Integrated spatial model based evaluation methodology for optimal invasive species management: common ragweed in the Republic of Korea

Hye In Chung¹, Yuyoung Choi¹, Youngjae Yoo¹, Robin Engler¹, Kyungil Lee¹ and Seong Woo Jeon¹,*

¹ Department of Environmental Science and Ecological Engineering, Korea University, Seoul 02841, Republic of Korea
² BK21 FOUR R&E Center for Environmental Science and Ecological Engineering, Korea University, Seoul 02841, Republic of Korea
³ SIB Swiss Institute of Bioinformatics, Amphipole building, CH-1015 Lausanne, Switzerland
⁴ National Institute of Environmental Research, Incheon 22689, Republic of Korea

* Author to whom any correspondence should be addressed.
E-mail: eepps_korea@korea.ac.kr

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Abstract
Invasive species have become a global problem owing to their wide-ranging adverse effects. With intensifying climate change and artificial impacts (human-mediated disturbances), which exacerbate the adverse effects of invasive species, there is an urgent need to implement strategies for the management of these species. Various removal policies have been implemented globally to manage the common ragweed (Ambrosia artemisiifolia var. elatior (L.,) Decs) owing to its high tendency to ‘spread’. Several studies on the control method, application of spatial perspective, and optimization have been conducted to establish and evaluate management strategies using different spatial models. Although each of these methods is essential for improving control efficiency, an integrated form of study is needed to determine the practicality of various policies. In this study, we developed an integrated spatial model using the species distribution model BIOMOD2, land change model LCM, dispersal model MigClim, and optimization model prioritizr, to construct an evaluation methodology. For modelling an optimal invasive species removal policy under climate change and human-mediated disturbances (2011–2079), we created two strategies from a spatial perspective, outside-in and inside-out, with the former entailing removal from the low-density outliers to the high-density centre of the colonized area and the latter processing in the opposite direction. The optimal removal sites for each strategy were set for each removal rate. Subsequently, a novel index, ‘removal effect index’, was proposed for the evaluation, in time series. The results indicate that the removal effect of the outside-in strategy was more effective, and the newly dispersed sites were efficiently removed. Furthermore, it was verified that with the implementation of the outside-in strategy having a removal rate of 65% by the 2070s, the species would be completely eradicated. Thus, this study is expected to help improve the efficiency of policy implementation for invasive species.

1. Introduction
Invasive species are increasingly becoming a global problem owing to their adverse effects on agriculture, fisheries, forestry, human health, and natural ecosystems (Moody and Mack 1988, Drake et al 1989, Mack et al 2000).

One of the main factors driving the spread of invasive species is climate change, which can both create newly suitable habitats (e.g. species limited by colder winter temperates can migrate north) (Dukes and Mooney 1999, Weltzin et al 2003, Moore 2004, Thuiller et al 2008), and disrupt existing ecosystems (Dukes and Monney 1999), thereby providing...
invasive species for an opportunity to occupy these disrupted areas—both in geographical and ecological space—in addition, some invasive plant species also show an increase in competitiveness relative to native species at higher ambient CO₂ concentrations (Sasek and Strain 1989, 1991, Smith et al. 2000, Ziska 2003, Nagel et al. 2004, Ziska et al. 2007, Bradley et al. 2010).

Another important factors in the spread of invasive species are human activities, both in the form of transport—which intensify the introduction and dispersal of invasive species—and in the forms of urbanization, that creates disturbed areas in which fast spreading invasive species have a competitive advantage over the native flora and fauna (Vittoz and Engler 2007, Storkey et al. 2014, Chu et al. 2017, Chung et al. 2020, Han and Keeffe 2021).

Considering that invasive species can irreversibly alter ecosystems (Blackwood et al. 2010, Chapman et al. 2016), and their economic costs to human societies (Schindler et al. 2016), tools for effective and long-term management are necessary. These tools, including spatially explicit projections of the spread of invasive species caused by both the impact of climate change and human driven environmental disruption (Ward 2007). Accordingly, both the control of invasive species and the evaluation of their effects have been intensively studied (Freckleton 2004, Taylor and Hastings 2004, Pimentel et al. 2005, Bullock et al. 2010).

Several studies and management strategies regarding the removal of invasive species and the evaluation of their effects are being proposed using various models. Based on the perspective that eradication to limit the expected proliferation is more realistic than prevention to control the populations that have already been established (Mack et al. 2000, Rejmánek 2000, Leung et al. 2002, Taylor and Hastings 2004), different control methods (e.g. chemical, and biological control) (Mattrick 2006) at various scales have been proposed (Whittle et al. 2007). Statistic-based demographic models were used to evaluate these control methods (Govindaraju et al. 2005, Blackwood et al. 2010). However, with the need of applying spatial concepts for controlling invasive species being recently raised, various studies have sought to determine the efficiency of removal strategies based on the density of the species (e.g. removal of recently colonized and low-density areas (outliers of colonized areas) or relatively long-established and high-density areas (core of a colonized areas)) using various spatial models, including species distribution models and dispersal models (Moody and Mack 1988, Higgins et al. 2000, Wadsworth et al. 2000, Taylor and Hastings 2004, Engler et al. 2012, Chapman et al. 2017, NYSDEC 2017, Chung et al. 2020). For example, the term ‘Early Detection and Raid Responses (EDRR)’ appeared in the field of policy (US General Accounting Office) and suggested a direction of control from localized populations (i.e. outliers) of the invasive species. This method increases the likelihood of successful control and thus promotes time/effort/cost effective decision-making for controlling the invasive species (NISC 2003, British Columbia Inter-Ministry Invasive Species Working Group 2014, NYSDEC 2016, Reaser et al. 2020). Furthermore, with the need of different level of management by different spatial characteristics (Storkey et al. 2014), the concept of ‘optimization’ has also been raised. Accordingly, recent studies have been developed to find the optimal removal strategies across time and space, considering factors such as population density and connectivity, and also to evaluate the effects using different optimization models from both statistical and spatial perspectives (Taylor and Hastings 2004, Pepin et al. 2020).

Although studies using various perspectives are essential for comprehending and improving the efficiency of controlling invasive species, an integrated form of study that includes all the factors, such as the optimization of removal from a spatial perspective, is necessary for establishing a more practical and realistic policy (Pepin et al. 2020). In addition, in terms of the evaluation, considering the fact that there is no standard framework, especially for comprehending the effects of a policy regarding adaptation to climate change (Hyun et al. 2019), a methodology using an integrated spatial model approach for both quantitative and spatial analysis needs to be developed.

Therefore, this study aimed to construct an integrated spatial model evaluation methodology for (a) an optimal invasive species removal policy by using optimal removal sites under climate change and human-mediated disturbances, and (b) quantitative-spatial evaluation of the effectiveness of each scenario in a time series. For the integration of models, we constructed an interconnected frame between four different spatial models: species distribution model BIOMOD2, land change model LCM, dispersal model MigClim, and optimization model prioritizr. For the quantitative analysis, we proposed a new index designed to evaluate the effects of removal under different scenarios.

In this study, the common ragweed (Ambrosia artemisiifolia var. elatior (L.) Desc), an annual species native to North America, was selected as the target species because of its highly invasives potential on a global scale (Harrison et al. 2003). The Republic of Korea was set as the study location as it can provide a large amount of monitoring data regarding vegetation, mammals, and fisheries at multiple spatial and temporal scales through in-depth systematic field surveys (Busan Development Institute 2016, National Institute of Ecology 2016).
2. Target species

2.1. Target species and occurrence data
With its high-frequency distribution over a wide spatial range, common ragweed has been designated as an invasive alien species by the Ministry of Environment of Korea (Research Institute of Gangwon. 2017). Given that the common ragweed alters the biodiversity, structure, and function of the ecosystem in which it is established (Sheppard et al. 2006) and has detrimental effects on both human health and agriculture (Bullock et al. 2010), various management policies and studies for controlling its spread are currently being proposed at the national level (Smith et al. 2013, Research Institute of Gangwon 2017, Case and Stinson 2018).

As it requires direct sunlight for germination, ragweed is generally found in non-forested habitats, such as roadides, riverbanks, and croplands (Case and Stinson 2018, Chung et al. 2020). Human-induced disturbances in the landscape, such as roads and various developments that occur within urban areas, thus favours the creation of suitable habitats for the species. In addition, human activity also contributes to the dispersal of the species along roads and water ways (Chu et al. 2017, Chung et al. 2020, Han and Keeffe 2021).

We obtained a total of 1,048 occurrence records of common ragweed from the National Institute of Ecology (2015–2018). After removing duplicate distribution points located in the same grid cell (a spatial resolution of all the predictor variables, 30 arcsec = 1 km²), the final 954 occurrence points were derived and used for analysis.

3. Materials and methodology

3.1. Species removal scenarios and overall modelling approach
Two different removal strategies, outside-in and inside-out, were established. In, the former, removal starts from the low-density outliers populations and progresses to the high-density centre of the colonized area, while in the latter, the progress is in the opposite direction (Moody and Mack 1988, Higgins et al. 2000, Wadssworth et al. 2000, Taylor and Hastings 2004).

To assess the effectiveness of these removal scenarios on the common ragweed, a modelling framework integrating four types of modelling—species distribution modelling (SDM), land use and land cover change (LULCC), dispersal modelling and optimization modelling—was developed (figure 1). The overall modelling was conducted in the following processes: (a) The habitat suitability maps under climate change were first derived through the interconnection between SDM and LULCC, then (b) the final habitat distribution was derived through applying the results of suitability maps within dispersal model, and finally, (c) the optimal removal for each scenario was finalized through optimization model (figure 1).

3.1.1. Habitat suitability projections under current and future climate conditions
SDMs relate species observations in the field (presence and absence records) to environmental variables (generally in the form of rasterized maps) in order to determine the likelihood of a given location to be suitable for the target species (Guisan and Zimmermann 2000). SDMs have long been used to support the management of invasive species (e.g. Anderson et al. 2003, Kumar and Stohlgren 2009, Adhikari et al. 2012), or to predict the spatial dispersal of invasive species under projected climate change (Anderson et al. 2003, Thomas et al. 2004, Thuiller et al. 2009, Saran et al. 2010). While a large number of statistical and machine-learning models are used in SDM (Hao et al. 2019), the approach used in recent years has often been to combine/average the projections obtained from different individual methods into so-called ensemble projections (Araújo and New 2007). This was proposed to reduce variability in individual
Table 1. Predictor variables.

| Variable type                | Name | Description                        | Resolution |
|------------------------------|------|------------------------------------|------------|
| Climatic                     | BIO11| Mean Temperature of Coldest Quarter|             |
|                              | BIO12| Annual Precipitation               |             |
| Topographical                | Slope| Slope                              |             |
|                              | Aspect| Aspect                             |             |
| Soil                         | Soil pH| pH of soil                         | 1 km² (resample) |
| Human-mediated disturbance   | Lv1  | Distance from urban areas          |             |
|                              | Lv7  | Distance from water                |             |

projections, improving the overall accuracy of results (Grenouillet et al 2011).

3.1.1.1. BIOMOD2
BIOMOD2 is the most well-known and well-established ensemble forecasting software using freeware and open-source R software (Thuiller et al 2009, Team 2017, Hao et al 2019). We used BIOMOD2 to derive the potential distribution of ragweed (i.e. habitat suitability maps) under climate change scenario. Specifically, since our species observation data consisted of presence information only (no absence records were available), and it is known that models that use both presence and absence data outperform the models that use only presence data (Elith et al 2006), the final eight models, generalized linear models, generalized additive models, multivariate adaptive regression splines, classification tree analysis, flexible discriminant analysis, artificial neural networks, generalized boosted models, random forest, excluding the maximum entropy algorithm (MaxEnt) and surface range envelope, were selected.

For generating the absence data, we formed pseudo-absence data through the parameters suggested from the (Barbet-Massin et al 2012). That is, selecting method, total number, ratio, and replicate number of pseudo-absences were set accordingly. In terms of ensemble methods, the mean probability (i.e. estimating the mean probabilities across predictions) method was selected for the study (Marmion et al 2009, Thuiller et al 2009).

Each of the eight individual models was evaluated using the AUC metric (Area Under the Receiver Operating Characteristic (ROC) Curve), computed using a repeated split sampling approach with 80% of the data used for model training/calibration and the remaining 20% for evaluation. Only projections from models with AUC > 0.7 were kept and averaged into a final, ensemble, projection (Marmion et al 2009, Thuiller et al 2009). The threshold of 0.7 for AUC values was chosen as it is the generally accepted threshold above which models are considered as acceptable (Mandrekar 2010, Gallien et al 2012).

Finally, the continuous habitat suitability projections (in the range 0–1000) were converted to binary values (habitat is projected as suitable or not) using a threshold maximizing the percentage of correctly predicted presence/pseud-absence records in the evaluation data set.

We considered climatic, topographical, soil and human-mediated disturbance factors as spatial predictor variables that can characterize the habitat distribution of common ragweed (table 1). These variables were selected based on the environmental conditions that contribute to the successful establishment of common ragweed populations (Bullock et al 2010).

For the climate dataset, we used RCP8.5 HadGEM3RA regional climate model scenario data produced by the Korea Meteorological Administration. Monthly climate average data (monthly minimum, maximum, and mean temperature, and precipitation) from 2011 to 2079 were obtained at a spatial resolution of 30 arcsec (approximately 1 km²). Because bioclimatic variables are known to affect the distribution and growth of vegetation (Park et al 2016, Choi et al 2020), we generated 19 bioclimatic variables for each decade from 2010s to 2070s (values from the 2010s are averages for 2011–2019, the 2020s are averages for 2020–2029, and so on until 2070–2079 for the 2070s) using the biovars package in R software (version 3.6.3).

Climate is known to be the greatest limiting factor for the spread and establishment of common ragweed. Specifically, germination does not occur at temperatures <5 °C; thus, cooler conditions are known to prevent the establishment of naturalized populations of common ragweed, whereas high temperatures have a relatively less profound effect (Bullock et al 2010). Common ragweed also favours moist condition. Through principal component analysis, seven bioclimatic variables—BIO1, BIO4, BIO10, BIO11, BIO12, BIO16, and BIO17—were found to represent all variables (Kim et al 2012). Therefore, considering the limiting factor, we used final two bioclimatic variables (BIO11, BIO12) as the climatic factors.

For topographical variables, slope and aspect were generated from elevation data (digital elevation model (DEM), Environmental Space Information Service database; http://egis.me.go.kr) and were selected as the final variables. The raw elevation data was not used due to its relatively high correlation (0.64) with one of the predictor variables, Lv1 THAT is, response tendency of each variable to species habitat.
do not appear properly when two variables with relatively similar spatial characteristics work together. Finally, as common ragweed favours less acidic soil conditions (Bullock et al. 2010), we downloaded soil pH data from the GIAT-CSI databases (www.cgiar-csi.org), with the pH data consisting of the values of 'pH' > 100.

Human-mediated disturbances are also likely to be a strong contributing factor to the distribution of common ragweed, both because it creates disturbed areas that are suitable for the species and promotes its dispersal along roads and water ways (Bullock et al. 2010). In this study, we therefore used Euclidian distance from urban areas and water ways as proxies for human impact, using ArcGIS (version 10.3).

LCM was used to generate land cover projections for the future time periods 2020s to 2070s (see LCM section below for details). Therefore, the final two human-mediated disturbance variables (Lv1, Lv7) were constructed (table 1).

3.1.1.2. LCM
In recent years, the modelling of LULCC has grown rapidly, with various models being developed (Hasan et al. 2020). Among various models (e.g. machine learning model, cellular based model, spatial based model, and etc), the machine learning approach is gaining popularity in LULCC studies (Shade and Kremer 2019). Therefore, Land Change Modeler of TerrSet software, which incorporates CA-Markov chain based multi perceptron (MLP) neural network (Kumar et al. 2015, Hasan et al. 2020), is widely used with its’ ability of high effectiveness and accuracy (Ahmed et al. 2013, Shade and Kremer 2019). More specifically, the MLP calculates transition potentials over time using a back-propagation learning algorithm, and with the combination of Markov chain process, the overall quantities of change over time are derived, thus the future land use land cover maps are predicted (Shade and Kremer 2019). As LCM was originally designed for both managing the biodiversity influences and forecasting LULCC (Dzieszko 2014, Mishra et al. 2014, Roy et al. 2014, Gibson et al. 2018, Hasan et al. 2020), it was chosen for this study.

In this study, LCM was used to predict future LULCC in the Republic of Korea from the 2020s to 2070s on a ten year basis. For the simulation, the land cover maps of the 2000s (2008–2010) and 2010s (2018–2019) were used to forecast future land cover maps (supported by the Ministry of Environment). Moreover, to apply the appropriate change rate for each land cover type, adequate parameters were selected based on the land cover change tendency by each land cover type through the transition matrix derived from the model, and the national statistics on land cover change (Kim 2016, Song et al. 2018).

Explanatory variables were constructed as, DEM, aspect, slope, distance from urban, cropland, forests, water, roads, and soil depth, through the previous research review (Song et al. 2018, Lee et al. 2010, Park and Jang 2020 and table A1 available online at stacks.iop.org/ERL/17/034047/mmedia). For constraint option, legally protected area (forest and water range) was incorporated to create more realistic projections.

All explanatory variables were resampled at a spatial resolution of 30 arcsec (approximately 1 km²), and the geographical coordinates for both the occurrence points and predictor variables were converted to WGS84 data using ArcGIS (version 10.3).

3.1.2. Dispersal simulations: refining future projected distributions by accounting for dispersal
Projections generated by species distribution models do not account for dispersal limitations, considering instead that species will occupy all of their potentially suitable habitats. While such an equilibrium might eventually be reached, ignoring dispersal constraints—especially when making projections under climate change scenarios—can result in large overestimations a species’ actual distribution (Engler and Guisan 2009, Engler et al. 2009, Lurgi et al. 2015).

3.1.2.1. MigClim
To refine our projections of the future distribution of common ragweed, we used the MigClim R package, a cellular automaton developed to simulate the dispersal of plant species in the landscape including the colonization, growth, and change in habitat suitability over time, (e.g. various climate change) (Engler and Guisan 2009). MigClim accounts for different ecological characteristics influencing a species dispersal, such as its seed dispersal kernel (probability of seeds to disperse at a given distance from their source) as well as rarer and more stochastic long-distance dispersal events that only occur to a small fraction of seeds, but involves an human-mediated activities such as dispersal by humans through transport and goods. The modelled organism’s life cycle can also be accounted for via simplified population dynamics parameter (seed production potential of a colonized cell as a function of time since colonization).

MigClim requires the following inputs: an initial distribution of the species, habitat suitability maps under current and projected future climatic conditions, maps representing landscape fragmentation (abarriers to dispersal, and locations that are permanently unfavourable for the species), and the parameters associated with the species dispersal and growth ability. In our simulations, the initial distribution of the common ragweed was set to it projected distribution in the 2010s, and the projected future habitat suitability maps were those we obtained from ensemble-modelling with BIOMOD2 for the time periods 2020–2070. The habitat suitability maps in
the simulations were updated every ten years, and dispersal was simulated on a yearly basis (i.e. one dispersal event per cell per year). For the Barrier data, as it can determine the possibility of species’ dispersal within the certain spatial ranges, it was later used as the alternative variables for applying the concept of ‘removal’ as explained in 3.1.3.

Accurate data of a species’ dispersal capabilities (e.g. seed dispersal kernels) are notoriously difficult to measure and are only found in the literature for a small minority of species (Vittoz and Engler 2007). To approximate the common ragweed’s dispersal abilities, we therefore used the simplified classifications proposed by Vittoz and Engler (2007), where seed dispersal distances are estimated based on seven types of dispersal mechanisms (Vittoz and Engler 2007). As common ragweed is considered an anthropogenically influenced species, human-mediated long-distance dispersal through via agricultural activities and transportation, is likely to be a strong contributing factor to the dispersal of the species (Bullock et al 2010). It thus more closely resembles a type 7 (Anthropochory) of the above classification, and parameters including dispersal probability as a function of distance and probability of long-distance dispersal were derived accordingly (see Engler et al 2009 for details on how seed dispersal kernel estimated can be derived for the MigClim model table A2). Furthermore, the function of a dispersal kernel, which indicates the probability of a propagule to disperse at a given distance from the source, was set as maximum due to common ragweed’s ecological characteristics of maintaining high coverage with high fecundity for its’ survival (Kang 2009, Bullock et al 2010).

Since dispersal simulations in MigClim have a stochastic component, we replicated out simulations 10 times and averaged the outputs of the different runs. Estimates for generalized results (Carvalho et al 2019). Considering the unit of ecological characteristics, all the input data for the model run were resampled at a spatial resolution of 50 m.

3.1.3. Optimization of the removal spatial range

The optimal removal spatial range should be selected based on the predicted dispersal sites (e.g. newly arriving sites; EDDR) (NISC 2003, British Columbia Inter-Ministry Invasive Species Working Group 2014) derived from MigClim. To reflect the strategy of ‘Removal,’ we alternatively applied the concept of ‘Barrier,’ one of the input types of landscape fragmentation in MigClim. Barrier cells are considered to be permanently unsuitable cells that also impede dispersal (Engler 2012). Therefore, we alternatively defined the concept of ‘impede’ as the ability to control the dispersal and utilized the ‘Barrier’ distribution as the distribution of ‘Removal’. Consequently, the selection of the optimal removal range (spatial range of ‘Barrier’) according to the target removal rate was conducted based on the spatial range predicted as the total distribution of each period.

We assumed that ‘complete removal’ (i.e. eradication) was performed; thus, no dispersal or appearance of the species was achieved in the area where the barrier was designated. The barrier layer is derived in cumulative terms and continuously reflects the barrier ranges of the previous years.

3.1.3.1. prioritizr

The prioritizr R package (R version 3.6.3) is a systematic conservation planning tool that uses integer linear programming techniques to provide an interface that is flexible for building and solving conservation planning problems (Rodrigues et al 2000, Billionnet 2013). Faced with the reality that conservation planners need to consider a wide range of factors at the same time, such as different biodiversity and management goals, the use of systematic decision support tools has become more popular (Hanson et al 2017). Moreover, given that the exact algorithms used within this model guarantee optimal solutions of spatial allocation (Rodrigues et al 2000, Billionnet 2013), this model was chosen as the optimization model for this study.

To run prioritizr, the problem needs to be defined first. Although this model is set to solve conservation-related problems, by manipulating the input data, we used the model for deriving an optimal solution to the ‘removal’ problems.

The objective of this study is to find the optimal removal sites (spatial ranges of ‘Barrier’) for each removal scenario. We generated prioritizations using the minimum set objective that seeks to minimize the value of the solution (similar to Marxan) (Lehtomäki and Moilanen 2013, Beyer et al 2016). For the values, we defined ‘removal priority value’, and different formulations were used depending on the spatial direction of the removal for each strategy. As the removal in the outside-in strategy starts with the outliers, the values were calculated as to implement the removal starting from the newly dispersed sites and to be sequentially performed to the remaining habitat distribution; the lower the value, the higher the priority. The ‘Euclidean distance’ tool in ArcGIS was used for calculating values that prioritize removal in the remaining habitat that is connected to the newly dispersed sites. Whereas, in the case of inside-out strategy, as it starts removal from the core where the species has already been distributed with high density, the removal priority values should be set conversely relative to that of the outside-in strategy. Therefore, to set the formulation such that the removal priority value at the sites where the species far from the newly dispersed sites to be low, the value of ‘Euclidean distance’ from the newly dispersed sites was reversed through the following formula;
1/(1 + value). For the target rate, defined as the ‘removal rate’, three different removal rates were set to conduct a more precise removal effect analysis. Based on the removal rates within the pre-established invasive removal policies (Park and Lee 2018), rate of 25%, 45% and 65% were set for the scenarios: [Out-1], [Out-2], [Out-3], and [In-1], [In-2], [In-3]. As a result, the optimal removal sites that minimize the total value of the removal priority value were derived, and the removal scenarios were applied starting from the 2020s.

Consequently, we generated a prioritization problem using a target-based minimum set formulation to find the optimal removal sites (i.e. barriers) that minimize the removal priority value of the solutions while ensuring that each relative target (i.e. removal rates) is met. The prioritization process was conducted using Gurobi (version 9.0.2; Gurobi Optimization 2018), and all the spatial models were implemented using R version 3.6.3 (R Foundation for Statistical Computing, Vienne, Austria; Team 2017).

3.2. Quantitative evaluation analysis

To quantitatively evaluate the removal effect in different scenarios, we developed a dedicated index: the ‘removal effect index (REI)’ (figure 2).

It is expected in this study that each removal scenario from the previous year \((i - 1)\) will affect the species’ habitat distribution in the next year \((i)\). Therefore, the decrease of the total area of habitat distribution by each removal scenario is as expected. To construct an adequate assessment index that reflect this assumption, the following formula was used to compute REI:

\[
\text{Removal Effect Index} = \left(\frac{\text{Habitat Distribution, (SE)} - \text{Habitat Distribution, (ST)}}{\text{Habitat Distribution, (ST)}}\right)_{i}
\]

where, the REI is calculated as the ratio of the changed area of the scenario Habitat Distribution (SE; Scenario) in the year \((i)\) with each scenario applied in the previous year \((i - 1)\), to the standard habitat distribution (ST; standard) where no scenario is applied. Accordingly, the smaller the values, the greater the removal effect.

4. Results

4.1. Habitat suitability map results

The BIOMOD2 ensemble model results using the mean probability indicated a high accuracy of performance with an AUC of 0.818 (figure 3).

Lv1, Lv7, Bio11, and Soil pH variables (listed here in order of decreasing importance in the model) were chosen for analysing the response curves of the environmental variables, as they account for over 0.05 of the ensemble variable importance. (Hellegers et al 2020). The response curves of these influential variables show the numerical tendency where the occurrence probability reacts (table 2).

In the case of Lv1 and Lv7, the simulation results of LCM were analysed to be similar to that of previous (Song et al 2018, Choi et al 2021), with relatively clear changes for urban and rather stable maintenance for water (figure A1 and table A2). Especially for urban, notable expansion was shown both in statistical and spatial terms, and more specifically, the expansion from the existing central urban areas along the road network was well simulated.

As shown by the response curve of the Lv1 variable (table 2), the statistical probability of ragweed occurrence increases sharply in the close vicinity of urban areas (distances < 1 km). Beyond 1 km, no specific effect is observed (the curve is essentially a horizontal line. This response curve is concordant with the known tendency of ragweed to frequently occur in human-disturbed landscape, that are located in the close vicinity of rivers and water bodies. A similar, although less stark tendency was found for Lv7 (distance from water ways). This again is in line with the ecological observation that ragweed is frequently found in the close vicinity of rivers and water bodies.

For Bio11, the overall occurrence probability exhibited a steady increase with an increase in the mean temperature of the coldest quarter (Bullock et al 2010). Moreover, with the rather dramatic increase shown starting at 5 °C, the threshold temperature of the species’ germination occurrence, the model proved to properly reflect environmental condition.

For soil pH, the occurrence probability increased with the increase in the soil pH. Considering that common ragweed favours moist less acidic soil conditions, these results coincide with the suitable conditions for the common ragweed (Bullock et al 2010).

4.2. Projected ragweed distribution results

The projected ragweed distribution (accounting for dispersal constraints), for the different future time points shows a tendency of expansion over time (figure 4 and table 3). More specifically, it was analysed that habitat expands to the nationwide range based on the intensive distribution of current urban regions (derived from the land cover map (2010s) supported by the Ministry of Environment), confirming the tendency of species dispersal through human-mediated impacts. Moreover, the gradual expansion in the southern region also successfully reflected the impact of projected warmer temperatures of making the area increasingly favourable as a habitat for the ragweed. (figure 4).
Figure 2. Detailed conceptual frame of the research methodology.
4.3. Scenario results

The removal effect was analysed to have cumulative increase over time (table 4). That is, after ten years of complete removal proceeded for each removal scenario, the distribution of the species' habitat gradually decreased over time. However, it was analysed that the final removal effect of each scenario by each period varied according to different removal strategies, different removal rates, and different extents of habitat expansion.

It was shown from the result that the higher the removal rate, the greater the removal effect for both strategies. In the case of the outside-in strategy, the models show that the total distribution of species could be reduced at a 65% removal rate. Specifically, it was shown that the REI value of −100% (indicates a situation in which the total distribution of the target species is removed using the same removal rate every 10 years) started from the year 2070s (rounding in the first place of the prime number of the REI

Table 3. Projected surface (km$^2$) of ragweed distribution (accounting for dispersal constraints) for different periods from the 2020s to 2070s.

| Period       | 2020s | 2030s | 2040s | 2050s | 2060s | 2070s |
|--------------|-------|-------|-------|-------|-------|-------|
| Final habitat distribution area (MigClim) | 35 811 | 36 080 | 38 681 | 40 676 | 42 659 | 47 703 |

Unit = km$^2$

Table 4. Results of REI values for each scenario by each period.

| Time       | Outside-in | Inside-out |
|------------|------------|------------|
|            | (Out-1)    | (Out-2)    | (Out-3)    | (In-1)    | (In-2)    | (In-3)    |
| 2030s      | −25.5      | −46.0      | −66.2      | −22.5      | −41.1      | −60.4      |
| 2040s      | −42.3      | −68.4      | −87.1      | −40.8      | −65.4      | −83.1      |
| 2050s      | −52.6      | −80.8      | −95.1      | −51.0      | −75.3      | −88.4      |
| 2060s      | −61.0      | −88.7      | −98.4      | −57.4      | −79.5      | −90.2      |
| 2070s      | −66.1      | −93.5      | −99.5      | −59.1      | −77.7      | −87.9      |

Unit = %
Figure 4. The results of final habitat distribution maps from the 2020s to 2070s, and the reference map (distribution of current urban (2010s) and the directionality of climate change impact) for the verification.
values); i.e. 65% removal for 50 years (from the 2020s to 2060s) using the outside-in strategy succeeded in eradicating the total invasive species. Whereas for the inside-out strategy, although the value of REI got closer to \(-100\%\) with the increase in the removal rate, none of the scenarios reached the value. That is, removal from denser regions proved to be not effective for controlling the species’ dispersal. This can be explained in more detail by analysing the different trends of REI graphs between two strategies.

From the REI graphs, a slight change of the slope between the 2040s to 2050s and 2060s to 2070s was observed for both strategies, and this is due to the different directionality of expansion and the relatively larger habitat expansion shown at those periods, respectively (figure 5). However, different extents of slope change were observed for each strategy (outside-in and inside-out), and that is expected to be derived by different terms of removal tendencies at each period.

In the case of the 2040s to 2050s, the habitat expansion tends to spatially move from the northwest to the southern part of the country, whereas the quantitative extent of the habitat expansion tends to increase for the 2060s to 2070s (figure 6). Considering that the removal direction of each strategy for the newly dispersed sites is different, the result of inside-out scenarios showing (a) a rather distinct change

| Graph | Removal Effect Index (%) |
|-------|--------------------------|
|       | Time                     |
| (a)   |                           |
|       | 2030 | 2040 | 2050 | 2060 | 2070 |
|       | Out-1 (25%)          | Out-2 (45%)     | Out-3 (65%) |
| (b)   |                           |
|       | 2030 | 2040 | 2050 | 2060 | 2070 |
|       | In-1 (25%)           | In-2 (45%)      | In-3 (65%) |

Figure 5. Removal effect index (REI) of the outside-in (a) and inside-out (b) scenarios for each period.
of slope in the 2040s–2050s and (b) a more rapid decrease in the increase width of the REI values compared to outside-in scenarios, is considered to be an adequate result.

This can be explained more specifically by visually comparing the removal spatial range (i.e. barrier) for each strategy with each removal rate. As shown in figure 7, while the barriers of outside-in scenarios are defined to a wider range, including the new dispersal sites, the barriers of inside-out scenarios are defined in a relatively dense and biased form, rather focusing on the spatial ranges where the invasion has already been done.

Consequently, the inside-out strategy was evaluated to have a lower removal effect than the outside-in by failing to preferentially remove newly colonized sites at the leading edge of the species’ distribution. This was more evidently shown in the 2060–2070s when the extent of species habitat expansion was more rapid. Therefore, for the inside-out strategy, the removal rate of 65% is not sufficient for reaching a REI value of $-100\%$ (figure 5), thus a significantly higher removal rate should be applied. Moreover, we found that the performance of removal is different according to the expansion tendency by each period, it is necessary to implement different scale of removal for each period to maximize the effect of the policy.

This time-series quantitative analysis is a meaningful result in that the value of REI represents the removal effect of each scenario over the standard habitat result, therefore the specific period when the value begins to represent $-100\%$ can be identified.
| Strategy    | 25% Removal Rate Scenario | 45% Removal Rate Scenario | 65% Removal Rate Scenario |
|-------------|----------------------------|----------------------------|----------------------------|
| Outside-in  | ![Map of outside-in]       | ![Map of outside-in]       | ![Map of outside-in]       |
| Inside-out  | ![Map of inside-out]       | ![Map of inside-out]       | ![Map of inside-out]       |

Figure 7. Spatial distribution of removal ranges (barrier) for each scenario for each strategy (outside-in, inside-out) in the 2040s.
5. Discussions

As the expansion of invasive species due to climate change and human-mediated disturbances is expected to cause increasing damages to native ecosystems, development of effective and cost-efficient removal policies are of great importance. However, owing to the lack of an integrational approach and the advanced methodology needed for evaluation, establishing and implementing a more practical and realistic policy is hindered.

In this study, we developed an evaluation methodology for the optimal invasive species removal policy using integrated spatial modelling (BIO-MOD2, LCM, MigClim, and prioritizr). Through the combination of these spatial modelling techniques, the final habitat distribution of common ragweed under climate change and human-mediated disturbances was successfully simulated, and the optimal spatial prioritization of removal (i.e. Barrier) was also successfully applied. Moreover, with the newly developed REI (removal effect index), the evaluation results for the effect of each scenario were derived from spatial and quantitative perspectives as well as the time series. The results indicate that the outside-in strategy is more effective for removing invasive species than the inside-out strategy and that different extents of REI values appear by applying different removal rates. Specifically, this study is important in that it logically confirmed the reliable tendency of the specific time period for each scenario, in which the final removal effect (i.e. REI value of $-100\%$) is expected to appear. Furthermore, it has spatially and quantitatively analysed the different extents of removal effect by different expansion tendency of a species.

This study can indicate the specific time when each policy effectively removes all the distributions of the invasive species with different removal rates, and through optimization, the results of this study can be used as a basis for policy establishment and implementation. Also, with the consideration of the species’ expansion tendency in both spatial and quantitative terms, the logical basis for controlling the optimal size and location of removal to maximize the policy implementation effect can be presented. Consequently, the optimal size and extent of time of each policy input can be set more realistically, thereby increasing the utility of each policy. Moreover, by deriving the optimal removal sites for each removal rate, the best monitoring sites for recording the species range can be suggested. Since the general framework constructed in this study is applicable to any species, with various characteristics (e.g. different types of ecosystems, landscapes, or spatial distribution) that have occurrence data, it may also be used for establishing practical conservation policies.

However, this study has several limitations. First, considering that the spatial characteristics of ‘expansion of urbans (urbanization impact)’ can greatly affect the introduction and dispersal of invasive species (Chu et al 2017), the impact of urbanization should also be applied in detail within the dispersal model MigClim in spatial terms. Although the impact of human-mediated activities was applied in statistical forms within MigClim in this study, in order to derive a more realistic distribution of species’ habitat, it is necessary to apply the concept of urbanization as a ‘dispersal source’ from a spatial perspective.

Also, the spatial extent of this study is likely to be somewhat insufficient to fully model the habitat characteristics of common ragweed (i.e. its response curve to environmental variables). As common ragweed is widely suitable throughout the Republic of Korea, the overall response tendency of each environmental variable was properly reflected. However, due to this wide suitability, the information about the environmental conditions not suitable for the species’ inhabit was not enough, and therefore our model might project overly suitable habitat values under the projected future climatic conditions. This is a general limitation due to the correlative nature of SDMs and is generally referred to as truncated response curves.

Finally, we did not consider the costs and economic feasibility that are involved in implementing the competing invasive species control policies. Given that budgeting is important for policy implementation and the financial resources of each country are different, it is necessary to tailor removal strategies so that they can actually be achieved on a given budget. Both the effect of the policy and economic feasibility can be improved by appropriately applying different mixed removal rates according to the budget’s input period and size. Considering that it is not realistic to apply policies for an infinite time, analyses from an economic perspective are very important. Also, as different extent of budget is expected for each type of removal strategy (i.e. outside-in and inside-out) according to the number of personnel and the length of distance, a more practical scenario should be constructed in detail.

We suggest that these limitations could properly addressed by (a) additionally applying urbanization impact within the species’ dispersal process from a spatial perspective, (b) expanding the geographical extent of the study area to cover a larger climatic gradient, and (c) conducting an economic feasibility of the evaluated removal strategies.

Data availability statement

The data generated and/or analysed during the current study are not publicly available for legal/ethical
reasons but are available from the corresponding author on reasonable request.

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