield. Third, the economic productivity of land use in the grid could be conserved if the same land use is allocated to that grid (Figure 2D-F; Supplemental Equation 4).

Minimization of conversion: Conversion refers to the total area (km2) over which land uses differ from the current situation. Reducing the conversion rate in the process of optimization is related to feasibility of results or costs of adaptation (Yoon et al 2017). We calculated the number of grids in which conversion occurred by setting all land use conversions to 1 (Supplemental Equation 5).

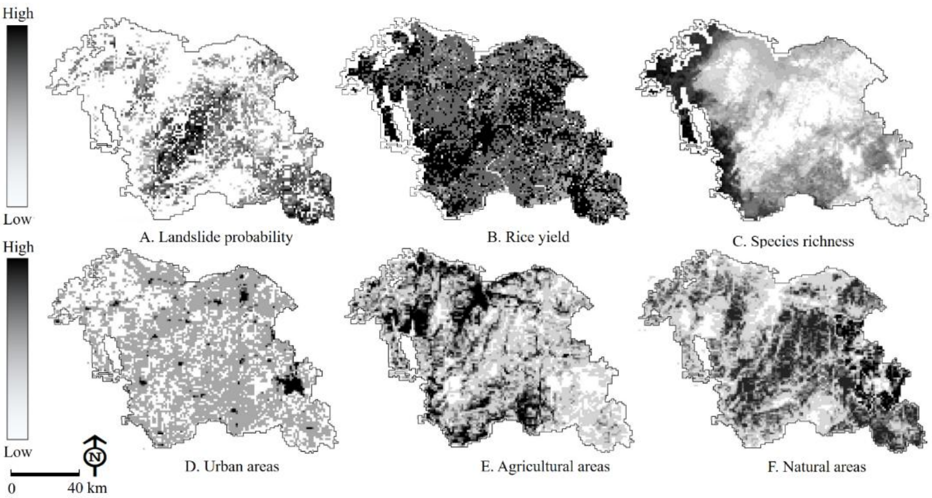

Figure 2. Projected future climate change impacts (A-C, RCP 8.5 in 2050s) and current productivity by land use type (D-F, in 2010s). These maps overlapped with spatial patterns of allocated and current land uses respectively; we then calculated potential disaster damage (A), potential rice yield (B), conserved target species (C), and conserved economic productivity by land use (D-F).

We excluded all water bodies and legally protected areas, and set an additional constraint to reduce the amount of conversion based on the current land use ratio in an individual grid (Supplemental Figure

1). This constraint ensured that a certain amount of new land use would originally exist in the grid even if land use conversion occurred at 1 km resolution. Thus, the actual amount of conversion was less than the value of the fifth objective, ‘minimization of conversion’ (Supplemental Equation 5).

2.3.2. Optimization model

1) Land use scenario

We set six weighting combinations for the five objectives: one consisting of equal weights, the others of one high weight (once for each objective) and four low weights. Since stochastic search methods show slightly different results in each run, we re-generated land use scenarios three times by weighting combinations and analysed each run (Table 1).

The performance of the three land use classes under future climate change was evaluated by comparing the values derived from the current land use patterns (e.g. level of rice production, $Current_{objective}$) with those from each of the alterative spatial scenarios ($Scenario_{objective}$) (Equations 1–2; Supplemental equations 1–5):

$$Performance_{objective} = \left(\frac{Scenario_{objective} - Current_{objective}}{Current_{objective}}\right) \times \alpha_j \times 100 \quad (1)$$

$$\alpha_j = \begin{cases} 1 & if\ maximization\ based\ objective \\ \frac{1}{total\ area} & if\ objective\ of\ conversion \\ -1 & if\ not \end{cases} \quad (2)$$

2) Optimization model

Optimization models can potentially provide better solutions than current land use patterns by exploring an enormous number of scenarios. We ran MOGA using a specially designed crossover operator to reduce spatial fragmentation (Yoon et al 2017). We allowed 30% random seeding of land use while 70% were selected from existing land uses to initialize each run. Then, ‘variation’ and ‘selection’ was repeated from 15,000 to 35,000 times in each run until the fitness of each scenario showed convergence (Figure 3). In ‘variation’, 0.05% of each land use scenario was changed by the crossover operator (Yoon et al 2017). In ‘selection’, after combining changed and previous scenarios, land use scenarios with better fitness were selected by the tournament method (Karamouz et al 2010). Fitness indicated how each scenario ranked relative to others in terms of weights and performances of objectives and in the direction of minimization; we selected land use scenarios with lower social costs:

$$\text{Fitness} = \text{Minmize}\left[\omega_{conv}\left(\frac{Best_{conv} - performance_{i,conv}}{Best_{conv} - Worst_{conv}}\right) - \sum_{j=1}^{J}\omega_j\left(\frac{Best_j - performance_{i,j}}{Best_j - Worst_j}\right)\right] \quad (3)$$

$$\mathrm{j} \in \{1,2,3,\dots,J\}, \mathrm{i} \in \{1,2,3,\dots,I\}$$

where I is the number of scenarios, J is the number of optimization objectives except for ‘minimization of conversion’, ωj and ωconv indicate weights of objectives in Table 1, and 'Best' and 'Worst' indicate the best and worst performances of all the optimized scenarios.

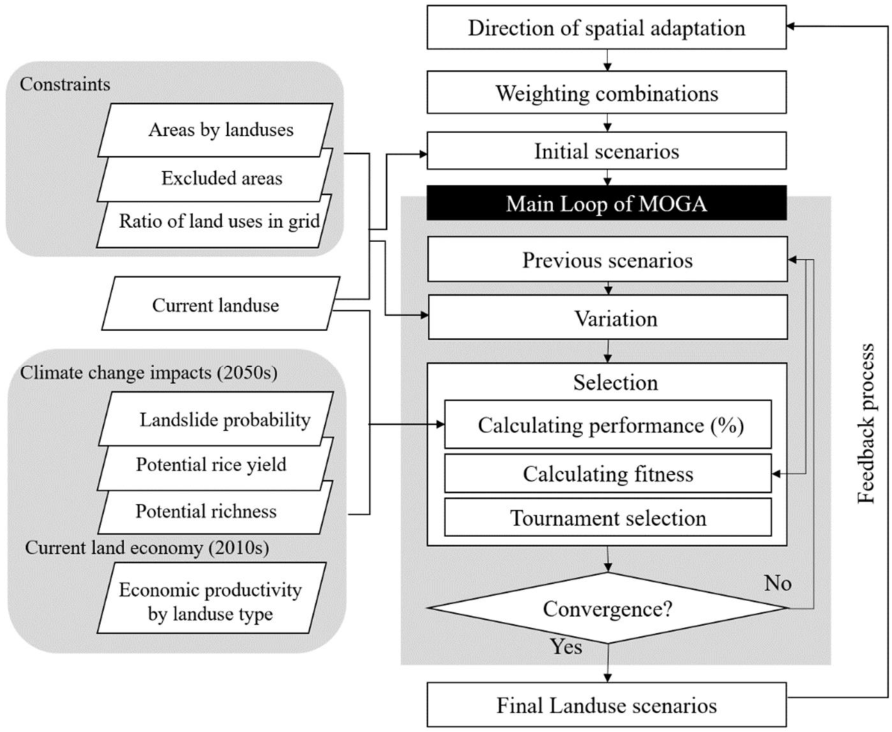

Figure 3. Optimization model based on MOGA

2.3.3. Analysis of land use scenarios

After we generated 18 optimal land use scenarios according to the 6 weighting combinations, we conducted the following analyses. First, we selected three representative scenarios that showed the best performances for disaster minimization, rice yield, and species richness. We calculated how these scenarios could mitigate climate change impacts and how much land use conversion was required.

Second, we analysed trades-off between scenarios and objectives by connecting performances of each Pareto scenario with lines, whose slopes and directions differed according to the weighing combinations.

Third, we synthesized land use scenarios based on spatial frequencies to quantify the locations of optimum land uses showing common trends (e.g., Caparros-Midwood et al 2015, Zhang et al 2015). For example, if the frequency of land use A was more than half in a given area, that area was assigned to A, using the same colour series expressed with darker shades as the frequency increased. Areas without a majority of specific land use were assigned to 'neutral', shown in white (Supplemental Table 2).

Table 1. Weighting combinations influencing adaption. The highest weighting in each combination is shaded. These weights can be used to prioritize objectives and here, it is composed with arbitrary numbers. T he weights can be adjusted with feedback from the previous results. Rel atively high weight up to 0.4 is given to show how performances can di ffer.

Emphasis	Disaster	Rice yield	Richness	Economic value	Convers ion	Scenarios
Equal	0.2	0.2	0.2	0.2	0.2	1a, 1b, 1c
Disaster	0.4	0.15	0.15	0.15	0.15	2a, 2b, 2c
Rice yield	0.15	0.4	0.15	0.15	0.15	3a. 3b, 3c
Richness	0.15	0.15	0.4	0.15	0.15	4a, 4b, 4c
Economic value	0.15	0.15	0.15	0.4	0.15	5a, 5b, 5c
Conversion	0.15	0.15	0.15	0.15	0.4	6a, 6b, 6c

2.4. Results

2.4.1. Representative land use scenarios for the climate change impact

In addition to the current land use pattern, we identified 18 land use scenarios, of which 17 were Pareto optimal. Of these, we chose three representative scenarios (2c, 3c, and 4b, Table 2) which had the best performance relative to the current land use pattern for the disaster, rice yield, and species richness objectives, respectively (Figure 5 A-C; Table 2). Scenario 2c had the best total performance (sum of all performances except conversion, 37.09%), and the best disaster performance (21.17%). Natural areas in scenario 2c were allocated mainly to areas where disaster probability was expected to be high under climate change because the higher the disaster probability, the more damage can be reduced by re-allocation to natural areas. Scenario 3c had the best performance for rice yield (8.85%), but its disaster performance decreased (-23.99%) compared to scenario 2c. Natural areas in scenario 3c were more fragmented than scenario 2c because agricultural areas were allocated to areas where both disaster probability and rice yield were expected to be high. In scenario 4b, which performed best with regards to species richness (41.45%), a large part of the natural areas distributed in the study area's centre in scenarios 2c and 3c were moved to the west, and spatial fragmentation decreased. This was consistent with areas where the richness of target species was expected to be high, but it differed the most from the current land use composition of all scenarios, with a conversion rate of 35.9%.

Table 2. Performance of scenarios compared to spatial pattern of curent land use (%). Highest three performances by objective are shaded. Except for conversion minimization, positive values indicate better than current land use patterns while negative values indicate worse.

Emphasis in weight	Scenarios	Objectives				
		Disaster Damage	Rice yield	Species richness	Economic value	Conversion
Equal	1a	10.38	5.69	11.71	1.11	26.63
	1b	12.51	5.76	10.25	1.23	27.19
	1c	8.71	6.10	16.02	−0.05	28.42
Disaster damage	2a	19.06	4.82	9.73	1.71	27.32
	2b	17.93	5.34	9.16	1.65	27.59
	2c*	21.17	4.66	9.6	1.66	27.86
Rice yield	3a	1.77	8.56	10.45	−0.85	28.67
	3b	1.18	8.84	10.92	−1.79	29.45
	3c*	−2.82	8.85	15.46	−2.95	31.01
Species richness	4a	−25.06	6.28	39.51	−8.76	34.72
	4b*	−30.55	6.38	41.45	−9.72	35.9
	4c	−15.32	5.93	35.50	−6.44	33.33
Economic value	5a	16.35	3.92	0.43	4.58	26.58
	5b	15.93	3.31	−0.08	4.75	26.47
	5c	15.51	3.34	1.27	4.87	26.77
Conversion	6a**	-0.16	3.98	6.44	0.82	21.66
	6b	1.75	4.13	4.94	1.45	21.42
	6c	1.25	4.15	6.89	0.91	21.61

*Representative scenarios show best performances in disaster minimization, rice yield, and species richness, respectively.
**Scenario 6a is a non-Pareto solution showing worse performances than scenario 6c in all objectives

2.4.2. Trade-offs between scenarios

In all 17 Pareto land use scenarios, scenarios 3abc, 4abc, and 6bc (emphasizing rice yield, species richness, and conversion minimization, respectively) showed the best performances for species richness and the next best performance for rice yield, but there were greater losses in disaster damage and economic value. In contrast, scenarios 5abc showed the best performance for disaster damage and the worst performance for species richness. This is the result of specific relationships between objectives as well as weighing combinations of objectives.

For example, disaster minimization competed with rice yield and species richness and correlates with economic value. In particular, competition between disaster minimization and species richness maximization was very strong and performances were very sensitive to weights. In scenarios 4abc, which gave the highest weight to species richness (richness 0.4, others 0.15), conservation was 35.50–41.45% higher than current land uses, but economic value and disaster minimization were negative (indicating a worse result than current land use). This contrasts with the other scenarios, which produced positive performances for almost all objectives. Areas where species richness was expected to be high did not match current natural areas, so a large amount of land conversion (33.33–35.90%) was required to maintain species richness, leading to losses in disaster minimization, economic values, and conversion that were highly relevant to current land use composition. Rice yield was the least sensitive objective, with performances ranging from 3.31-8.85%, regardless of the scenario (Table 2), because the difference in rice yields by locations was relatively small (Figure 2).

2.4.3. Spatial frequency of scenarios

Analysing the spatial frequency of the 17 Pareto scenarios showed that the central areas of all land uses were consistently allocated to the same land use, mirroring the current land use distribution (Figure 5). However, marginal areas were transformed to mitigate climate change impacts. Neutral areas, 1.52% (143 grids) of the total area, were scattered throughout the study area (Supplemental Table 2 and Figure 5). Neutral areas could play an important role in spatial decision-making because all land use types were mixed within these grids (Supplemental Figure 1) and all land use types could be allocated in future according to different scenarios. Depending on which land use is expanded within grids of neutral areas, the whole study area could adapt differently to the three climate change impacts.

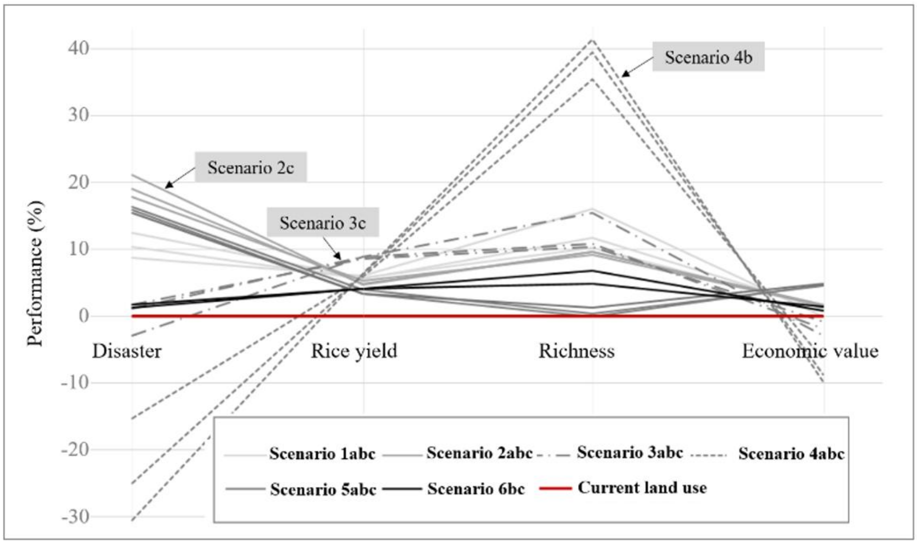

Figure 4. Trade-offs between adaptation scenarios

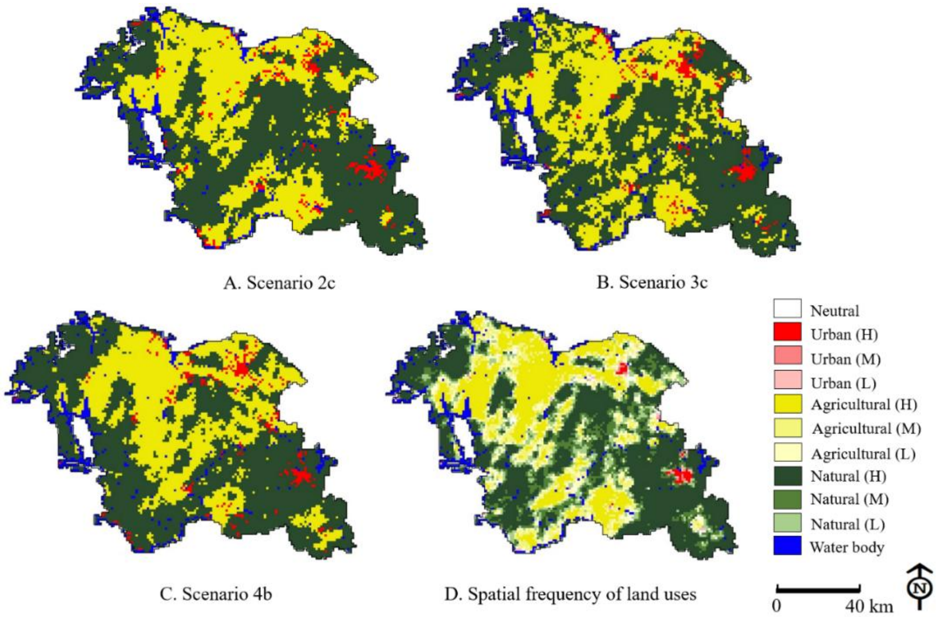

Figure 5. Representative scenarios (A-C) and spatial frequency of land use (D). If the frequency of a specific land use was more than half,

it was assigned to the land use with same colour series (red for urban, yellow for agricultural, green for natural area). High (15–17), medium (12–14), and low (9–11) frequencies are expressed as 'H', 'M', and 'L', respectively. Neutral indicates no majority of specific land use.

2.5. Discussion

The MOGA optimization approach allows for simultaneous consideration of climate change impacts, economics, multiple land use types, and other constraints, which we used to develop spatial land use adaptation scenarios. We found that it was possible to increase performance for all five objectives slightly, relative to current land use performance, visible in scenarios 1, 2, and 6 (Figure 4). However there were trade-offs, and scenarios that greatly improved on one objective such as minimizing landslides typically did so at the cost of other objectives, particularly for preserving species richness, and vice versa (Figure 4). Each land use scenario performed best for its high-weighted objective: to enhance the capacity to achieve adaptation capability (8.56-41.45% better than current land use), or conserve the most land productivity in all scenarios. The scenarios with equal weights (1abc) also showed slightly improved land use climate adaptation than the current spatial pattern of land use for all objectives. This indicates that not only does this approach provide spatially-explicit alternatives to make land use to be more resilient to climate change, but that options for overall improvements could made without greatly impacting performance of the five objectives are available.

The spatial patterns of land use change steadily over time and we expect will continue to do so depending on changes in population, climate, and other factors. Therefore, we suggest that reasonable guidelines for land use adaptation can contribute to reducing social costs of climate change (Folke et al 2005). Land use scenario that are more responsive to climate change can be a basis for identifying options and implementing adaptation strategies for entire regions. Based on optimized land use scenarios, local government can question whether current spatial patterns of land use are appropriate or optimal for future conditions. This can also lead to local review of the extent to which land use can be designed and operated to promote resiliency and adaptive capacities. The reallocation of land uses will impact landowners differently. The outputs from this study will need to be discussed, and could be used to identify and support disadvantaged owners or vulnerable group in areas not relevant to climate change impacts. Finally, the approach can be used to mitigate climate change impacts related to natural disasters, food security, and ecological aspects by prohibiting development in increasingly high disaster-risk areas, moving agricultural lands into future high-productivity areas, and conserving future ecologically important areas (Bajracharya et al 2011). In addition, if such land use scenarios are considered in zoning ordinances, developers and landowners can improve public safety and welfare while conducting business.

Uncertainties related to future climate change conditions are in part related to the multiple climate change models and emission scenarios, which can affect the establishment of adaptation strategies (Hallegatte 2009). To respond appropriately, it is important to identify a range of scenarios which have high uncertainties but that can cover a wide range of options in the decision space (Ligmann-Zielinska et al

2008). Furthermore, the decision space can be easily widened further by adjusting objective weights or replacing of input datasets. Weight adjustment can also be regarded as an iterative feedback process by stakeholders. In this case, we expect communication of the scenarios to proceed smoothly because the performance of each scenario is expressed in a way easy for non-optimization experts to understand (e.g., increased rate of rice yield compared to current land use). Also, since the optimization model has a highly flexible structure that can change input data and related fitness functions (Yoon et al 2017), other land use scenarios can be generated to simulate pressures on and mitigation of other climate scenarios or land use goals. Here, we focused on creating land use scenarios using pre-determined impact maps, but for practical applications, sensitivity to climate change scenarios or assessment models and the extent of uncertainty should be identified. How landscapes should be designed eventually depends on the choice of decision makers such as policer and planners referring to this identified uncertainty. Considering that the land use scenarios are potential solutions, the robustness and ability to perform satisfactorily over a broad range of future conditions also should be evaluated.

Scenario planning also has some limitations. First, high rates of land use conversion can be a reason not to implement a given scenario for climate adaptation. When we tried to keep the conversion rate below a certain level, it resulted in greater performance losses for other objectives. This indicates that regional climate change impacts will be significant, and that current land use patterns are likely vulnerable. It can be argued, therefore, that adaptation measures are urgently needed even while likely to be expensive. However, if the mitigation of climate change impacts on disaster damage, rice yield, and species richness are translated into reduced social costs, much of the cost from land use conversion could be offset.

Second, our spatial resolution of 1 km means the results cannot be regarded as definitive land-use compositions but instead as a ‘strategic planning direction’. The entirety of each 1 x 1 km grid would not necessarily be converted to the allocated land use; our results simply suggest the direction in which to increase or decrease each land use within each grid (only currently existing land uses were allocated in the model). Third, factors related to specific spatial patterns of natural areas (e.g. connectivity, Keely et al 2018, and minimum patch size, Siitonen et al 2003, Westphal et al 2007) and urban areas (e.g. distance from infra structure, Cao et al 2012, Neema and Ohgai 2010) were not considered, because too many objectives and constraints can burden the optimization process. These factors can be a prerequisite for individual species or at the facility level, so it is necessary to incorporate them by modifying fitness functions or changing the optimization parameters (Haque and Asami 2014, Yuan et al 2014, Zhang et al 2016) in further studies. Fourth, while this study examined three potential impacts from climate change, we recognize that there are many other possible impacts that were beyond the scope of this study, including extreme events such as hurricanes or large wildfire. Further research efforts are needed to incorporate forecasts for these types of impacts. Fifth, we focused on reallocating land uses using the current extents, instead of comparing these with a ‘no change’ or considering expansion of existing urban areas. This is appropriate for South Korea because the population is expected to decline starting in the 2030s (http://kosis.kr/).

In general, however, land use patterns change continuously even without political pressure, and it is important to define the costs and benefits of optimized scenarios relative to no change scenarios (Li et al 2011). From the view of climate change adaptation, 'land use optimization' and 'land use prediction' can play different roles: the former refers to a concrete plan for changing land use patterns for climate adaptation, while the latter shows the predicted effects of adaptation strategies on land use patterns, considering past trends (Yoon et al 2017, Zhang et al 2014). However, we are confident that more reasonable results can be achieved by combining these two approaches in further studies.

Adaptation is an important aspect of resiliency to climate change (Adger et al 2005, Scarano, 2017), but concrete methodologies for adaptation on the ground have not been sufficiently addressed. Multi-Criteria Analysis (MCA), which can consider competing issues to prioritize adaptation options using the full aggregation or the outranking method, is often used to support adaptation decisions (Trærup et al 2015, De Bruin et al 2009, Ishizaka and Nemery 2013). However, it cannot describe spatially-explicit solutions. Multi-objective optimization models can be an alternative. In recent studies, agricultural growth pathways were identified based on land use optimization (Dunnett et al 2018), and urban expansion was optimized considering climate-induced events (Caparros-Midwood 2015). Nevertheless, in the context of adaptation, few studies have addressed multiple climate impacts affecting different sectors and land uses in a single model; our study is thus a new starting point for this approach.

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2.7. Supplemental Material

Supplemental Table 1. Variables and assessment model of input data. We set five objectives for adaptation based on predicted climate change impacts and economic conditions in the region. For the three objectives considering climate change impacts (A-C), we used predictive maps of landslide probability, potential rice yield, and the potential species under the RCP8.5 climate projections in the 2050s. In supplemental equation 1-3, the values of independent variables, $Landslide\ Probability_{mn}$, $Potential\ Rice\ Yield_{mn}$, and $Potential\ Richness_{mn}$ are referenced in these predictive maps respectively. For the other two objectives considering economic aspects (D-E), we used economic productivity maps by landuses and land cover map in current time, 2010s. In the supplemental equation 4, the value of $Economic\ Productivity_{mnk}$ is referenced in economic productivity map of landuse k. And supplemental equation 5, the value of l is referenced in current cover map.

	Objectives	Input data	Related variables	Source	Assessment Model
A	Minimization of Disaster damage	Map of landslide susceptibility in the 2050s	8.5 representative concentration pathway (RCP) scenarios (2046–2055)	KMA[a], 2016	Ensemble model[1]
			Survey of landslide occurrence	NIFS[b], 2014	
			Topography	MOE[c], 2013	
			Vegetation	KFS[d], 2013	
			Deepness of roots	Candadel et al., 1996	
B	Maximization of Rice yield	Potential rice yield in the 2050s	8.5 RCP scenarios (2046–2055)	KMA[a], 2016	DSSAT[2]
			Soil	RDA[e], 2016	
			Rice cultivation / management nformation	Jeong et al., 2014	
C	Maximization of Species richness	Potential richness in the 2050s	8.5 RCP scenarios (2046–2055)	KMA[a], 2016	MigClim[3]
			National field survey data on vascular plant resources (for 30 target species)	MOE[c], 2015	
			6 Bioclimatic variables	Koo et al., 2017	
D	Maximiza	Economic	Residential transition	MOLIT[f], 2016	Net

	tion of Economic value	productivity maps of urban, agricultural, and natural areas	price Added value of service industry Rice production and unit price Timber yield Land cover map	 Statistics Korea, 2015 Statistics Korea, 2016 Statistics Korea, 2015 MOE[c], 2013	operating income[4]
E	Minimization of Conversion	-	Land cover map	MOE, 2013	-

[a] Korean Meteorological Administration, [b] National Institute of Forest Science, [c] Ministry of Environment, [d] Korean Forest Service, [e] Rural Development Administration, [f] Ministry of Land, Infrastructure and Transport

Ensemble model[1]: Probability of landslide in 2050s was simulated by ensemble model combining MaxEnt and the Random Forest method.

DSSAT[2]: Potential yield of rice in 2050s was projected using the CERES-Rice model included in the DSSAT (Decision Support System for Agricultural Transfer).

MigClim[3]: Potential habitat of target species in 2050s was simulated using an ensemble method considering its dispersal ability.

Net operating income[4]: Current economic productivities of landuses is calculated using area, location, and economic factors such as transaction prices, added value, and rice and timber yield.

Supplemental Equations. Each land-use scenario can be evaluated with regard to five objectives using supplemental equations 1–5 (below), in which M is the number of rows, N is the number of columns, and K is the number of landuse types.

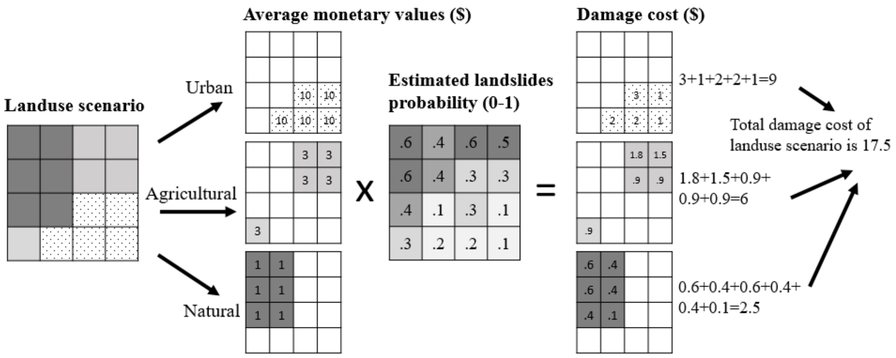
Supplemental Equation 1. Disaster damage of the ith scenario ($Scenario_{disaster}$) can be calculated as follows. x_{mnk} is a binary variable, which allows only one land-use type to be allocated to the individual grid. Monetary values of land-use types ($\mathrm{Monetary\ Value_k}$) are scaled referring to a previous study focused on another city in South Korea (Yoon et al., 2017). Disaster probability of each grid ($\mathrm{Landslide\ Probability_{mn}}$) is from the landslide probability map for the 2050s under the RCP8.5 climate change scenario. S_k is the total number of grids in the study area.

$$Scenario_{disaster} = \sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{k=1}^{K}(x_{mnk} \times \text{Monetary Value}_{k} \times \text{Landslide Probability}_{mn}) \quad (1)$$

$$x_{mnk} \in \{0,1\}; \quad \sum_{k=1}^{K} x_{mnk} = 1;$$

$$\forall k = 1,2,\ldots,K; \quad \sum_{m=1}^{M}\sum_{n=1}^{N} x_{mnk} = S_k$$

The process for calculating disaster damage in the landuse scenario is as follows.

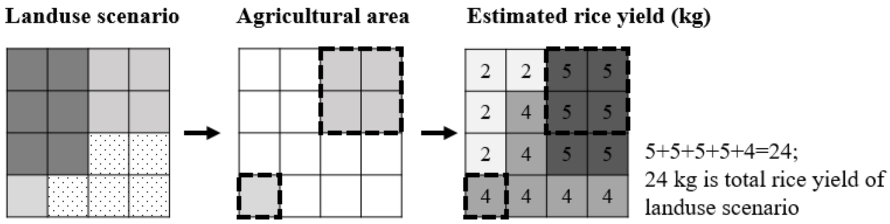


Supplemental Equation 2. Rice yield of the *i*th scenario ($Scenario_{rice}$) can be calculated as follows. y_{mnk}, is a binary variable limiting the calculation to the grids allocated only as agricultural land. Potential rice yield of each grid ($Potential\ Rice\ Yield_{mn}$) is from the maximum rice yield map for the 2050s under the RCP8.5 climate change scenario. A_k is the total number of grids in agricultural land.

$$Scenario_{rice} = \sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{k=1}^{K}(y_{mnk} \times Potential\ Rice\ Yield_{mn}) \quad (2)$$

$$y_{mnk} = \begin{cases} 1 & if\ k = Agriculture \\ 0 & if\ \text{not} \end{cases}; \quad \sum_{m=1}^{M}\sum_{n=1}^{N} y_{mnk} = A_k$$

The process for calculating rice yield in the landuse scenario is as follows.

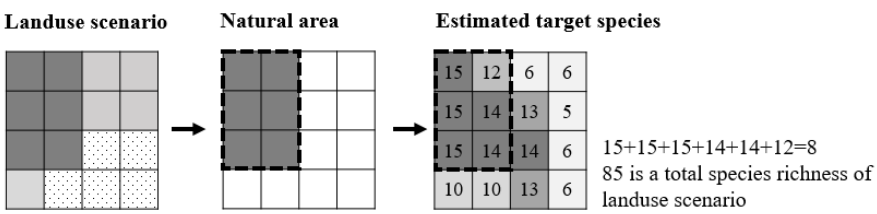


Supplemental Equation 3. Total species richness of the ith scenario ($Scenario_{richness}$) can be calculated as follows. z_{mnk}, is a binary variable limiting the calculation to the grids allocated only as natural land. Potential species richness of each grid ($Potential\ richness_{mn}$) is from the potential species richness map generated by superimposing the potential habitats of 30 target plant species for the 2050s under the RCP8.5 climate change scenario. N_k is the total number of grids in natural land.

$$Scenario_{richness} = \sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{k=1}^{K}(z_{mnk} \times Potential\ Richness_{mn}) \quad (3)$$

$$\mathrm{z_{mnk}} = \begin{cases} 1 & if\ k = Natural \\ 0 & if \text{ not} \end{cases}; \quad \sum_{m=1}^{M}\sum_{n=1}^{N} z_{mnk} = N_k$$

The process for calculating species richness in the landuse scenario is as follows.



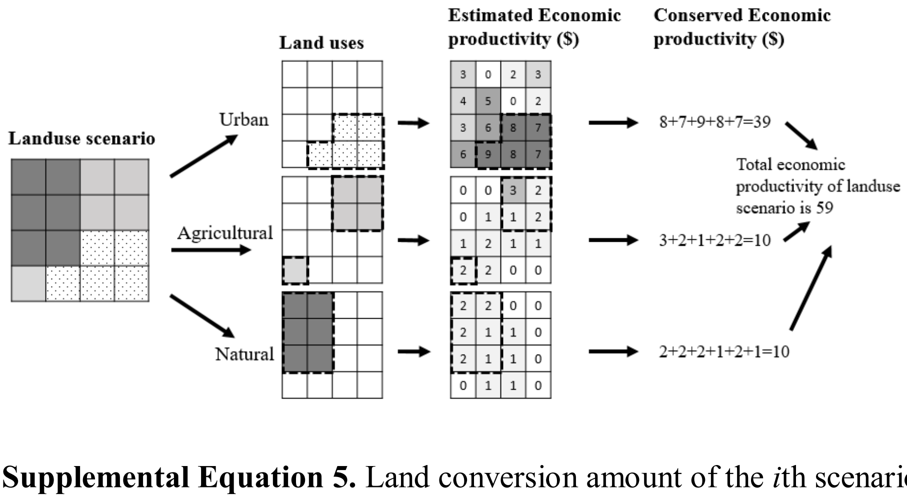
Supplemental Equation 4. Economic value of the ith scenario ($Scenario_{economic}$) can be calculated as follows. x_{mnk} is a binary variable, which allows only one land-use type to be allocated to the individual grid. Economic productivity of each grid ($Scenario_{economic}$) is from the economic productivity maps generated for the three land-use types (urban, agricultural, and natural areas) under current conditions (2015–2016). The economic productivity map of the urban area was conducted using actual transaction prices, added values, and areas within 1km grid. Similarly, economic productivities of agricultural and natural areas were conducted using actual rice production, timber yield, related unit price, and areas within grid (Supplemental Table 1). S_k is the total number of grids in natural land.

$$Scenario_{economic} = \sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{k=1}^{K}(x_{mnk} \times Economic\ Productivity_{mnk}) \quad (4)$$

$$x_{mnk} \in \{0,1\}; \quad \sum_{k=1}^{K} x_{mnk} = 1,$$

$$\forall k = 1,2,\ldots,K; \quad \sum_{m=1}^{M}\sum_{n=1}^{N} x_{mnk} = S_k$$

The process for calculating economic value in the landuse scenario is as follows.



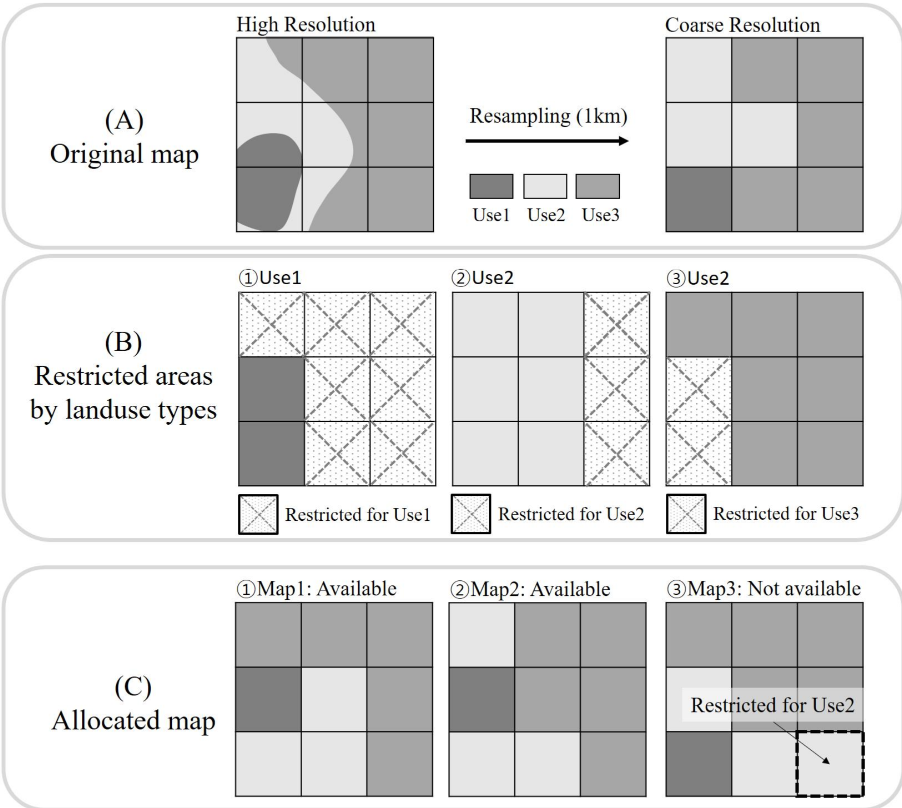
Supplemental Equation 5. Land conversion amount of the ith scenario ($Scenario_{conversion}$) can be calculated as follows. k and l indicate land-use types of current and scenario, respectively, in individual grids

(K and L indicate the number of land-use types). If k is not equal to l in each grid, a value of 1 is assigned to the grid ($Conv_{mnkl}$).

$$Conversion_{i} = \sum_{m=1}^{M} \sum_{n=1}^{N} Conv_{mnkl} \quad (5)$$

$$Conv_{\mathrm{mnkl}} = \begin{cases} 1 & if\ k \neq l \\ 0 & if\ not \end{cases}; \quad \forall k = 1,2,\ldots,K; \quad \forall l = 1,2,\ldots,L$$

Supplemental Figure 1. Restrictions based on current landuse composition. Although landuses are allocated in 1 km grids (coarse resolution), this restriction is based on current land-use composition in high resolution (B1–3). Allocated maps have four changed grids in common from current landuse (C1–3), but C3 is not available since “Use 2” is allocated to the grid where “Use 2” did not originally exist in the current composition at high resolution.



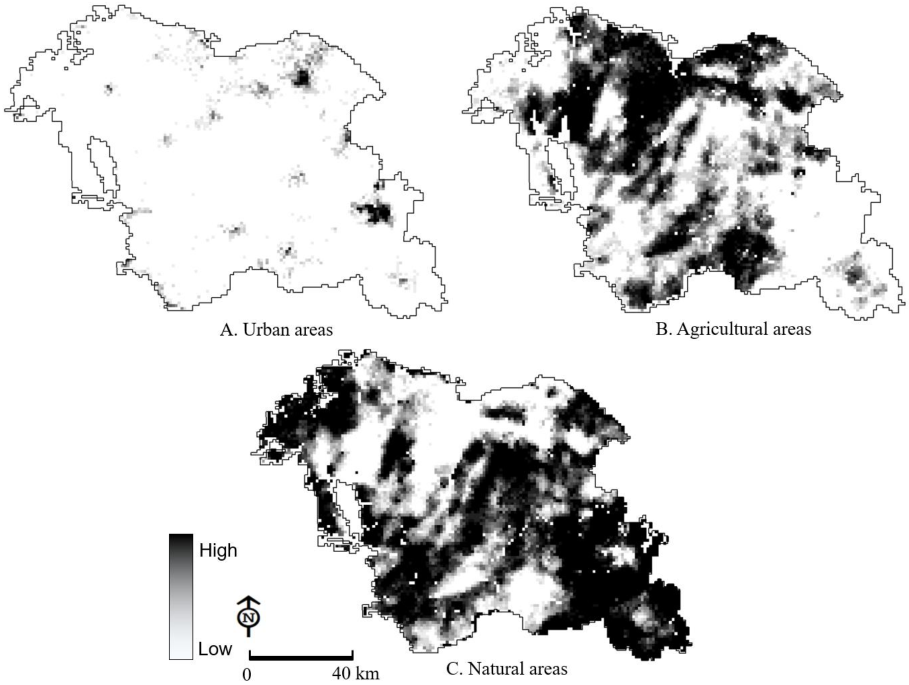
Supplemental Table 2. Color palette for frequency map. Spatial frequency of optimized landuse scenarios are expressed using follow color palette. If the frequency of landuse A is more than half of the number of scenarios on the grid, it is assigned to landuse A, using same color series expressed with darker shades as the frequency increases.

Frequency	Majority by one use			Neutral
	High	Medium	Low	Others
Urban				
Agricultural				
Natural				

Supplemental Table 3. Areas by frequency level (unit: km2). This frame is matched to supplemental table2. Considering total area is 9,420km, most of the area (98%, 9,277km2) show a tendency to be allocated more frequently by specific landuse.

Frequency	Majority by one use				Neutral
	High	Medium	Low	Total	
Urban	48	31	47	126	
Agricultural	1743	919	836	3498	143
Natural	3622	1170	861	5653	
Total	5413	2120	1744	9277	143

Supplemental Figure 2. Spatial frequency of each landuse in Pareto scenarios. Darker shades represent increasing spatial frequency of each landuse.



3. CHPATER 2: Multi-Objective Land-Use Allocation Considering Landslide Risk under Climate Change: Case Study in Pyeongchang-gun, Korea

3.1. Introduction

In recent years, the increasing variability in precipitation patterns has triggered frequent extreme landslides [1,2]. Landslides are one of the critical natural phenomena that lead to serious problems in hilly regions on a global scale [3]. In the case of Gangwon-do, a typical mountainous region in Korea, 44 casualties (including 19 missing persons) resulting from flooding and landslides were reported in 2006. The Baduella District of Sri Lanka, El Cambray Dos of Guatemala, Maharashtra of India, and the Sindhupachok District of Nepal have also experienced severe damage, with more than 100 casualties in the last three years. These cities are still at risk for potential landslide damage because the frequency and scale of landslides may further increase in the near future due to climate change. Therefore, we are concerned with where the landslides may occur and how we should respond to the risk of landslides in these cities.

Over the past two decades, numerous researchers have assessed landslide hazard under the present and future conditions influenced by climate change to estimate potential probabilities [4–9]. In those studies, the amount of overlapping urban and hazardous areas represents the regional risk level because landslide damage, such as property loss and casualties, is concentrated in urban areas. Even though the reduction of risk in advance is extremely important for mitigating large-scale disasters, only a few studies have addressed how to respond to potential landslide damage, i.e., landslide risk. For urban planning purposes, landslide risk can be reduced by placing urban areas in safe zones that have lower landslide hazard grades [10,11].

Land-use composition is driven by social, economic, and environmental factors and cannot be allocated based on the mitigation of landslide risk alone. In reality, numerous objectives, constraints, and stakeholders are involved in planning, which can be conflicting [12]. Researchers have called this a “nonlinear problem,” which cannot be solved with qualitative knowledge or traditional linear modeling. In many cases, land-use planning systems have failed to balance different values, such as economic benefits, protection of natural resources, and social safety [13]. Therefore, we require scientific and quantitative tools that can incorporate numerous factors and help us create comprehensive plans.

Genetic algorithms (GA) are the most popular optimization tools to address multi-objective problems in land-use planning [14–18]. Unlike other heuristic approaches, the GA approach is a general-purpose search method, combining elements of directed and stochastic searches, which can create a superior balance between the exploitation and exploration of a search space [19]. Additionally, the application of a GA allows for immediate feedback to stakeholders because it can run a number of experiments with different parameter values. Therefore, we suggest a quantitative tool, the Multi-Objective Genetic Algorithm (MOGA), which can generate a comprehensive land-use allocation plan that considers landslides under climate change, and apply it to the Pyeongchang-gun area of Korea. Pyeongchang-gun, a typical mountainous city, is the fastest changing region in Korea due to its development for the 2018 Winter Olympics. Urban sprawl into natural areas in this city has caused an increase in potential disaster risk, especially with regard to landslides. We also considered the “minimization of land-use change” and the “maximization of compactness” as optimization objectives. Land-use change is associated with a certain amount of economic cost and compactness is an important factor for land management. The optimized land-use plans that we created can be used as guidelines or as basic data by regional stakeholders. They can also contribute to the spatial adaptation plans against climate change impacts. We are careful to note that the optimization results are not the only good alternatives; rather, they are meant to support further detailed design or analysis by stakeholders [14,20].

In Section ‘Materials and Methods’, we introduce the study areas and describe the datasets, the method of landslide hazard analysis, and optimization. The optimization objectives and constraints are also described in this section. In Section ‘Results’, we present the changes in landslide hazards with climate change and related optimal land use patterns. In Section ‘Discussion’, we present the implications and limitations of the optimization results and directions for future research.

3.2. Materials and Methods

3.2.1. Study Area

Our study area is Jinbu-myeon, located in Pyeongchang-gun, in the mountainous Gangwon-do region of Korea (Figure 1). The Gangwon-do region has high landslide probability, owing to its high elevation, a dynamic topography, and large elevation differences [4]. In 2006, a large-scale shallow landslide was caused by Typhoon Ewiniar. Furthermore, we expect that the landslide probability could increase in the future according to the Representative Concentration Pathways (RCPs) climate change scenarios. However, most regional policies on landslides focus on management after the event, such as debris barrier installations, and cannot address potential landslide damage not yet incurred.

Jinbu-myeon in Pyeongchang-gun has a higher landslide risk than the other cities in Gangwon-do, because urban zones are sprawling into mountainous areas; 69% of Pyeongchang-gun is at altitudes greater than 500 m above sea level. The 2018 Winter Olympics increased the pressure for development/expansion and the migration rate into the city. Jinbu-myeon is the second-most populous city in Pyeongchang-gun and has good accessibility supported by highways and a new railway that is under construction. According to the city master plan, the potential developed area in Jinbu-myeon may increase by 69.4% by 2020 to accommodate the increasing population and the facilities for the Olympics [21]. Therefore, we must determine the direction of land-use change in Jinbu-myeon, while considering the potential for landslide damage.

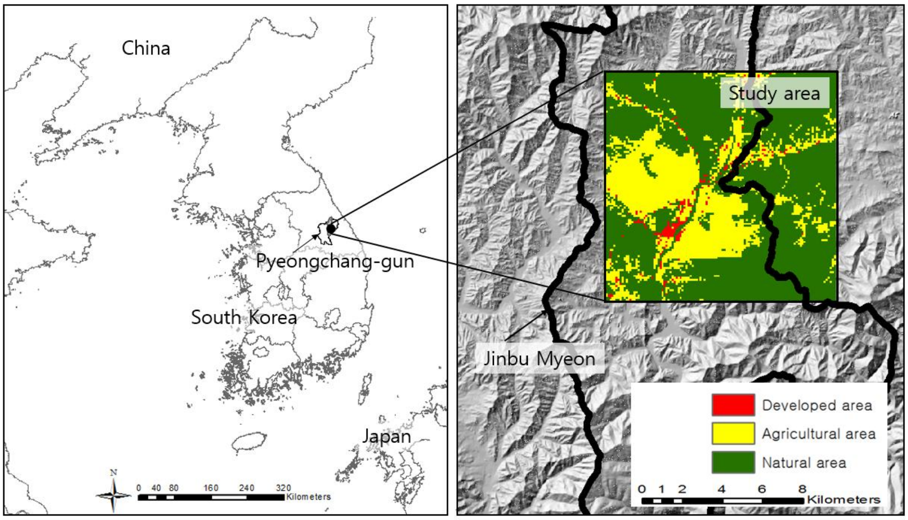


Figure 1. Study area: Jinbu-myeon, Pyeongchang-gun

3.2.2. Dataset

We used input variables describing climate factors, topographic factors, ground material, and vegetation factors to analyze landslide hazard and conduct optimized land-use planning (Table 1). With respect to climate factors, we focused on calculating the extreme rainfall variables during 2006 using Automatic Weather System (AWS) data. In 2006, the Gangwon-do region, including the study area, experienced a large-scale shallow landslide and flood damage from Typhoon Ewiniar, primarily in urban and farmland zones, which resulted in 25 casualties and 19 missing persons. Because the detailed investigation for the landslide was conducted in 2006 and there has been no further investigation since then, the study period was limited to 2006. We then used the 8.5 RCPs scenario to estimate the climatic conditions in the 2050s, referred to as "mid-term future" in climate change research. The scenario predictions for 2041–2070 were averaged to reduce the uncertainty caused by using model data rather than observational data. In this regard, climate change was directly reflected as a variable in hazard analysis, while it was reflected indirectly through hazard analysis in land-use optimization. We also used a digital elevation model (DEM), a soil map, and a map of forest types to define the topography, ground material, and vegetation factors, respectively.

The land cover map shows 22 land-use types that were re-categorized into three groups: urban, agricultural, and natural areas. Our purpose is to generate land-use allocation maps that are not final land-use plans, but rather alternatives to support the stakeholder's decision or detailed design because simplified land-use types are more easily incorporated into planning as they provide only the approximate spatial extent of each land-use. Dataset resolution varied from 30 m to 1 km (Table 1); thus, it was necessary to unify them at an appropriate resolution. Finally, the entire dataset was converted to 100-m resolution raster data composed of 116 rows and 114 columns. The difficulties of objectively determining the resolution of the final data are described in Section 4.

Table 1. Dataset and variables for the study

Section	Data Source and Type	Reference	Data Format
Landslide hazard	AWS (Automatic Weather System) [a] -Daily maximum rainfall (mm) -5 d of maximum precipitation (mm) -Number of days with over 120 mm of rainfall	KMA [c], 2006	Point
	2041–2070 8.5 RCPs scenario [b]	KMA, 2011	Raster, 1 km
	DEM (Digital Elevation Model) -Slope -Elevation	KME [d], 2008	Raster, 30 m
	Soil map -Soil depth/soil drainage/soil type	WAMIS [e], 2006	Raster, 30 m
	Map of forest type -Coniferous/Deciduous/Mixed forest -Natural forest, Artificial forest	KME, 2005	Raster, 30 m
Land-use allocation	2020 Master plan	Pyeongchang-gun, 2014	Tables
	Land cover map -Urban/agricultural/natural data	KME, 2006	Raster, 30 m
	DEM -Elevation	KME, 2008	Raster, 30 m
	Regional statistics -Crop yield -Industrial/commercial production -Forest production	Pyeongchang-gun, 2005–2015	Tables

a AWS data originally provided in hourly format was modified into daily format to be consistent with the climate change scenario.
b Korea Meteorological Administration (KMA) downscaled the global model (HadGEM2-AO, 135 km unit) to the regional model (HadGEM3-RA, 12.5 km unit) using a dynamic technique. Additionally, the KMA revised the regional model to 1-km units using PRISM based downscaling estimation model.

c Korea Metrological Administration.
d Korea Ministry of Environment.
e Water Resources Management Information System.

3.2.3. Landslide Hazard Analysis

Landslide hazard was simulated using a maximum entropy model (MaxEnt) based on the variables in Table 1. MaxEnt, developed by AT&T Labs, has been applied to various fields, including statistical physics, optimization, and image construction [22]. Recently, MaxEnt has been applied to landslide assessment and has shown better performance regarding the area under curve (AUC) values than other models: multiple adaptive regression splines, logistic regression, and classification and regression trees [22]. Since the local government of the Gangwon-do Province possesses the only occurrence data of landslides, configuring MaxEnt to use the occurrence data is appropriate for this study area. We classified the potential landslide hazard for the future into ten grades, using the standard deviation values of the future landslide hazard and the threshold value in the present hazard model. The 10th grade represents the most dangerous areas for landslides, while the first grade represents the safest areas with respect to landslides. If the landslide hazard were classified into fewer than ten grades, the optimization of moving the hazardous urban areas to safe areas could not proceed well because the majority of safe areas would be located in high altitude areas that restrict urban development.

1) Objectives and Constraints

We defined three objectives for land-use allocation: the minimization of landslide risk, the minimization of change, and the maximization of compactness. The risk is a very useful concept when addressing the potential damage of future disasters under climate change [23]. Risk can be measured as the combination of the probability and consequences of an adverse event [24] (Equation (1)). We divided the probability into ten categories equal to the grades of landslide hazard because we assumed that the higher the hazard grade, the higher the probability of occurrence. We divided the consequences into three grades by land-use type: catastrophic, major-moderate, and minor-insignificant. Exposure to landslides differs by the intensity of development, namely, the land use [11]. We categorized urban areas as the highest consequence grade, “catastrophic”, while agricultural areas and forest areas were categorized as “major-moderate grade” and “minor-insignificant grade”, respectively. The spatial distribution of the consequences is altered by the optimized land-use plans. We calculated relative risk scores by comparing the average monetary value of real properties, movable assets, and services contained in each land-use type in Pyeongchang-gun. We assumed that all those monetary values were under the threat of landslides if allocated to the 10th probability grade. The risk scores decrease in proportion to the decrease in landslide probability (Table 2).

$$\mathrm{Risk} = \mathrm{Probability(hazard)} \times \mathrm{Consequence(land - use\ type)} \quad (1)$$

Table 2. Risk matrix for the landslides (unit: ratio of monetary values)

Probability Consequence	1	2	3	4	5	6	7	8	9	10
Urban	0	0	1	4	10	20	33	48	59	65
Agricultural	0	0	0	1	3	3	10	14	17	19
Natural	0	0	0	0	0	1	1	1	2	2

Land-use change is associated with a certain amount of economic cost; thus, it is important to maintain the current land-use pattern as much as possible while also reducing the landslide risk. We used cost factors for converting land-use i to land-use j (Table 3). To reduce the error caused by using real cost, we applied dimensionless costs indicating the relative relationship of different types of land-use changes [25].

Table 3. Cost factors for land-use change

Land-Use Type		Change to (Land-Use *j*)		
		Developed Area	Agricultural Area	Natural Area
Change from (land-use *i*)	Urban area	0	1	1
	Agricultural area	0.6	0	0.2
	Natural area	0.7	0.4	0

In our study region, some of the urban and agricultural areas are spatially scattered within the natural areas. It is very costly to manage and allocate resources in these areas, which may generate larger negative edge effects of urban and agricultural areas [26,27]. Therefore, we employed the third objective: maximization of compactness. The compactness of each cell can be measured by the number of neighboring cells that have the same land-use type as the focused cell. The neighboring cells of the focused cell i(r, c) form a single rectangle from (r−1, c−1) to (r+1, c+1), consisting of eight cells. If a cell i is allocated to land-use k and there are no neighboring cells allocated to k, the compactness of cell i is at a minimum, whereas, if cell i has eight neighboring cells allocated to k, the compactness is at a maximum.

We considered the increase in urban areas to accommodate the future population to be a constraint. In accordance with the 2020 master plan of Pyeongchang-gun, we assumed that urban areas would increase by 70% by the 2050s. The relative risk score for the first objective (minimization of landslide risk) decreases in the order of urban, agricultural, and natural areas, even though these areas possess the same landslide probability. If we optimize the area of each land-use type, it is highly likely that the optimization of the first objective will be achieved by reductions in urban or agriculture areas. We also excluded the areas with altitudes above 800 m from this optimization because these areas are difficult to develop in practice (Table 4).

Table 4. Areas of actual land-use types and constraints (unit: 10,000 m2)

Total	Urban	Agricultural	Natural (9,132)	
			Above 800 m (Fixed)	Below 800 m (non-Fixed)
13,224	264	3828	3975	5157

2) Model Formulation

The objectives for the optimization can be expressed using the following formulations. There are K different land-use types and the model is divided into a regular grid with N rows and M columns. According to the formulas (2), (3) and (4), only one land-use k is assigned to each cell (i, j), because the binary variable x_{ijk} equals to 1 or 0. The value a_{ijk} associates the costs or benefits with the allocation of any particular land use to the specific cell. In the first and second objectives, each cell is assigned an a_{ijk} value based on the score matrices defined in Section 2.4.1 (Tables 2 and 3). The sum of all a_{ijk} values across the study area is considered to be the optimization level for each objective. The value of b_{ijk} is the number of neighboring cells that have the same land-use type as the focused cell (i, j) and the sum of all b_{ijk} values is the optimization level of the third objective. The sum of the areas of all land-use types is equal to the area of the whole study area, S_k (Equations (5) and (6)).

Minimize:

$$-\sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{M} a_{ijk}x_{ijk} \quad (2)$$

Maximize:

$$\sum_{i=1}^{N}\sum_{j=1}^{M} b_{ijk}x_{ijk} \quad (3)$$

Subject to:

$$\sum_{k=1}^{K} x_{ijk} = 1 \quad \forall k = 1, \dots, K; i = 1, \dots, N; j = 1, \dots, M \quad (4)$$

$$x_{ijk} \in \{0,1\}$$

Where:

$$\sum_{i=1}^{N}\sum_{j=1}^{M} x_{ijk} = S_k \;\; \forall k = 1, \dots, K; i = 1, \dots, N; j = 1, \dots, M \quad (5)$$

$$\sum_{k=1}^{K} S_k = N \cdot M \quad (6)$$

3) Non-Dominated Sorting Genetic Algorithm II

We found that GA was more successful in guaranteeing the optimal solution than other heuristic approaches, such as simulated annealing, greedy growing algorithms, and tabu search [19]. Therefore, land-use allocation in this study was optimized using a Non-dominated Sorting Genetic Algorithm II (NSGAII) [28] and a specially designed crossover operator. The NSGAII generally shows good performance for optimizing three objectives and it can efficiently produce a high-quality diverse Pareto set using a non-domination rank and crowding distance. Non-domination rank can reduce the computational time, while the crowding distance can guide the selection process toward uniformly spread-out Pareto optimal [28]. If all the fitness values of solution j are less than solution i, solution j dominates solution i and has a better rank.

If solutions i and j have the same rank, the solution located in less crowded regions is a better solution for the selection [28] (Figure 2). In our study, we used NSGAII to generate solutions that are diverse but appropriate for the three objectives: minimization of landslide risk, minimization of change, and maximization of compactness.

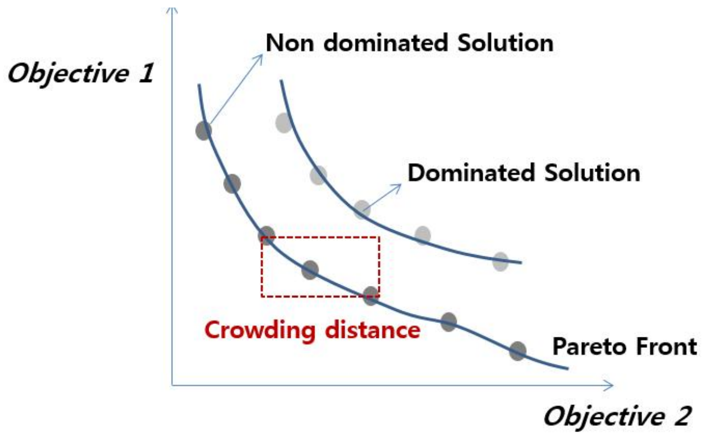


Figure 2. Crowding distance & non dominated solutions

We used a fixed-length chromosome representation method, which consists of grids of genes. Each gene represents a unit and the land-use type of the unit is determined by the fitness value. The iteration process of the GA applied to our study consists of several steps, including initialization, crossover, and selection. The main loop was repeated until the convergence was achieved for all objectives (Figure 3). Population size, iteration size, and crossover rate were determined empirically.

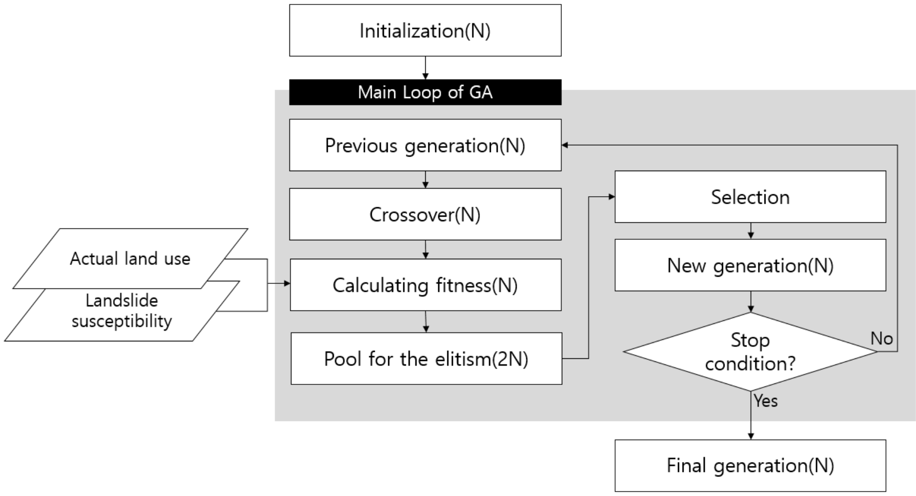


Figure 3. Process of the genetic algorithm (GA)

Initialization: Initial populations were randomly generated to prevent convergence to the local optimum.

Crossover: Two focused cells, A and B, were selected randomly within one parent and then exchanged if the number of boundary cells of A and B had the same genes as B and A (Figure 4). Previous researchers developed a crossover operator similar to this method to dramatically improve the compactness [26].

Selection: First, we produced a solution pool composed of both the previous generation and new solutions generated by the crossover to ensure elitism. Then, solutions for the next generation were selected based on the non-domination rank and crowding distance. First, non-dominated solutions (number-one ranking) were selected and then the solutions of the next rank (dominated more than once) were selected. If the selected solutions by rank were greater than the population size, the solutions of the lowest rank would be re-sorted by the crowding distance and selected until they satisfied the population size.

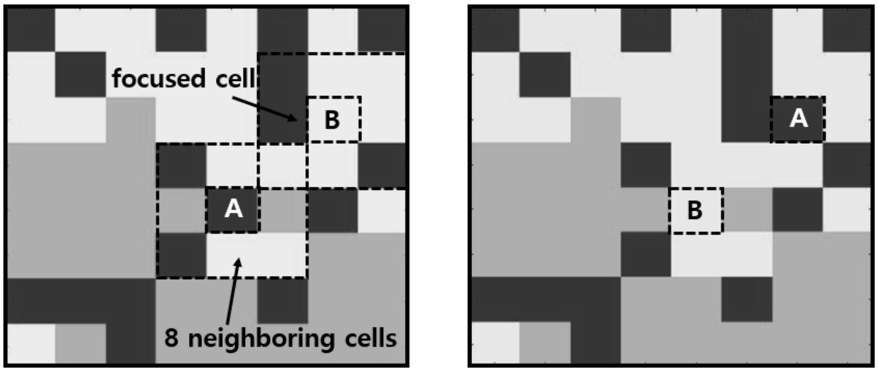
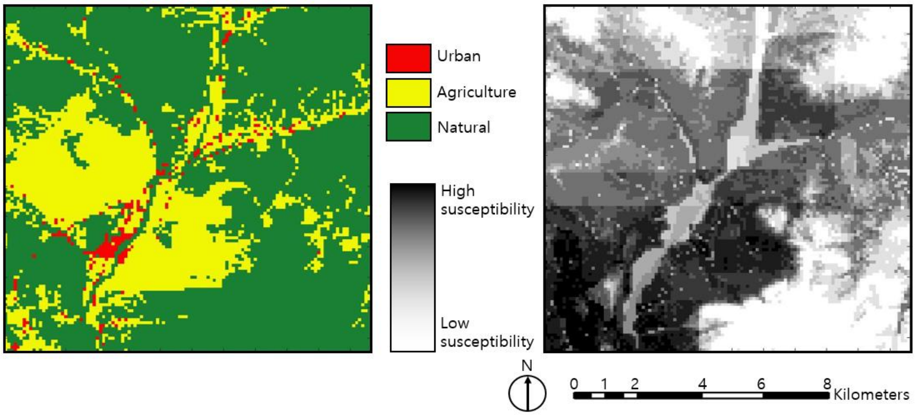


Figure 4. The crossover operator

3.3 Results

3.3.1. Landslide Hazard

Figure 5 shows the urban and agricultural areas that are exposed to potential landslide damage with ten grades of landslide hazards. Lower hazard grades are distributed on the peak of a mountain where development is generally restricted. Outside of this peak, the higher hazard grades (greater than 6) account for 49.3% of the study area (less than half), but 65.2% of urban areas and 70.0% of agricultural areas overlap with these grades (Table 5, Figure 5). In particular, the ninth and tenth grades are present in the lowest proportions but are distributed around the center of urban areas in the southwestern study area. The sixth to eighth grades overlap with much of the steep agricultural area around the plain.



(a) (b)

Figure 5. Current land use (a) and grades of landslide hazard (b)

3.3.2. Optimization

The optimization model was simulated over 350 iterations with a population size of 100 and a crossover rate of 0.05, which were determined empirically. Non-dominated solutions in the final iteration were greatly moved to the inner fitness space. This indicates that solutions are optimized to a better status for all objectives during the simulation (Figure 6a). The fitness value of each objective decreases steadily and then converges at the point of certainty (Figure 6b,c,d). However, if we consider all non-dominated solutions, the coefficients of variation in the final generation would be different for each objective. The coefficient of variation of the third objective is lower than that of the first and second objectives. This indicates that all non-dominated solutions satisfy the third objective to some extent, but tradeoffs between the first and second objectives are relatively strong (Table 5).

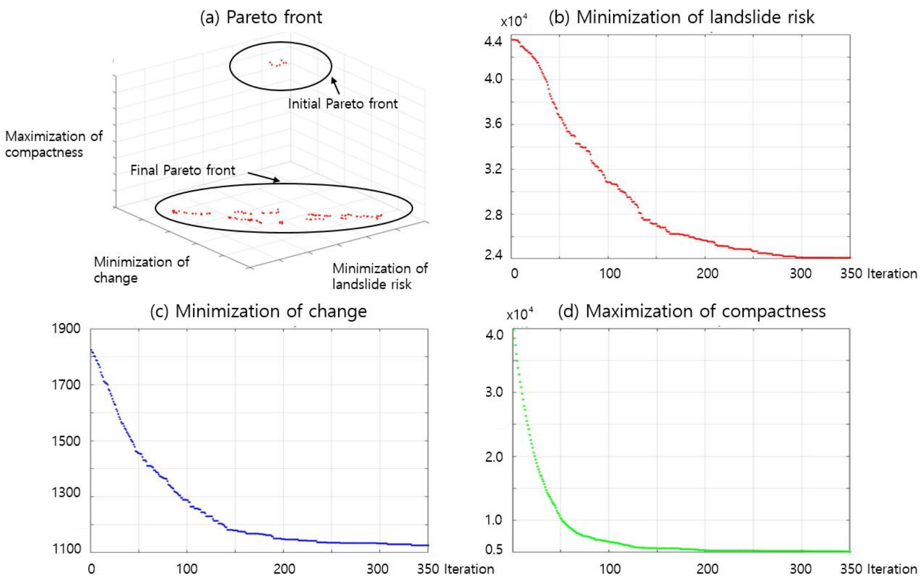


Figure 6. Change in the non-dominated solutions

Table 5. Statistics of the final Pareto plans

Objectives	Average	Minimum	Maximum	Standard Deviation	Coefficient of Variation
First objective	36,362	28,009	45,981	5281	14.52
Second objective	1418	1150	1756	173	12.20
Third objective	6420	5316	7558	624	9.72

We organized six of the non-dominated solutions, A, B, C, D, E and F, along the two dimensions that explain the tradeoffs between the first and second objectives (Figure 7). Certain points that appear to be “dominated solutions” on two dimensions correspond to non-dominated solutions on three dimensions (including the third objective, maximization of compactness). For example, plan D shows a more compact land-use pattern than the other plans that are located near and inside of plan D. If we consider the actual land as a reference point, plans A, B, C and D, which are located on the left side, can reduce the potential landslide risk by one-third compared to the actual land use. In contrast, plans E and F can increase the potential landslide risk despite conversion because conversion contributes to the improvement of compactness (Table 6, Figure 7). Additionally, all plans are better than the actual land use for the third objective-maximization of compactness (Table 6).

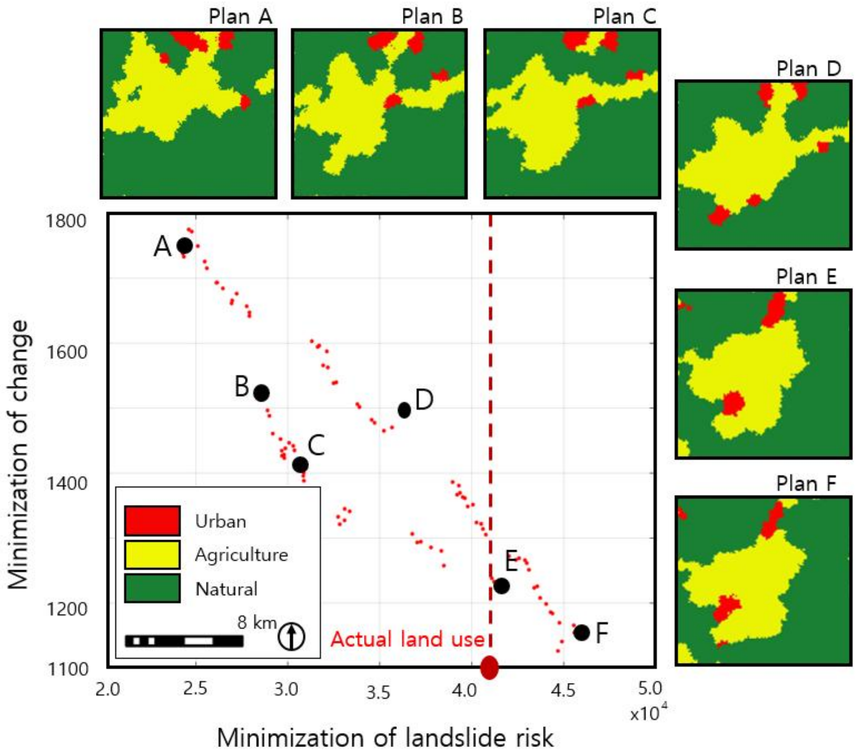


Figure 7. Final optimized plans considering trade-offs. Red line indicates the level of landslide risk in actual land use; Plan A and F are the most effective alternatives for the first and second objective respectively. Plan B, C and D (plans between A and F) are alternatives by various combination of weights.

Table 6. Fitness values of the optimized plans

	Plan A	Plan B	Plan C	Plan D	Plan E	Plan F	Current
First objective	24,089	28,408	30,982	36,363	41,224	46,239	41,100
Second objective	1747	1516	1407	1503	1232	1161	0
Third objective	6067	6684	6288	5814	5778	5814	17,870

3.4. Discussion

We generated a range of optimized plans for the multi-objective problems without the relative weighting factors. From the perspective of reducing the landslide risk, land-use plans optimized on one objective could be better than the other plans optimized on multi-objectives, but this can result in unacceptable plans for stakeholders with different interests. In multi-objective problems, however, defining the relative importance of each objective is very difficult. Additionally, the determined weights have difficulty in handling the changing environment; the most important objective under current conditions may not be the most important one in the future. The non-dominated land-use plans we suggested using NSGAII include all possible combinations of weighting factors [29]. The planners or decision makers can choose one plan, depending on their knowledge or problem-related factors [30] and use it to conduct detailed planning.

All the optimized plans are better than the actual land use for at least one objective: minimization of landslide risk or maximization of compactness. All plans showed a dramatic improvement—especially in compactness—by at least 60%. However, in case landslides become a major issue, plans E and F are difficult to select (Figure 7) because of the landslide risk increase from the current level. Land conversion in these plans occurs only to improve compactness. Compactness is one of the most important objectives considered in most related studies [17,26,27,31–37], but landslide risk also needs to be reduced to some extent, because land use conversion is very costly. We have obtained 100 non-dominated plans of various weight combinations, but the range of plans that can actually be selected is narrow. If the Pareto front line is moved inward (southwestward), we can obtain more plans distributed on the left side of the red line (Figure 7). We expect this can be done in future studies by incorporating the actual land use in the initial population or by establishing strict constraints such as the conversion ratio [37,38] and maximum cost [39]. In this study, we employed some climate variables from the RCP scenario to reflect the long-term future of the study area in land-use planning. The spatial resolution of the RCP scenario can create some problems in generating land-use plans. The scenario data are produced at the resolution of 1 km by KMA and the resolution of other variables is 30 m. We considered a resolution of 100 m because further downscaling could decrease the reliability of the scenario data. However, the resolution of 100 m is too large to express linear land-use patterns such as rivers, railroads, and highways and subtle changes in soil and topography. In fact, the linear land-use types tend to disappear in all optimized plans. Therefore, we expect that the resolution problem of climate scenarios will be solved in future studies on land-use planning.

Our optimized results can also be considered spatial adaptation options or solutions for the potential landslide problem under climate change. Climate change research has so far focused on the assessment of the impacts of climate change on disasters, ecology, and industry. We now need to discuss spatial adaptation: how to change the actual space in response to climate change impacts because climate change is already happening [23]. Adaptations to disasters such as landslides are a priority, as these events can lead to the loss of life and property. There are two ways to simulate land-use changes for adaptation: land-use predictions based on scenarios and land-use optimization to generate scenarios. Land-use prediction simulates land-use changes by a transition rule set based on the past trends and agent behavior. If we want to solve problems using land-use predictions, we have to establish related strategies first, then change the transition rule set, and finally simulate future land-use changes. It is not guaranteed, however, that simulated land-use change is appropriate for the problem at hand. Using the second approach, the land-use optimization, we can simulate appropriate land-use changes for the initial problem and then establish strategies to facilitate land-use optimization. GA is considered one of the most effective optimization tools. In some studies, these two approaches were applied in the coupled form to complement each other [40,41], but the optimization model was better than the prediction model in terms of problem-solving performance [42].

To obtain more reasonable adaptation options, we plan to conduct future research that considers the positive possibilities together with the negative impacts of climate change [43]. This study focused only on reducing the negative impacts of climate change by avoiding planning in urban areas where landslides are most likely to occur. However, by considering positive possibilities such as the expansion of suitable cultivation areas or habitats together, we can link the optimized results to sustainability in future climate change research, which will consider the balance among the social, environmental, and economic aspects.

3.5. Conclusion

In this study, we suggested tools to identify comprehensive land-use alternatives that could contribute to the reduction of the potential landslide risk in Pyeongchang-gun. This approach can provide guidance to municipal governments when allocating urban, agricultural, and natural areas and when establishing spatial adaptation plans that consider extreme meteorological disasters under climate change. The model developed based on GA is generally flexible and thus, can easily be applied to other similar problems. We only need to modify some part of the fitness function and dataset according to the objectives or adjust model parameters that suit the problem. For example, to consider the landslide hazard under different climate change scenarios, we could generate new optimized plans for that problem by replacing landslide hazard maps derived from new scenarios. Our model could also be used to generate land-use allocation plans for other cities suffering from landslides. A risk matrix for the land-use priority, objectives, and constraints, however, should be identified for any new cases.

Acknowledgments

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4. CHPATER 3: Multi-Objective Planning Model for Urban Greening based on Optimization Algorithms

4.1. Introduction

Improving urban environments is becoming a major concern with the continuously growing urban population (Yu et al., 2017; Bayulken & Huisingh, 2015). Green space is generally composed of relatively small and fragmented patches, but it is a critical factor for the quality of an urban environment (Smith et al., 2017; van der Jagt et al., 2017; Gaitani et al., 2014). The green spaces in urban environments provide multiple benefits, including runoff reduction (Li et al., 2017; Giacomoni & Joseph, 2017; Fintikakis et al., 2011), urban heat island (UHI) mitigation (Zhang et al., 2017a; Zhang et al., 2017b; Yang et al., 2017b), aesthetic experience (Lay & Leone, 2017), and formation of a network for species movement (Aronson et al., 2017; Lay & Leone, 2017). Flooding and UHI have recently been particularly emphasized because of the increasing variation in precipitation and temperature caused by climate change (Meerow and Newell, 2017; Jaganmohan et al., 2016; Yu et al., 2017). The multiple benefits of green spaces have driven the continued effort to expand them (van der Jagt et al., 2017; Rutt & Gulsrud, 2016) despite their high implementation cost (Jermé & Wakefield, 2013; Mathers et al., 2015) and relatively low economic feasibility compared to other public facilities.

However, although some have considered the implementation cost, most studies supporting the planning of green spaces with a quantitative basis focused on a single benefit of greening. Some studies suggested the optimal arrangement of trees or new green spaces to improve the cooling benefit (Wu and Chen, 2017; Zhang et al. 2017a) or runoff regulation (Giacomoni and Joseph, 2017). Yang et al. (2017a) analyzed the linear regression relationship between green coverage ratio and physiological equivalent temperature for the design of public urban spaces. Li et al. (2017) sought to develop a performance evaluation system of low impact development measures from the viewpoint of the hydrological process. There is a dearth of studies that provide a comprehensive treatment of the multiple benefits generated from urban green spaces. This gap in the literature has resulted in the failure to meet various stakeholder preferences and achieve regional sustainability (Chen et al., 2014); however, identifying an optimal spatial pattern subject to multiple benefits is challenging (Brooks, 2001). In the process of maximizing a specific benefit by changing the location and the composition of green spaces, other benefits can be enhanced or diminished because of trade-off or synergistic relationships. In contrast, for land use problems, numerous studies have integrated heterogeneous issues, such as flooding, heat hazards, greenhouse gas emissions, soil erosion, and compactness based on the optimization approach (Caparros-Midwood & Dawson, 2015, 2016; Cao et al., 2011; Cao & Ye, 2013). Similarly, studies focusing on public facilities (e.g., health care center, water distribution system, and radiation sensors) have considered multiple criteria of utility and cost with an optimization model (Eusuff et al., 2006; Beheshtifar et al., 2015; Jankowski et al., 2014).

The present study aims to develop a planning model that can determine the optimal location and type of greening to maximize its multiple benefits in a neighborhood scale by using an optimization approach. This study differs from those using the existing planning models for urban greening in the following four aspects:

1) Our model can quantitatively consider the synergies or trade-offs between the greening benefits and cost by incorporating them into a single planning model.

2) It can be performed at the neighborhood scale. Obtaining large spaces for greening is often difficult in highly dense cities; hence, the benefits from greenery must be maximized by utilizing distributed small spaces. The related scientific studies on the benefits of green spaces have focused on coarser resolutions, but we can address the problems of neighborhood scales with a few assumptions and a hypothetical landscape.

3) It can determine the optimal location and type for greening and the amount of green space. Actual planning is the process of determining "where to allocate the amount of green space" and "where to invest a limited budget" as well as the "total required amount." The majority of the literature has only addressed the amount of specific uses instead of location (Giacomoni & Joseph, 2017; ex. Galán-Martín et al., 2017 and Reichold et al., 2010).

4) We dynamically consider the effects derived from the newly installed green space by coupling meta-heuristic algorithms with the objective model to evaluate the benefits and cost of greening. Albeit these advantages, the results from this model are not the final plans, but should be used as guidelines or quantitative evidence for a detailed design (Yoon et al., 2017).

The method section describes the main components of the planning model, that is, the three objectives achieved in greening plans and the optimization process. We establish a hypothetical landscape appropriate for effectively showing the problem of the neighborhood scale. The result section presents the results of the planning model on the hypothetical landscape (i.e., greening plans and related performance). The last section, which is the discussion section, describes the contribution of this model to the existing planning process and some tasks for application to actual spaces.

4.2. Method

4.2.1. Outline of the multi-objective planning model for urban greening

Our model used an optimization approach that determines the location and the type of new green spaces by comprehensively considering the maximization of two kinds of greenery benefits (i.e., cooling of land cover and formation of an ecological network) and the minimization of cost as an implementation constraint. The cooling effect is related to human health and comfort, while the ecological network is a fundamental factor for urban biodiversity. Three assumptions were used for modeling: first, a green space can be installed only in an "empty lot," which refers to land that has not been used for a specific purpose because of its small size or unfavorable location; second, three options can be selected for empty lots: vegetation type A, vegetation type B, and no vegetation (type A is a single-layered vegetation with grass only, while type B is a multi-layered vegetation comprising grass and trees); and third, only one greening option can be applied to each empty lot at 100%. Appendix 1 lists the related model parameter, abbreviation, and unit.

1) Maximization of the cooling effect

Green spaces can reduce UHI because they can reduce the land surface temperature (LST) by changing the albedo of the space (Wu & Chen, 2017). Trees can also reduce the LST of the surrounding areas by shading and evapotranspiration (Yu et al., 2017; Chang et al., 2007). Thus, we calculated the cooling effect of new green spaces based on the changes in the LST. The LST shows a significant correlation with air temperature (Zhang et al., 2017a); hence, it can be an important criterion for urban thermal environment (Yang et al., 2017a). Many studies found that the LST of a green space is lower than the regional average in common; however, the differences vary depending on the spatial context, climate zone, and season from 1.61 °C to 4.4 °C (Zhang et al., 2017a; Zhang et al., 2017b; Yu et al., 2017). And other study presented that the small green spaces can reduce air temperature up to 1.93 °C (Park et al., 2017). The cooling range of a green space must be ascertained based on an in-situ measurement of the target site. However, this study focused on developing a planning methodology and applying it to the hypothetical landscape. Thus, we set the default value of the cooling effect according to the relative magnitude order in the previous studies.

Considering the abovementioned factors, the cooling effect of the kth plan ($Cooling\ Effect_{plan_k}$) can be calculated based on the location, area, and type of green spaces, as shown in Eq. (1). Every plan showed different cooling effects because vegetation types A and B were distributed differently by the optimization algorithms. The total area of green space ($Area_{green}$) and the surrounding areas of type B ($Area_{surround\_a}$ and $Area_{surround\_b}$) were calculated by summing up the grids corresponding to the respective conditions [Eqs. (2)–(4)]. N and M indicate the number of rows and columns, respectively. In Eq. (5), parameter α indicating the direct cooling effect on the green surface was set to 3 °C as the highest cooling effect. Parameters β and γ denote the indirect cooling effect on the surrounding surface of type B, which consists of grass and trees. We set the indirect cooling effect to 1.0 °C (β), which is the lowest cooling effect, if the surrounding surface is affected by only one lot with type B. However, assuming that the cooling effects can be increased proportional to the amount of the neighboring green spaces, the indirect cooling effect is increased from 1.0 °C to 2.0 °C (γ) if the surrounding surface is affected by more than one lot (Zhang et al., 2017, Figs. 1 and 3). Finally, the total cooling effects of the kth plan was averaged by the total study area.

$$\mathrm{Cooling\ Effect}_{\mathrm{plan}_\mathrm{k}} = (\mathrm{Location}_{\mathrm{green}}, \mathrm{Areas}_{\mathrm{green}}, \mathrm{Type}_{\mathrm{green}}) \quad (1)$$

$$\mathrm{Area}_{\mathrm{green}} = \sum_{\mathrm{n}=1}^{\mathrm{N}} \sum_{\mathrm{m}=1}^{\mathrm{M}} \mathrm{x}_{\mathrm{nm}} \quad (2)$$

$$\mathrm{Area}_{\mathrm{surround\_a}} = \sum_{\mathrm{n}=1}^{\mathrm{N}} \sum_{\mathrm{m}=1}^{\mathrm{M}} \mathrm{y}_{\mathrm{nm}} \quad (3)$$

$$\mathrm{Area}_{\mathrm{surround\_b}} = \sum_{\mathrm{n}=1}^{\mathrm{N}} \sum_{\mathrm{m}=1}^{\mathrm{M}} \mathrm{z}_{\mathrm{nm}} \quad (4)$$

$$\forall j = 1,2, \ldots., J; i = 1,2, \ldots, I;$$

$$x_{nm} = \begin{cases} 1 & \text{if grid with type A or B} \\ 0 & \text{if not} \end{cases}$$

$$y_{nm} = \begin{cases} 1 & \text{if surrounding area of single lot with type B} \\ 0 & \text{if not} \end{cases}$$

$$z_{nm} = \begin{cases} 1 & \textit{if surrounding area of multi lots with type B} \\ 0 & \textit{if not} \end{cases}$$

$$Cooling\ Effect_{plan_k} = (\alpha \times Area_{green} + \beta \times Area_{surround\_a} + \gamma \times Area_{surround\_b})/Total\ area \quad (5)$$

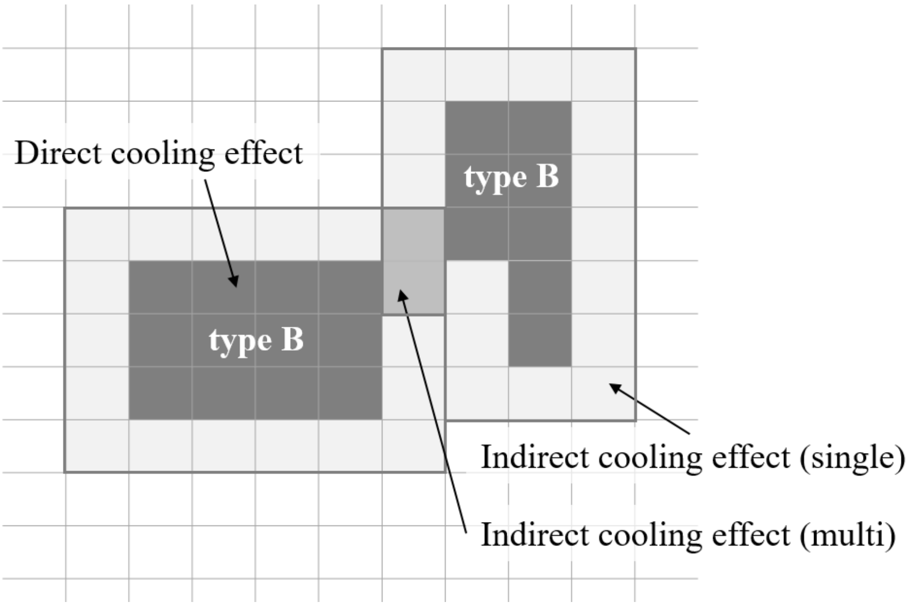

Figure 1. Cooling effect of vegetation type B with grass and tree

2) Maximization of connectivity

Urban green spaces are generally small and fragmented compared to suburbs or forests, but they play an important role as a stepping stone for species movements in urban environments (Lay & Leone, 2017). The common methods for measuring spatial connectivity include gamma index, alpha index, and gravity model. However, the gamma and alpha indices are not appropriate for fragmented urban green spaces because they assess networks, where nodes and links are physically interconnected. The gravity model describes the degree of connectivity, which can be applied to fragmented green spaces, but lots adjacent to large forest patches are likely to be overestimated. In this model, we focused on individual “empty lots,” which are separate from other green spaces, but can make different levels of contribution to the species movement. According to the island biogeography theory, the closer the green areas are to each other and the larger the green areas are, the better the ecological connectivity achieved (Forman & Godron, 1986). When new vegetation is installed in the lot, a “moving window” that is enlarged in proportion to distance d from the lot is created. All green areas distributed within the moving window are then summed up to evaluate the contribution of the new vegetation to the local connectivity improvement (Fig. 2).

The connectivity of the kth plan ($\mathrm{Connectivity}_{\mathrm{plan_k}}$) can be calculated based on the distance between the new green space and others and the area and type of green spaces [Eq. (6)]. Every plan showed a different connectivity because vegetation types A and B were distributed differently by the optimization algorithms. In Eq. (7), J indicates the number of empty lot, while I denotes the number of lots with the vegetation located within the distance d from the boundary of the jth lot. Distance d has to be set according to the spatial resolution and movement ability of the target species. However, this study was based on a hypothetical landscape, and the general movement of species in a fine scale has not yet been defined (Forman, 2014); thus, we set the default value for distance d as 10 m through repetitive pilot experiments such that it can show the variance of connectivity at the study site. The lots without vegetation were excluded from the connectivity analysis; therefore, the binary variable x_j was equal to 0 or 1. The green area of lot_j ($Area_{lot_j}$) was controlled by variable y_j corresponding to the vegetation type because the green area of type B, including the vertically layered vegetation, was larger than that of type A despite being in the same lot (Figs. 2 and 3). The ith green areas within distance d from the jth lot ($Area_{lot_i}$) were summed together.

$$Connectivity_{plan_k} = f(Distance_{green},\ Area_{green},\ Type_{green}) \quad (6)$$

$$Connectivity_{plan_k} = \sum_{j=1}^{J} x_j \left(y_j \times Area_{lot_j} + \sum_{i=1}^{I} Area_{lot_i} \right) \quad (7)$$

$$\forall j = 1,2,\ldots.,J;\ i = 1,2,\ldots,I;$$

$$x_j = \begin{cases} 1 & if\ lot\ with\ type\ A\ or\ B \\ 0 & if\ not \end{cases}$$

$$y_j = \begin{cases} 1 & if\ lot\ with\ type\ A \\ 2 & if\ lot\ with\ type\ B \end{cases}$$

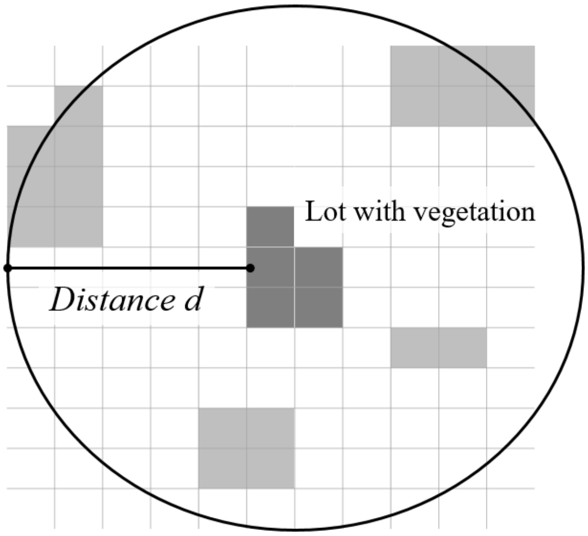

Figure 2. Moving window for new vegetation. The areas of green patches with a light-gray color are summed to calculate the contribution of the selected lots to connectivity

3) Minimization of cost

Without cost constraint, the best strategy would be to install vegetation wherever possible. However, actual greening plans are created and executed within a certain budget range. The changes in the benefit of greening must be visually presented against the changes in cost to support related decision making. Therefore, the implementation cost of the kth plan ($Cost_{plan_k}$) can be calculated based on the location (which block), area, and type of green spaces [Eq. (8)]. The costs of all plans were different because they also depend on where the vegetation type was chosen. The implementation cost of each lot for the kth greening plan was calculated using the unit land purchase cost ($Cost_{land}$), unit planting cost ($Cost_{vegetation}$), and area of the jth lot ($Area_{lot\_j}$), then summed up. The land purchase cost is very different and varies according to the ambient conditions and location of cities, blocks, and buildings. We referred herein to the average land price of small–medium-sized cities in South Korea and provided some variations based on it. In other words, we used the representative land price by block within the range of $900 to $1200 [$Cost_{land}$, Eq. (9)]. Referring to South Korea's tables of construction in 2018, the planting cost ($Cost_{vegetation}$)l including the material and labor costs, was set to $30 and $600 for types A and B, respectively [Eq. (9)].

$$Cost_{plan_k} = f(Block_{green},\ Area_{green},\ Type_{green}) \quad (8)$$

$$Cost_{plan_k} = \sum_{j=1}^{J} x_j\left(Cost_{land} + Cost_{vegetation}\right) \times Area_{lot_j} \quad (9)$$

$$\forall j = 1,2, \ldots, J;$$

$$x_j = \begin{cases} 1 & if\ lot\ with\ type\ A\ or\ B \\ 0 & if\ not \end{cases}$$

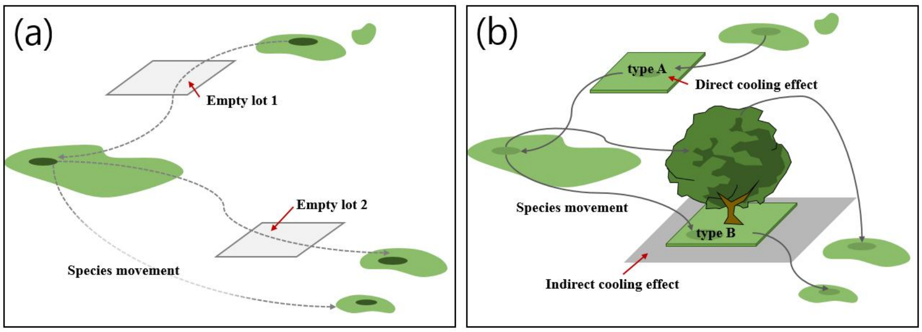

Figure 3. Greenery effects of type A with grass and type B with grass and tree. Different cooling effects and connectivity improvement

shown after vegetation types A and B are installed in empty lots 1 and 2, respectively: (a) before and (b) after greening

4) Optimization process

Urban greening plans are optimized using a non-dominated sorting genetic algorithm II (NSGAII,) which can efficiently produce a high-quality diverse Pareto set using non-domination rank and crowding distance (Deb et al., 2002). A total of 30 initial plans were randomly created for the planning process to expand the search space beyond the existing knowledge (initialization step in NSGAII). A repetitive pilot test showed a threshold of 30, in which the search space was not expanded anymore. Thirty new plans were then created by combining previous plans or adding new attributes not in the previous plans (crossover and mutation steps in NSGAII). Among the previous and new plans, 30 plans for the next iteration were stochastically selected in terms of the "maximization of cooling effect," "maximization of connectivity," and "minimization of cost" (selection step in NSGAII). The process of creating new plans was repeated until no better plan can be found. The last created plans corresponded to the optimal result, that is, the Pareto set (Fig. 4, Appendix 2). The location and the shape of the Pareto line indicate trade-offs or synergy of the optimization objectives, allowing decision-makers to make a better selection. The optimization of the three objectives can be expressed as follows by Eq. (4):

$$\text{Minimize}\left(-Cooling\ effect_{plan_k}, -Connectivity_{plan_k}, Cost_{plan_k}\right) \quad (10)$$
$$\forall k = 1,2,\ldots,K;\ K = the\ number\ of\ greening\ plans$$

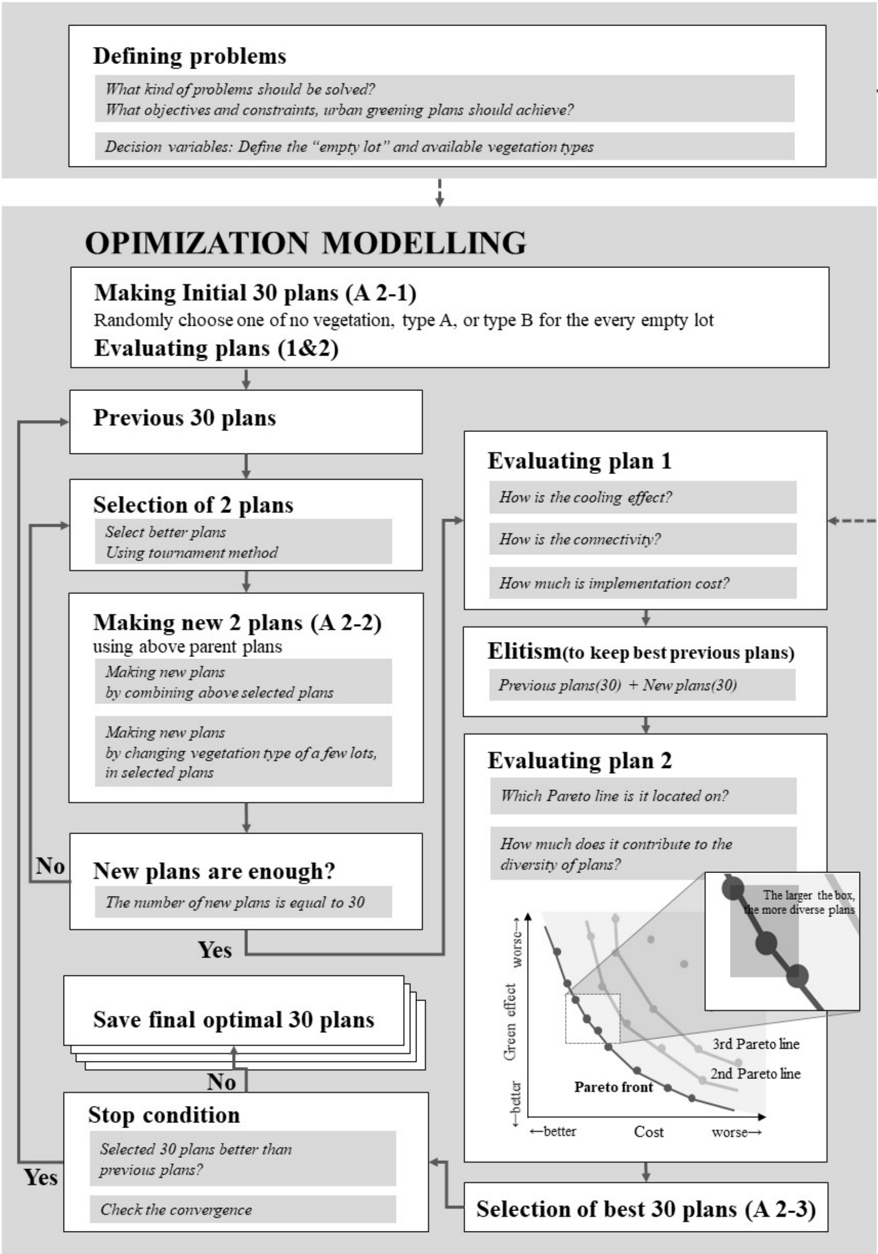

Figure 4. Process of the multi-objective planning model for urban greening (Appendix 2)

4.2.2. Hypothetical landscape

This study aimed to propose a new quantitative planning model for urban greening, but it could be limited using an actual space (to identify empty lots in actual space and determine appropriate model parameters, such as distance d require complicated procedures). We employed a hypothetical landscape in a raster format with a 2-m resolution and consisting of 50 rows and 60 columns (100 × 120 m). The 2 m spatial resolution was adequate for describing the green patch, road, building, canopy of tree, and empty lots in a highly dense urban environment at the neighborhood scale. The widths of the roads between the blocks and the inner side, building size, and spacing, and size of street trees were based on the laws related to urban design in South Korea (http://www.law.go.kr/; Fig. 5). In the whole hypothetical landscape, the area of the existing forest patches and roadside trees was 16.6%, and the number of "empty lots," where new vegetation can be installed was 66, constituting an area that was 8.7% of the total area (Table 1). The hypothetical landscape was divided into blocks, I, II, III, and IV to examine how the spatial distribution of the green spaces changes according to each characteristic (Figure 4). Block I shows a poor green space with only a few roadside trees, but with larger empty lots compared to other blocks. Block II has some forest parts and a few roadside trees, but empty lots that are smaller than those of the other blocks. Blocks III and IV show better existing green spaces compared to blocks I and II. They also have more abundant roadside green spaces in addition to some forest parts. Block IV is expected to have great potential for applying the largest number of greening strategies because it has empty lots of various sizes and locations. Considering the range of land prices (as mentioned in the minimization of cost, \$900–1200), the representative land prices of blocks IV, III, II, and I were set to \$1200, 1100, 1000, and 900, respectively, in the order of good greenery assuming that living conditions, such as infrastructures, are the same.

The numbers of empty lots and options to choose from are 66 and 3 respectively; hence, 3^{66} possible greening plans are available. The best plan derived from examining all the possible plans was optimal, but was actually unavailable because of its time-consuming process. Moreover, involving various stakeholders requires repetitive feedback and simulation based on the adjustment of model parameters. Thus, the goal of this planning model was to create enough good plans that can meet the desired implementation cost, enhance connectivity, and reduce UHI within a reasonable time by exploring only some parts of the search space.

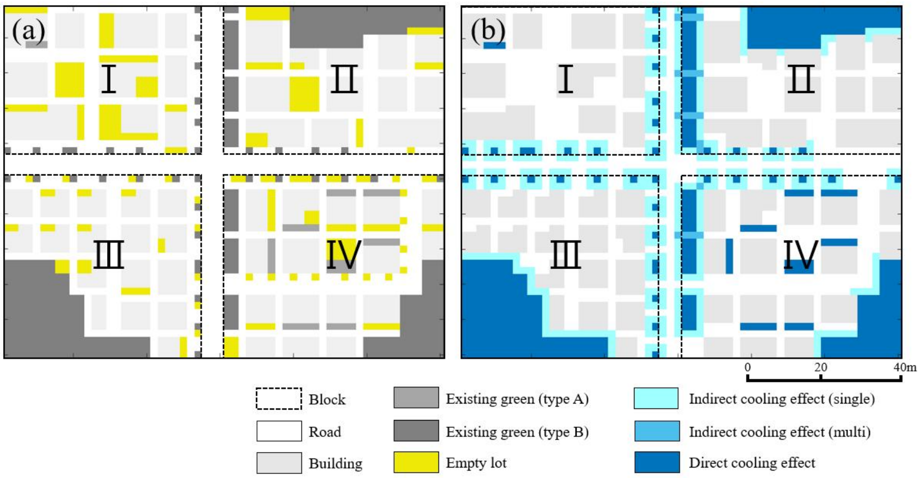

Figure 5. Study site. (a) composition and (b) cooling effect of domain

Table 1. Description of the hypothetical study site (unit: m2, the number of lot/patch)

Block	Existing green				Defined empty lot	Building	Total
	Forest patch	Green patch (planted)		Total			
		Inside	Road side				
A	0	12(1)	48(11)	52(12)	360(10)	988(10)	2268
B	668(1)	0(0)	56(13)	724(14)	148(19)	1004(17)	2808
C	396(1)	0(0)	152(8)	548(9)	244(10)	1064(12)	2520
D	336(1)	180(8)	152(9)	668(18)	296(27)	1092(16)	3120
Road						-	1284
Total	1400(3)	192(9)	408(41)	1992(53)	**1048(66)**	4148(55)	**12,000**

4.2.3. Analysis of alternatives for urban greening

The final optimal plans on the hypothetical landscape can be displayed as a Pareto surface on three dimensions: cooling effect, connectivity, and implementation cost. However, for these plans to be effectively used by stakeholders, more information (e.g.., representative plans and trade-offs between the objectives) should be provided. Using the Interactive Decision Maps (IDM) technique, we can represent the swap between the objective values while moving along the Pareto front on the two dimensions (Lotov et al., 2005; Jankowski et al., 2014). On the IDM map, we can define the key trade-off positions that show significant performance drop or increase of the two objectives under the selected value ranges of the other objectives (Jankowski et al., 2014). The plans on these key positions can be regarded as representative plans. We analyzed the spatial distribution of the green spaces based on them. Lastly, a frequency analysis was performed for vegetation types A and B to identify the commonly selected empty lots despite the differences between the alternative plans.

4.3. Result

We applied our planning model for urban greening to a hypothetical landscape and obtained the final 30 Pareto plans (each dot filled with blue or black color indicates individual optimal plan, Fig. 6). A synergistic relationship between the two planning objectives (i.e., maximization of cooling effect and connectivity) was defined (Fig. 6b). The increase in the amount of green space led to a higher implementation cost (from red to blue color in Fig. 6b), but the greening benefits were improved. In contrast, the “minimization of cost” objective strongly competed with the other planning objectives (Fig. 6c and d). For efficient decision making, we placed 30 dots over the two dimensions and matched them with one of the greening benefits and the implementation cost. The other planning objective, which was not matched with a dimension, was represented by the bounded areas with a specific range of values. The dots located in more dark-blue bounded areas represent the lower performance for the two objectives matched to the dimensions, but better performance for the other objective matched to each bounding. For example, the 14th plan represents the performances in the two objectives related to connectivity and cost lower than those of the 15th plan (Fig. 6c); however, the 14th plan can lower the surface temperature by 0.06 °C more than 15th plan (0.8930 °C–0.8357 °C, Table 2).

Moving along each boundary from the top in the direction of improved connectivity (Fig. 6c) or cooling effect (Fig. 6d), we can define a few plans located on the inflection point where the slope abruptly changes. These plans are interesting alternatives for decision makers because they show significant performance drop and increase in the specific planning objective. For example, if we are moving from top to bottom along the third bounding (represented as black dashed line), we can meet three plans to the 14th plan. These three plans have similar cooling effects, but their connectivity performances significantly improved with the low implementation cost input. However, the two plans located after the 14th plan represent a poor improvement of connectivity, even with the same implementation cost. From this point of view, plans 16, 25, 15, 14, 8, and 26 (described as big-black dots) on the inflection points were selected as the representative plans (Fig. 6c and d), and further analysis was applied to them. Table 2 shows the performance of the three objectives for these plans. The gray boxes indicate a performance better than the mean value of all plans. The two greening benefits showed similar patterns (distributed on the left side), but the greening benefits and the implementation cost depicted a contrastive pattern.

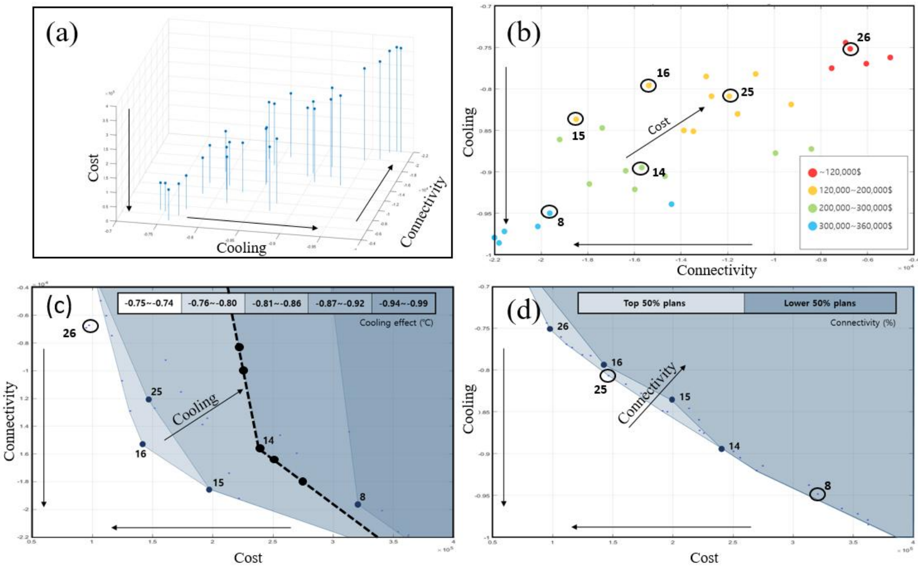

Figure 6. Trade-offs between the Pareto-optimal greening plans. (a) Pareto-optimal plans on three dimensions, (b) relationship between cooling effect and connectivity, (c) relationship between connectivity and cost, and (d) relationship between cooling effect and cost (the black arrows on each figure indicate the direction to a better performance of each objective)

The 8th plan showed the most aggressive greening strategy (Fig. 7a). Types A and B were installed in most of the empty lots existing on the roadside and the inner side of all blocks. Type B, which consisted of grass and tree, was installed in Block I, which had no forest sculpture. This led to the best performance in the planning objectives related to the greening benefits while requiring highest cost (Table 2, Fig. 8a). The 14th (Fig. 7b) and 16th (Fig. 7c) plans showed a numerically similar connectivity (Table 2), but the distribution pattern of the green spaces was different. The 14th plan had a strategy of improving connectivity by dispersing the green spaces, whereas the 16th plan had a strategy of installing type B around the existing forest sculptures. Such a strategic difference led to the differences in the performance of the other planning objectives. The 14th plan had a better cooling effect than the 16th plan, but was worse in the implementation cost reduction (Table 2). The implementation cost of the 25th plan (Fig. 7d) was the most similar to that of the 16th plan, but had a slightly better cooling effect and worse connectivity than the 16th plan (Table 2) by allocating a limited budget to the empty lots on the roadside rather than around the existing forest patches. As such, no plan had the best performance in all planning objectives; rather, the plans derived by our model can be used as options with different scenarios. Even though the plans showed similar performances in specific objectives, trade-offs always occurred depending on the strategic differences.

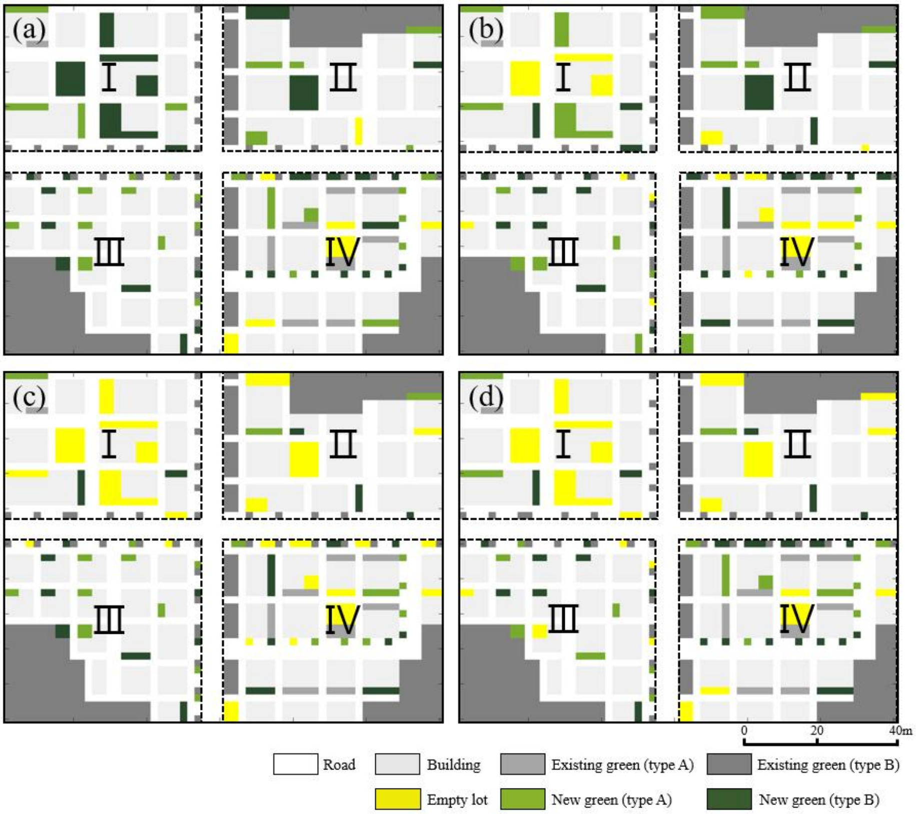

Figure 7. Selected plans for urban greening. (a) 8th, (b) 14th, (c) 16th, and (d) 25th plans

Table 2. Fitness values of the selected plans. the gray boxes indicate a performance better than the mean of all plans.

Objectives	8th plan	14th plan	15th plan	16th plan	25th plan	26th plan	Mean
Cooling effect (°C)	−0.9483	−0.8930	−0.8357	−0.7937	−0.8070	−0.7503	−0.8574
Connectivity	19,635	15,666	18,482	15,320	11,948	6,724	13,907
Cost ($)	320,530	239,690	198,370	141910	146,450	97,220	212,268
New green (lot)	59	49	53	42	45	33	47.0

New green (m^2)	226	178	144	101	106	70	150.4

Empty lots that are commonly selected for greening must also be identified, despite the differences between the plans. Concerning the cooling effect, the 8th plan (Fig. 8a) performed the best, while the 16th plan (Fig. 8b) was the second worst among the representative plans. However, in practice, green spaces are often installed in empty roadside lots, which are smaller in size and separated from other buildings or empty lots. This makes it possible to obtain a relatively large amount of area where the indirect cooling effect occurs with type B. This strategy, in which the empty lots on the roadside are prioritized, can be seen as pursuing the cost-effective cooling effect. The result of the frequency analysis for vegetation type B consisting of grass and tree showed that some empty lots located on the roadside of Block IV were the most frequently selected (empty lots filled with dark-blue color, Fig. 9b).

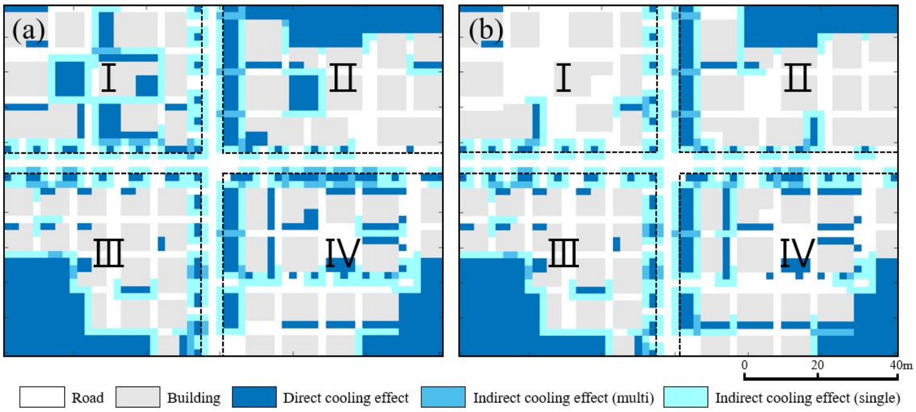

Figure 8. Cooling effect of the selected plans. (a) 8th and (b) 16th plans

The frequencies of vegetation types A and B were analyzed for the 30 generated plans and ranged from 0 to 30. Empty lots were generally selected more frequently for one vegetation type and less selected for the other vegetation type. The colors of most empty lots were contrasted (Fig. 9). In the case of Block I, vegetation type B was frequently installed in several empty lots with large areas (Fig. 9b). This strategy can be interpreted as a result of the combination of the following reasons: first, green spaces can be connected vertically from the forest patch in Block II to the upper side of Block I using this strategy (i.e., improvement of connectivity); second, the area where indirect cooling effect occurs is relatively large because three or four sides of the empty lot are open to the road (i.e., improvement of cooling effect); and third, Block I requires the lowest cost for creating the same greening benefits, given its cheapest land price (i.e., reduction of implementation cost). However, a few empty lots were also commonly considered less attractive for greening, regardless of the type (inner side of blocks I and IV, Fig. 9).

The optimization of our model was processed based on the benefit or loss of the whole study site; hence, interpreting why each empty lot was chosen or not was difficult. However, the empty lots that were commonly chosen (or not chosen) in lots of plans can be considered "critical lots" in the process of actual planning because they are prioritized above other lots, regardless of which objectives are emphasized in the planning strategies.

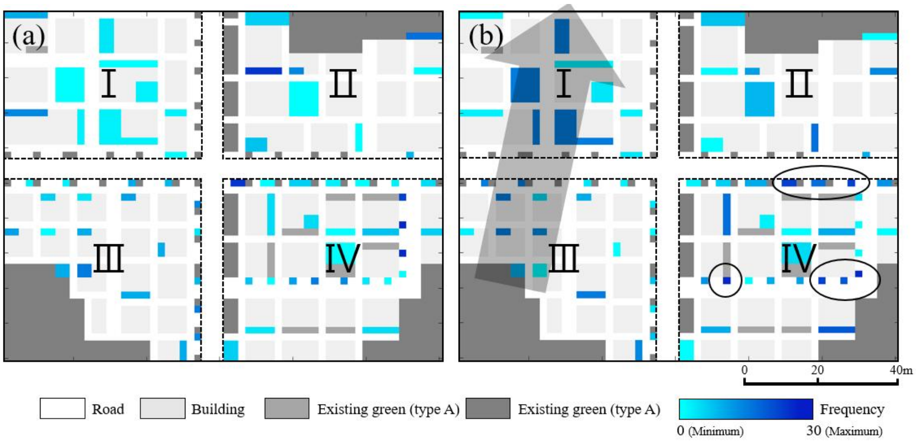

Figure 9. Frequency analysis on types A and B. (a) type A with grass and (b) type B with grass and tree

4.4. Discussion

Our model is a planning tool that determines the location and the type of green spaces considering two kinds of greenery benefits and implementation cost. The study was motivated by the lack of studies that consider the relationship between multiple benefits of greening, even though the connectivity, cooling effect of green spaces, and implementation cost are common factors in the existing planning. The planning process often omits certain factors or arbitrarily assigns relative importance based on the planner's preferences (Fintikakis et al., 2011). Furthermore, while the effectiveness of the draft plan is quantitatively assessed, the modifications afterwards are often qualitatively conducted. This study sought to improve this planning process by creating a positive feedback loop by repeating random modification (crossover and mutation in NSGA II), quantitative evaluation (fitness evaluation in NSGA II), and objective selection of better plans (selection according to dominated rank and crowding distance in NSGA II) for a number of cases. Our model proposed a range of possible scenarios for urban greening that can satisfy environmental, economic, and social requirements in the early stages of the project.

The results can be used as base maps or guidelines for planners who try to incorporate considerations, such as UHI, conservation of species diversity, and cost–benefit analysis, among others. This study can also reduce the gap between scientific assessment and its application to actual spaces. Most studies linking scientific assessment with spatial composition are limited to the suggestion of the appropriate amount or proportion of uses in a watershed or regional scale (Reichold et al., 2010; Galan-Martin et al., 2017; Liu et al., 2017). As such, where and how to change actual spaces at the neighborhood scale remain to be a problem for planners. To resolve this problem, our model provides plans with a 2-m resolution that can describe individual trees and incorporate the benefits and cost derived from new green spaces. This can be a methodological distinction as a tight-coupling approach that dynamically connects the input and the output of the objective model to assess the benefits and cost and the optimization model (Li et al., 2011).

Some studies have developed comprehensive models to synthesize multiple aspects of green space related to the environment, society, and economy based on a multi-criteria analysis (Meerow & Newell, 2017; Gül et al. 2006). In terms of the methodology, these models present possible options and choose the most viable ones by evaluating and comparing the options step by step (Gwak et al., 2017; Li et al., 2017). This approach aims to search for options within an existing expert's knowledge; therefore, it cannot obtain creative options beyond the already known ones. If the options are not sufficiently representative, we cannot be sure that the options are optimal solutions (Zhang and Chui, 2018). Furthermore, the options with an extremely good performance for one objective generally show major loss for the other planning objectives because of trade-offs; hence, there is a high possibility that these options are eliminated in a specific step even though it can be Pareto-optimal. However, in practice, these plans can be very useful options for some decision-makers or stakeholders under a specific condition. Contrary to that, our model can provide options could be sure of the best one by searching for an enormous number of options within a reasonable time. These options could be that we did not know before (i.e., this model takes 20 s).

We applied the planning model to the hypothetical landscape, not an actual space, to focus on its performance. The default values of the spatial resolution, cooling effect of green spaces, the distance d in which the green spaces interact with each other, land purchase price, etc., were set within a reasonable range. The application of this model to actual sites is expected to be covered in future studies; hence, tasks that would adjust these model parameters will be needed. First, the spatial scope and resolution of the study site should be set by considering the size and the distribution of the empty lot and the existing green spaces. Second, the LST variations in the green areas, surrounding areas, and other areas should be defined using remote sensing. Third, the distance d for the connectivity evaluation should be set according to the movement of the target species in the study sites. Fourth, the real land price should be considered in the implementation cost by using regional statistics. If issues more important than connectivity, cooling effect, or implementation cost for the region exist, other appropriate metrics can be used with the optimization model. For example, if runoff reduction is particularly important, the objective model of connectivity or cooling effect can be replaced with a hydrological model, such as stormwater management model (Giacomoni & Joseph, 2017). The NSGA II employed in the planning model has a very flexible structure to incorporate diverse evaluating techniques. Relying on the related studies, the evaluation techniques can be attached to NSGA II, including regional statistics (Karamouz et al. 2010; Yazdi et al. 2013; Zhang et al. 2014), expert judgment (Zhang et al. 2010; Liu et al. 2015a), and result or models of validated previous studies (Li and Parrott, 2016; Yuan et al. 2014). Therefore, this planning model would be applicable to various problems and sites by considering the distinct characteristics of the site and securing expertise in relevant fields (Yoon & Lee, 2017).

4.5. Conclusion

In this study, we suggested a planning model to describe comprehensive greening plans satisfying prerequisites prior to detail design, and showed the performance based on hypothetical landscape and data. Considering the conditions of high-density cities where installation of large green areas is difficult, we focused on neighborhood scale problems that were rarely addressed in previous studies. Although only two benefits of greening, namely cooling effect and enhancement of connectivity between habitats were selectively incorporated, it is expected to cover a range of issues with a little modification of the model owing to its flexible structure. Competing issues between various stakeholders have been barriers of co-design to achieve regional sustainability. This model can support co-design by providing spatially explicit options considering trade-off between competing issues. Furthermore, as the scientific basis for the greening effects in the neighborhood scale is accumulated in the future, the actual applicability of this model is also expected to increase.

Acknowledgments

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4.7. APPENDIX

Appendix 1. Abbreviations and parameters
Lot. All patches, including existing green areas and newly installed green areas in the plan

Empty lot. A patch that has not been used for a specific purpose because of its small size or unfavorable location; in this study, new green spaces can be installed at empty lots only

Vegetation type A. A single-layered vegetation with grass only

Vegetation type B. A multi-layered vegetation consisting of grass and trees

Urban heat island (UHI). The phenomenon of the urban area being significantly warmer than its surrounding areas

Land surface temperature (LST). Radiative skin temperature of the land surface that is generally measured with remote sensing

N (n). The number of rows in the gridded hypothetical landscape

M (n). The number of columns in the gridded hypothetical landscape

I (n). The number of lots with green areas located within distance *d* from the boundary of the *j*th lot

J (n). The number of empty lots (i.e., 66 empty lots in this study)

$\mathbf{Cooling\ Effect_{plan_k}}$ **(°C/m^2).** The average cooling effect that can be obtained from all green areas on the *k*th plan

$\mathbf{Connectivity_{plan_k}}$**.** The total connectivity that can be obtained from all new green areas on the *k*th plan

$\mathbf{Cost_{plan_k}}$ **($).** The total cost of implementing all new green areas on the *k*th plan, including the costs of purchasing land and planting (labor and material)

Distance *d* (m). Threshold distance at which the interaction between the green areas occurs in a neighborhood scale

Cooling effect α (°C). Direct cooling effect on the green surface (i.e., set herein to 3 °C as the highest cooling effect)

Cooling effect β (°C). Indirect cooling effect affected by only one lot with type B on the surrounding areas of that (i.e., set herein to 1.0 °C as the lowest cooling effect)

Cooling effect γ (°C). Direct cooling effect affected by multiple lots with type B on the surrounding areas of that (i.e., set herein 2.0 ℃.

$\mathbf{Area_{green}}$ **(m^2).** Total area where the green space (type A or B) exists

$\mathbf{Area_{surround\_a}}$ **(m^2).** Total area affected by only one lot with type B among the surrounding areas of that

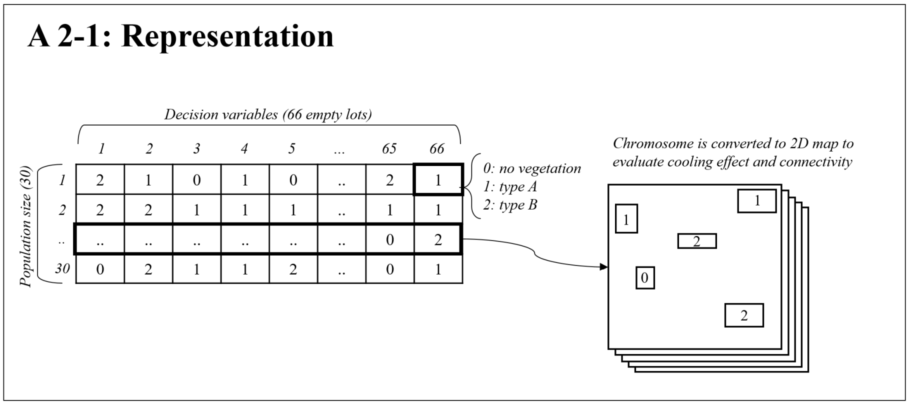
$\mathbf{Area_{surround\_b}}$ **(m^2).** Total area affected by multiple lots with type B among the surrounding areas of that.

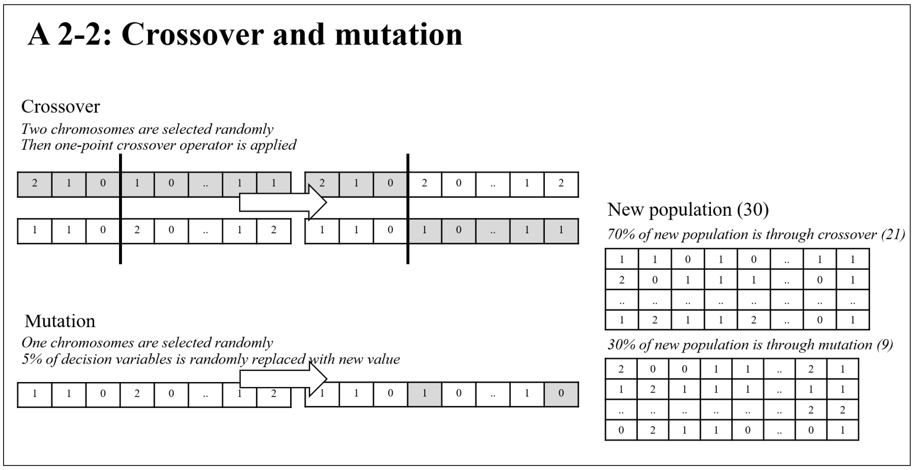
$\mathbf{Area_{lot_j}}$ **($\mathbf{Area_{lot_i}}$) (m^2).** Area of *j*th (*i*th) lot with or without vegetation

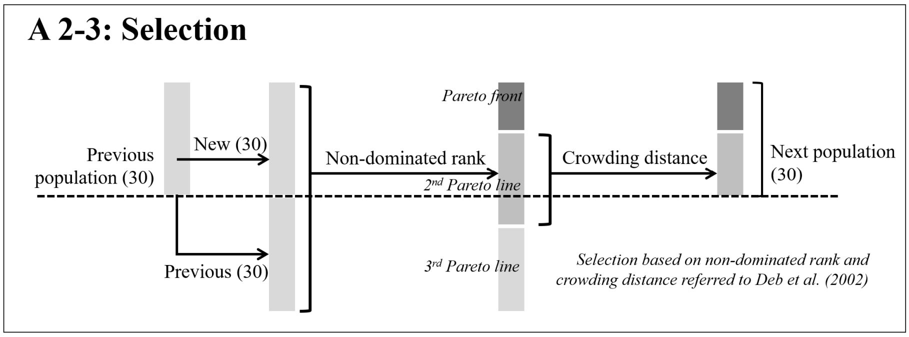
$\mathbf{Cost_{land}}$ **($).** Cost to purchase land for greening

$\mathbf{Cost_{vegetation}}$ **($).** Cost related to planting, including material and labor costs

Appendix 2. Representation, crossover, mutation, and selection







5. CONCLUSION

In South Korea, spatial planning has been established on the basis of the Constitution and the National Territorial Law, in order to promote the quality of life of citizens and ensure sustainability of land use in the long term. It is specified from the national comprehensive plan, the provincial comprehensive plan, to the county comprehensive plan. In addition, there are various kinds of regional and sectoral plans related to development, infrastructure, housing, resource management etc. At each level of planning, it considers the specificity of the region while taking into account the planning direction presented in the upper plan. In order to achieve inter-sectoral goals and strategies of each planning level, it is important to determine “where”, “when”, and “how much” of the planning elements should be put on the ground. Through this, it is possible to present development direction to residents, to provide guidelines for lower level plans, and to suggest investment directions for the private sector.

However, it can be seen that the linkage is insufficient between the proposed goals and the spatial planning (or the spatial diagram) done to achieve those goals. For example, in the 4th National Comprehensive Plan (2011–2020, the nation's top-level plan), the main targets are “responding to climate change and disasters” and "environment friendly and safety society”. Correspondingly, the South Chungcheong Province’s comprehensive plan focused on strengthening conservation and restoration of ecological networks, adjusting land uses where disasters frequently occurred, and establishing a response system for the climate change agreement (Paris Agreement). In the process of spatializing those goals and strategies however, environmental information such as the impact of climate change, hazardous area, and species habitat was not considered, and therefore the reliability of the results is also low. This is due to the limitation of the planning methodology in that it does not incorporate accumulated diverse environment information into spatial plans and adjust conflicts between sectors. Therefore, in this study, contribution of the spatial optimization models for the planning field can be emphasized as follows.

Firstly, the spatial optimization model can contribute to spatial planning on national and provincial scales by synthesizing various kinds of environmental information for a specific issue. This means that the output of the optimization model can be utilized as one of the input data in the process of planning. In the existing process of planning, planners determine appropriate locations of specific facilities or uses, referring to information by overlapping related thematic maps. However, as environmental issues are complex and ever increasing, related information is also diversified, leading to increased complexity in planning. Thus, synthesizing a variety of environmental information in accordance with the goals can contribute to reducing the complexity of planning. For example, in this study, the land use optimization model on a provincial scale suggested expansion direction of each land use by 1 km grids according to the adaptation path by synthesizing six kinds of environmental information, including climate change impacts. It is expected that this can be referred to comprehensive planning on national or provincial scales, when drawing a conceptual diagram of land use in response to climate change.

Second, the spatial optimization model can also be used as critical methodology to draw the draft for detailed planning. Since actual space is limited and all sectoral plans target the same space, problem of competition among sectors can occur. However, in the national, provincial, and county comprehensive plans, there are no guidelines to resolve such problems. Actually, in South Korea, unreasonable patterns of green belts (protected areas to limit expansion of urban areas) were often found because of being steadily and separately affected by the conservation and development regimes. Therefore, it is necessary to simultaneously reflect inter-sectoral objectives in a single planning model. This will help achieve reasonable spatial patterns based on limited resources. This is consistent with the main advantage of multi-objective optimization models proposed in this study. Since the existing objective(s) and assessment methodologies of each sector can directly match with optimization objectives and related fitness function, applicability of the optimization model is also expected to be high.

Although research on spatial optimization is increasing rapidly, the cases used in actual planning or administrative process are rare. However, if it is utilized for challenging problems as is the approach of this study, it is expected to contribute to sustainability of the actual space in the long term.

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국문초록

유전 알고리즘을 이용한 다중스케일/다목적 공간계획 최적화모델 구축

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공간계획 과정에서 다양한 이해관계자와 결부된 목표와 제약 요건을 만족시키는 것은 복잡한 비선형적 문제로서 해결하기 어려운 것으로 알려져 왔다. 그러나 최근 이러한 문제에 유전 알고리즘 (genetic algorithms), 담금질 기법 (simulated annealing), 개미 군집 최적화 (ant colony optimization) 등의 다목적 최적화 알고리즘이 응용되고 있으며, 관련 연구 역시 급증하고 있다. 이 중 유전 알고리즘은 공간 최적화 부문에 가장 빈도 높게 적용된 최적화 알고리즘으로 “exploration”과 “exploitation”의 균형으로 합리적인 시간 내에 충분히 좋은 계획안을 제시할 수 있다. 그러나 공간 최적화 연구가 보여준 좋은 성과에도 불구하고 대부분의 연구가 특정 용도 혹은 시설의 배치에 집중되어 있으며, 기후변화 적응, 재해 관리,

그린인프라 계획과 같은 최근의 환경 이슈를 다룬 사례는 매우 미흡하다. 따라서 본 연구에서는 유전 알고리즘과 비지배 정렬 유전 알고리즘 (non-dominated sorting genetic algorithm II)에 기초하여 기후변화 적응, 재해 관리, 도시의 녹지 계획 등과 같은 환경 이슈를 공간계획에 반영할 수 있는 일련의 공간 최적화 모델을 제시하였다. 개별 환경 이슈에 따라 공간 해상도, 목적, 제약요건이 다르게 구성하였으며, 공간적 범위가 좁아지고 공간해상도는 높아지는 순서대로 나열하였다.

논문의 첫번째 장에서는 행정구역 도 규모 (province scale, 해상도 1㎢)에서 미래의 기후변화에 적응하기 위한 토지이용 시나리오를 모의할 수 있는 공간 최적화 모델을 제안하였다. 기후변화가 먼 미래가 아닌, 현재 이미 진행되고 있으며 관련한 다수의 피해가 관찰되고 있기 때문에 공간적 관점에서 기후변화에 대한 적응의 필요성이 지적되어 왔다. 그러나 구체적으로 기후에 대한 회복 탄력성을 향상시키기 위하여 토지이용의 공간적 구성을 어떻게 변화시켜야 할지에 대한 방법론 제시는 미흡하다. 지역계획에서 기후변화 영향을 고려한 토지이용 배분은 매우 유용한, 기본적인 중장기 적응 전략에 해당한다. 본 연구에서는 다목적 유전 알고리즘 (MOGA, multi-objective genetic algorithm)에 기초하여 9,982㎢에

350만의 인구가 거주하는 한국의 충청남도 및 대전광역시 일대를 대상으로 기후변화 적응을 위한 토지이용 시나리오를 제시하였다. 지역적인 기후변화 영향과 경제적 여건을 고려하여 재해 피해 및 전환량의 최소화, 벼 생산량, 종 풍부도 보전, 경제적 가치의 최대화 등 다섯 가지의 목적을 선택하였다. 각 목적 별 가중치를 변화시키며 여섯 가지 가중치 조합에 대한 17개의 파레토 최적 토지이용 시나리오를 생성하였다. 대부분의 시나리오는 정도의 차이는 있으나 현재의 토지이용에 비해 기후변화 적응 부분에서 더 좋은 퍼포먼스를 보였으므로, 기후변화에 대한 회복탄력성이 개선할 수 있을 것으로 판단하였다. 또한 공간 최적화 모델의 유연한 구조를 고려하였을 때, 지역의 실무자 역시 가중치와 같은 모델의 파라미터, 기후변화 영향 평가와 같은 입력자료를 변경함으로써 효율적으로 새로운 시나리오를 생성 및 선택하는 것이 가능할 것으로 예상하였다.

논문의 두 번째 장에서는 행정구역 군 규모 (local scale, 해상도 100m)에서 기후변화에 따른 재해 피해를 관리하기 위한 토지이용 시나리오를 모의할 수 있는 공간 최적화 모델을 제안하였다. 산악지형에서 폭우로 인한 산사태는 인명과 재산에 심각한 피해를 초래할 수 있는 것으로 알려져 있다. 더욱이 기후변화에 따른 강우의 변동성 증가로 이러한 산사태 빈도 및 강도 역시 증대될 것으로

예상된다. 일반적으로 산사태 리스크가 높은 지역을 피해 개발지역을 배치하는 것이 피해를 저감 혹은 회피할 수 있는 가장 효과적인 전략으로 알려져 있으나, 실제공간에서의 계획은 매우 복잡한 비선형의 문제로서 이것을 실현하는 데 어려움이 있다. 따라서 본 연구에서는 비지배 정렬 유전 알고리즘 II에 기초하여 산사태 리스크 및 전환량, 파편화의 최소화 등의 다양한 목적을 만족시키는 종합적인 토지이용 배분 계획을 제안하였다. 대상지는 2018년 동계올림픽 개최지인 한국의 평창군으로서 2006년에 산사태로 인한 대규모의 피해를 경험하였으나, 올림픽 특수 등의 개발압력으로 인한 난개발이 우려되는 지역이다. 최종적으로 한번의 모의를 통해 현재의 토지이용 보다 적어도 한가지 이상의 목적에서 좋은 퍼포먼스를 보이는 100개의 파레토 최적 계획안을 생성하였다. 또한 5개의 대표적인 계획안을 선정하여 산사태리스크 최소화와 전환량 최소화 간에 발생하는 상쇄 효과를 설명하였다. 본 연구결과는 기후변화와 관련된 공간 적응 전략의 수립, 보다 향상된 개발계획을 위한 의사결정을 효과적으로 지원할 수 있을 것으로 예상하였다.

논문의 세 번째 장에서는 블록 규모(neighborhood scale, 2m)에서 도시 내 녹지계획안을 모의할 수 있는 공간 최적화 모델을 제안하였다. 녹지 공간은 도시민의 삶의 질에 결정적인 영향을 미치기

때문에 다양한 도시 재생 및 개발계획에는 녹지와 직 간접적으로 관련된 전략이 포함된다. 녹지 공간은 도시지역 내에서 열섬 현상 완화, 유출량 저감, 생태 네트워크 증진 등 다양한 긍정적 효과가 있음이 알려져 있으나, 공간 계획의 관점에서 이러한 다양한 효과를 종합적, 정량적으로 고려된 사례는 매우 미흡하다. 따라서 본 연구에서는 비지배 정렬 유전 알고리즘 II에 기초하여 녹지의 생태적 연결성 증진, 열섬 효과 완화와 같은 다양한 효과와 설치에 따르는 비용을 종합적으로 고려하여 적절한 녹지의 유형과 위치를 결정한 녹지계획안을 제시하였다. 블록 규모의 가상의 대상지에 본 최적화 모델을 적용함으로써 30개의 파레토 최적 녹지계획안을 생성하였으며, 각 목적 간 퍼포먼스를 비교하여 녹지의 열섬 완화 효과와 생태적 연결성 증진 효과 간의 상승 관계 (synergistic relationship), 이러한 긍정적 효과와 비용 절감 간의 상쇄 효과 (trade-off relationship)를 분석하였다. 또한 다양한 계획안 중 대표적인 특성을 지니는 계획안, 다수의 계획안에서 공통적으로 녹지 설치를 위해 선택된 주요 후보지역 역시 규명하였다. 본 연구에서 제시된 모델은 계획안의 수정에서부터 정량적 평가, 계획안 선택에 이르는 일련의 긍정적인 피드백 과정을 수없이 반복함으로써 기존의 녹지계획 과정을 개선하는 데 기여할 수 있을 뿐만 아니라 모델의 결과 역시 다자간

협력적 디자인 (co-design)을 위한 초안으로서 활용될 수 있을 것으로 예상하였다.

▣ *주요어: 기후변화 적응, 산사태 피해, 비지배정렬 유전 알고리즘 II, 녹지 계획*

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