LETTER

Modeling spatial climate change landuse adaptation with multi-objective genetic algorithms to improve resilience for rice yield and species richness and to mitigate disaster risk

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Keywords: scenario planning, landslides, economic value, landuse conversion, trade-offs, South Korea

Supplementary material for this article is available online

Abstract

As climate change is ongoing, many studies have recently focused on adaptation to climate change from a spatial perspective. However little is known about how changing the spatial composition of landuse could improve climate change resilience. Consideration of climate change impacts when spatially allocating landuse could be a useful and fundamental long term adaptation strategy, particularly for regional planning. Here, we identify climate adaptation scenarios based on existing extents of three landuse classes using multi-objective genetic algorithms for a 9982 km² region with 3.5 million inhabitants in South Korea. We selected five objectives for adaptation based on predicted climate change impacts and regional economic conditions: minimization of disaster damage and existing landuse conversion, maximization of rice yield, protection of high species richness areas, and economic value. We generated 17 Pareto landuse scenarios by six weighted combinations of the adaptation objectives. Most scenarios, although varying in magnitude, showed better performance than the current spatial landuse composition for all adaptation objectives, suggesting that some alteration of current landuse patterns could increase overall climate resilience. Given the flexible structure of the optimization model, we expect that regional stakeholders could efficiently generate other scenarios by adjusting model parameters (weighting combinations) or replacing input data (impact maps), and selecting a scenario depending on preference or a number of problem-related factors.

1. Introduction

Ongoing climate change has increased the frequency and severity of droughts, flooding, and urban heat islands (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 (Polasky et al 2008, Klijn et al 2012, Lehmann et al 2013, Galán-Martin et al 2017, 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 landuse is needed (Klein et al 2013). Although landuse decisions have long-term consequences and can be very climate-sensitive (Hallegatte 2009), relatively little
is known about best management practices from a spatial perspective relative to climate change (Campbell 2006, Hurlimann and March 2012).

At multiple scales, allocating landuse categories to appropriate areas with consideration of climate change impacts is an aggressive and important adaptation strategy (Wilson 2006, Hurlimann and March 2012). This can be a pre-emptive measure because most climate adaptation measures for water stability, agriculture, and forestry are implemented through landuse or land management. For landuse 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 (Kennedy et al. 2016, Galán-Martin et al. 2017). 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 (Matthews et al. 2000, Stewart et al. 2004, Eikelboom et al. 2015). 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 landuse to respond to a single climate impact (Reichold et al. 2010, Zhang and Huang 2014, Zhang and Huang 2015, Yoon et al. 2017) or repositioning a single landuse (Cáparros-Midwood et al. 2015, Li et al. 2009, Neema and Ohgai 2010, Reichold et al. 2010, Mehri et al. 2014). However, landuse conversions in specific areas may lead to other conversions to maintain the current landuse proportions, or produce changes in regional resilience. Thus, it is important to incorporate multiple landuses and climate-induced events into one computational process. Repeated optimization modeling provides a range of landuse 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 landuse and climate adaptation using MOGA. In this methodology, several objectives and constraints that should be achieved for adaptive and sustainable landuse scenarios were selected taking into account current and future condition of study area. There is much more involved in actual landuse, but it is important to describe landuse 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 2013, 2017, Dunnett et al. 2018). However here, we established five objectives related to multi landuse 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 landuse 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 landuse change strategies (Ligmann-Ziefinska et al. 2008).

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 (Korean Statistical Information Service: 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 (Architecture & Urban Research Institute: http://www.aurum.re.kr), but strategic spatial planning has not been included due to a lack of relevant methodologies (Yoon et al. 2018).

3. Methodology

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

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 (figure 1). Three of these considered the direct impacts of regional climate change on landuse, inconsistencies with the current landuse 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) (figures 2(A)–(C); supplemental table 1) is available online at stacks.iop.org/ERL/14/024001/mmedia; Korea Integrated Model for Climate Change Adaptation: 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 (Rahimi 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 landuse 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 to 2016 (figures 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.

3.1.1. 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 landuse types in the 2050s. We assumed that maximum economic loss equalled the monetary value of land if landslide probability was 100%, reduced in proportion to reducing landslide probability (figure 2(A); supplemental equation (1)).

3.1.2. 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 landuse 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 2(B); supplemental equation (2)).

3.1.3. 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 landuse patterns are inconsistent with projected future species richness patterns (figure 2(C)). 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 landuse scenarios in the 2050s. We assumed that conserved grids overlapped with allocated natural areas (figure 2(C); supplemental equation (3)).
3.1.4. Maximization of economic value

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

3.1.5. Minimization of conversion

Conversion refers to the total area (km$^2$) over which landuses 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 landuse conversions to 1 (supplemental equation (5)).

We excluded all water bodies and legally protected areas, and set an additional constraint to reduce the amount of conversion based on the current landuse ratio in an individual grid (supplemental figure 1). This constraint ensured that a certain amount of new landuse would originally exist in the grid even if landuse 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)).

3.2. Optimization model

3.2.1. Landuse scenarios

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 landuse scenarios three times by weighting combinations and analyzed each run (table 1).

The performance of the three landuse classes under future climate change was evaluated by comparing the values derived from the current landuse patterns (e.g. level of rice production, $E_{\text{objective}}$) with those from each of the alterative spatial scenarios.
(Scenario\_{objective}) (equations (1), (2); supplemental equations (1)–(5)):

\[
\text{Performance}_{\text{objective}} = \frac{\text{Scenario}_{\text{objective}} - \text{Current}_{\text{objective}}}{\text{Current}_{\text{objective}}} \times \alpha_j \times 100,
\]

\[
\alpha_j = \begin{cases} 1 & \text{if maximization based objective} \\ \frac{1}{\text{total area}} & \text{if objective of conversion} \\ -1 & \text{if not} \end{cases}
\]

3.2.2. Optimization model
Optimization models can potentially provide better solutions than current landuse 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 landuse while 70% were selected from existing landuses to initialize each run. Then, ‘variation’ and ‘selection’ was repeated from 15 000–35 000 times in each run until the fitness of each scenario showed convergence (figure 3). In ‘variation’, 0.05% of each landuse scenario was changed by the crossover operator (Yoon et al 2017). In ‘selection’, after combining changed and previous scenarios, landuse 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 landuse scenarios with lower social costs:

\[
\text{Fitness} = \text{Minimize} \left[ \sum_{j=1}^{I} \omega_j \left( \frac{\text{Best}_{\text{conv}} - \text{performance}_{i,\text{conv}}}{\text{Best}_{\text{conv}} - \text{Worst}_{\text{conv}}} \right) + \sum_{j=1}^{J} \omega_j \left( \frac{\text{Best}_j - \text{performance}_{i,j}}{\text{Best}_j - \text{Worst}_j} \right) \right] 
\]

where \(I\) is the number of scenarios, \(J\) is the number of optimization objectives except for ‘minimization of conversion’, \(\omega_j\) and \(\omega_{\text{conv}}\) indicate weights of objectives in table 1, and ‘Best’ and ‘Worst’ indicate the best and worst performances of all the optimized scenarios.

3.3. Analysis of landuse scenarios
After we generated 18 optimal landuse scenarios according to the six 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 landuse conversion was required.

Second, we analyzed trades-off between scenarios and objectives by connecting performances of each

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Figure 3. Optimization model based on MOGA.
Table 2. Performance of scenarios compared to spatial pattern of current landuse (%). Highest three performances by objective are shaded. Except for conversion minimization, positive values indicate better than current landuse patterns while negative values indicate worse.

| Emphasis in weight | Scenarios | 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           | 27.39      |
|                    | 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.

Pareto scenario with lines, whose slopes and directions differed according to the weighing combinations.

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

4. Results
4.1. Representative landuse scenarios for the climate change impact
In addition to the current landuse pattern, we identified 18 landuse 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 landuse pattern for the disaster, rice yield, and species richness objectives, respectively (figures 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 reallocation 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 center 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 landuse composition of all scenarios, with a conversion rate of 35.9%.

4.2. Trade-offs between scenarios
In all 17 Pareto landuse 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 (figure 4).

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 landuses, but economic value and disaster minimization were negative (indicating a worse result than current landuse). 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 landuse composition. Rice yield was the least sensitive objective, with performances ranging from 3.31% to 8.85%, regardless of the scenario (table 2), because the difference in rice yields by location was relatively small (figure 2).

4.3. Spatial frequency of scenarios
Analyzing the spatial frequency of the 17 Pareto scenarios showed that the central areas of all landuses were consistently allocated to the same landuse, mirroring the current landuse 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 landuse types were mixed within these grids (supplemental figure 1) and all landuse types could be allocated in future according to different scenarios. Depending on which landuse is expanded within grids of neutral areas, the whole study area could adapt differently to the three climate change impacts.

5. Discussion
The MOGA optimization approach allows for simultaneous consideration of climate change impacts, economics, multiple landuse types, and other constraints, which we used to develop spatial landuse adaptation scenarios. We found that it was possible to increase performance for all five objectives slightly, relative to current landuse 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 landuse scenario performed best for its high-weighted objective: to enhance the capacity to achieve adaptation capability (8.56%–41.45% better than current landuse), or conserve the most land productivity in all scenarios. The scenarios with equal weights (1abc) also showed slightly improved landuse climate adaptation than the current spatial pattern of landuse for all objectives. This indicates that not only does this approach provide spatially-explicit alternatives to make landuse 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 landuse 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 landuse adaptation can contribute to reducing social costs of climate change (Folke et al 2005). Landuse 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 landuse scenarios, local government can question whether current spatial patterns of landuse are appropriate or optimal for future conditions. This can also lead to local review of the extent to which landuse 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 (Bajra-charya et al 2011). In addition, if such landuse 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 landuse). Also, since the optimization model has a highly flexible structure that can change input data and related fitness functions (Yoon et al 2017), other landuse scenarios can be generated to simulate pressures on and mitigation of other climate scenarios or landuse goals. Here, we focused on creating landuse 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 landuse 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 landuse 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 landuse 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 landuse 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 × 1 km grid would not necessarily be converted to the allocated landuse; our results simply suggest the direction in which to increase or decrease each landuse within each grid (only currently existing landuses 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, Neema and Ohgai 2010, Cao et al 2012) 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 landuses 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 (Korean Statistical Information Service: http://kosis.kr).

In general, however, landuse patterns change continuously even without political pressure, and it is important to define the costs and benefits of optimized landuse patterns relative to no change scenarios (Li et al 2011). From the view of climate change adaptation, ‘landuse optimization’ and ‘landuse prediction’ can play different roles: the former refers to a concrete plan for changing landuse patterns for climate adaptation, while the latter shows the predicted effects of adaptation strategies on landuse patterns, considering past trends (Zhang et al 2014, Yoon et al 2017). 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, Scaramo 2017), but concrete methodologies for adaptation on the ground have not been sufficiently addressed. Multi-criteria analysis, which can consider competing issues to prioritize adaptation options using the full aggregation or the outranking method, is often used to support adaptation decisions (De Bruin et al 2009, Ishizaka and Nemery 2011, Trerup and Bakkegaard 2015). 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 landuse optimization (Dunnett et al 2018), and urban expansion was optimized considering climate-induced events (Caparros-Midwood et al 2015). Nevertheless, in the context of adaptation, few studies have addressed multiple climate impacts affecting different sectors and landuses in a single model; our study is thus a new starting point for this approach.

Acknowledgments

This work was supported by the Korean Ministry of Environment (MOE) as the ‘Climate Change Correspondence Program (Project number: 2014001310006)’ and supported by the BK21 Plus Project in 2018 (Seoul National University Interdisciplinary Program in Landscape Architecture, Global leadership program towards innovative green infrastructure).

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