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Validating management strategies for invasive species from a spatial perspective: Common ragweed in the Republic of Korea

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ABSTRACT

Owing to their potentially wide-ranging adverse effects, invasive species are a growing global problem. The common ragweed (*Ambrosia artemisiifolia* var. *elatior* (L.) Desc) is one of the most important invasive plants, necessitating management because of its tendency to “spread.” Various studies and management strategies are being conducted based on the concept of “density” because of the increasing importance of the spatial perspective in this application. Although eradicating from the outliers (low-density regions) has a high efficiency, there is a lack of validation methodology for deriving both spatial and statistical results. We formed a general validation methodology by assessing various removal scenarios based on two removal strategies, namely Outside-in and Inside-out. These approaches exhibited several removal rates, and take into account the spatial perspective by considering species density. The Outside-in strategy entails the removal of species, which commences from the low-density regions, whereas the Inside-out removal initiates from the high-density regions. To classify the spatial regions for priority removal using each strategy, we defined the density level and then processed the removal of the occurrence points for each strategy to derive generalized results. We used the species distribution model MaxEnt to determine the predicted distribution of the target species for each removal strategy applied; subsequently, the final randomly generalized occurrence point results were used as model input data. Assessment analyses were conducted based on the final probability distribution and appearance level for each scenario, which included a newly proposed index was termed the “removal effect index.” Results indicated that the efficacy of the Outside-in removal strategy exceeded that of the Inside-out strategy for all assessment analyses, with the removal effect index showing a difference of about 2–5 times between strategies in each removal rate. In addition, through numerical analysis of the changed area of each scenario, the Outside-in strategy showed a successful removal effect in the “removal management priority spatial range,” whereas the Inside-out strategy showed limitations. We confirmed the efficacy of the Outside-in strategy as an optimal removal approach that takes into account spatial information of the priority spatial range for eradication in terms of the removal effect.

1. Introduction

Invasive species, which are known to have adverse effects on agriculture, fisheries, human health, forestry, and the natural ecosystem, are becoming an increasing global problem (Drake et al., 1989; Moody and Mack, 1988; Mack et al., 2000). Given that these species can irreversibly alter ecosystems if not effectively controlled (Blackwood et al., 2010), a fundamental approach to managing them is necessary (Ward, 2007).

From the perspective of invasive species management, prevention is generally acknowledged to be more cost-effective than post-entry eradication (Mack et al., 2000; Rejmánek, 2000; Leung et al., 2002). However, such a strategy cannot be adopted where invasive populations have already established (Taylor and Hastings, 2004). Invasive species management has mainly focused on eradication to limit proliferation using different control methods (e.g., mechanical control, physical removal of species through cutting or pulling, chemical control, use of herbicides to kill and suppress regrowth, and biological control [use of plant pathogens or insect predators to target specific invasive species]) (Mattrick, 2006) at different scales (Whittle et al., 2007). However, with regard to the spread of invasive species, an additional spatial perspective in the management of these species is needed, as indicated in studies that consider the density of invasive species (Moody and Mack, 1988; Taylor and Hastings, 2004;

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Wadsworth et al., 2000; Higgins et al., 2000).

A number of studies have sought to identify the most efficient removal strategies based on the density of the target species, by considering the spatial concept and the general principles of the spreading process; the size of the areas colonized by outlying populations are eventually observed to exceed those of the central populations after a given amount of time. Accordingly, these studies have examined whether it is more efficient to prioritize the removal of recently colonized and low-density areas (outliers) at the edge of colonized areas or relatively long-established, high-density areas (core) at the center of a colonized area (Moody and Mack, 1988; Taylor and Hastings, 2004; Wadsworth et al., 2000; Higgins et al. others 2000). The need to consider the direction of control efforts for invasive species as determined by the density of established populations has been proposed (NYSDEC, 2017), identifying low-density regions as the highest priority for eradication to prevent the subsequent expansion of small infestations.

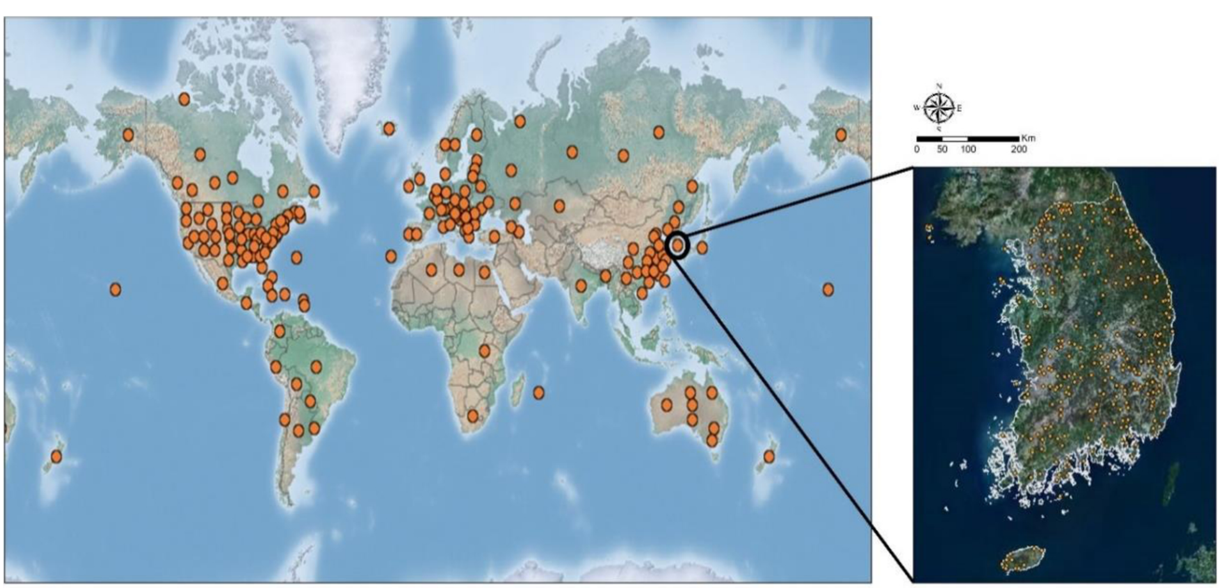
In the field of policy, the term "Early Detection and Rapid Responses (EDRR)" first appeared in 2001 (US General Accounting Office (GAO)), and has become as a standard approach in invasive species policy and management in the publications, since (Reaser et al., 2020). The goal of this policy is to promote time/effort/cost effective decision-making and communication in controlling a new invasive species infestation, with a coordinated set of management strategies that could increase the likelihood of successfully controlling invasions. If populations are still localized (i.e., outliers), they may have minimal detrimental effects (NISC., 2003; British Columbia Inter-Ministry Invasive Species Working Group, 2014; NYSDEC, 2016).

This policy mainly consists of two separate but interrelated phases, Early Detection (ED) and Rapid Responses (RR). Early Detection (ED) reveals the physical extent of the identified invasion and determines the potential for a rapid and successful eradication, whereas Rapid Response (RR) includes a carefully planned, decisive action designed to eradicate the incipient population (NYSDEC, 2016; Campbell, 2007). Because the framework is intended to be applied to any situation at any scale and with various remote sensing and satellite imagery, the number of case studies of effective EDRR-relevant initiatives and the amount of investment in EDRR are increasing (Reaser et al., 2020; NYSDEC, 2016; Martinez et al., 2020).

For spatial analysis, among various modelling approaches, species distribution models are important tools in aiding invasive species management (Anderson et al., 2003), which includes predicting and mapping the potential ranges of suitable habitats on a spatial scale (Qin et al., 2014). These models can be used to predict those areas in which environmental conditions are suitable for the survival and proliferation of a given species (Ward, 2007) and are obtained by combining species occurrence data with environmental variables required for species viability. Habitat suitability maps can be used to facilitate planning and prioritize certain locations for surveillance, especially, (1) where invasive species may actually be present (but have not been detected), and (2) where invasive species may disperse in the future (Ward, 2007). This information can contribute to determining both the extent and efficacy of a given management strategy (Ward, 2007). By predicting habitat suitability from a spatial perspective, species distribution models can be used to assess and improve the efficacy of specific control measures.

Although application of the EDRR policy and relevant management strategies are increasing due to various studies that apply the concept of density in terms of spatial perspective, the effectiveness of the policy has not been comprehensively assessed because there are only a few validation studies that assess management strategies through spatial models in spatial-statistical forms (Reaser et al., 2020). Although this study was conducted in the Republic of Korea, we sought to form a general validation methodology that can assess the effects of different removal strategies, which were established from a spatial perspective based on previous studies and basic concepts of actual policy.

In this study, we focus on common ragweed (*Ambrosia artemisiifolia* var. *elatior* (L.) Desc), which is an annual species native to North America. This species has high potential for colonizing new areas (Harrison et al., 2003) both globally and locally (Fig. 1). Our study location is the Republic of Korea, which has a fundamental system for successful ED, including field survey data for different time series that are sufficient at national and regional levels, and a need for RR application where common ragweed density is high. Korea has developed in-depth systematic field survey data for vegetation, mammals, and fisheries through monitoring. Korea has also conducted monitoring projects at a multiple spatial and temporal scales (National Institute of Ecology, 2016; Busan Development Institute, 2016), providing a large amount of data. The MaxEnt species distribution model was used as the spatial model, and we proposed a new index designed to compare the effects of removal under different scenarios.



(a) (b)

Fig. 1. Distributions of the common ragweed: (a) global; (b) Republic of Korea (Source: CAB International (cabi.org); 3rd National Ecosystem Survey).

Table 1
Predictor variables.

Variable			
Climatic data	Topographical data	Environmental data	Resolution
BIO1 (Annual mean temperature)	DEM (digital elevation model)		
BIO2 (Mean diurnal range)			30 arcsec
BIO6 (Min. temperature of coldest month)		Road (distance from roadsides)	1 km^2
BIO12 (Annual precipitation)	Aspect		
BIO15 (Precipitation seasonality)			
Wind speed			
PET (Potential evapotranspiration)	Slope		

2. Target species and materials

2.1. Target species and occurrence data

Common ragweed has deleterious effects on the environment via alterations in the biodiversity, structure, and function of ecosystems where it has become established (Sheppard et al., 2006), with detrimental effects on human health and agriculture (Bullock et al., 2010). Notable examples include crop yield losses and the release highly allergenic pollen (Qin et al., 2014). Various attempts to control the spread and limit the population densities of common ragweed at a national level highlight the importance of managing this invasive plant (Smith et al., 2013).

Given that the common ragweed is one of the invasive alien species designated by the Ministry of Environment of Korea, and has a high-frequency distribution across the country, a number of management policies for control are currently in force (Research Institute of Gangwon, 2017). Moreover, a range of studies are being conducted with the aim of predicting current and future potential distributions; quantifying the direct and indirect harmful effects in various sectors, including economic, social, and environmental perspectives; and assessing measures designed to control the introduction and spread of this species (Bullock et al., 2010; Case and Stinson, 2018).

On the basis of the 3rd National Ecosystem Survey (2006–2010), we obtained 330 occurrence records for common ragweed in Korea. Using these data, we converted species localities to geographical coordinates (WGS84 datum) using ArcGIS 10.3. After removing duplicate distribution points located in the same grid cell based on the spatial data resolution of predictor variables (30 arcsec = 1 km^2), we obtained 328 occurrence records for the subsequent analysis.

2.2. Predictor variables

We considered climatic, topographical, and environmental data as spatial data for potential predictor variables characterizing the habitat distribution of common ragweed (Table 1), which were selected based on their biological relevance to the distribution of the target species and prior use in other habitat modeling studies (Qin et al., 2014; Case and Stinson, 2018; Lee et al., 2016; Cunze et al., 2013; Rasmussen et al., 2017; Barbet-Massin et al., 2012). To reduce multicollinearity and minimize model fitting, we performed pairwise correlation analyses to filter redundant climatic variables that showed a correlation > 0.90 (Lee et al., 2015). We detected no redundancy among the selected climatic variables, so they were all retained. Finally, all predictor variables were resampled at a spatial resolution of 30 arcsec (approximately 1 km^2).

Current climatic data were downloaded from the WorldClim database (1970–2000), available at a spatial resolution of 30 arcsec (Hijmans et al., 2005). WorldClim contains 19 bioclimatic variables derived from climatic data (monthly precipitation and monthly mean, minimum, and maximum temperatures) obtained through the interpolation of climate station records from 1950 to 2000 *(available online)*.[1] Among the variables obtained from the WorldClim database, six bioclimatic variables (Bio1, Bio2, Bio6, Bio12, and Bio15) and wind speed were selected. Global-PET (global potential evapotranspiration) data, downloaded from the GIAT-CSI database *(available online)*,[2] were used as an alternative variable for humidity. As topographical data, we obtained elevation data (digital elevation model, DEM) from the Environmental Space Information Service database supported by the Ministry of Environment *(available online)*[3] ; these data were used to generate information with regard to slope and aspect (both in degrees).

Common ragweed requires full sun for germination, and is typically found growing in non-forest habitats, including roadsides, agricultural croplands, and the banks of rivers and streams (Case and Stinson, 2018). Furthermore, human-mediated disturbance, such as agricultural activities and the dispersal of seeds via the transport of goods and crops, is a prominent factor contributing to the spread of ragweed (Vittoz and Engler, 2007). Given that there are numerous localities where agricultural land and streams lie in close proximity to roads, and roads are one of the main routes for ragweed spread, we designated distance from roadsides as environmental data that expresses the influence of humans (obtained from the Ministry of Land, Infrastructure, and Transport of Korea [*available online*]).[4]

3. Methods

We conducted this study in three stages (Fig. 2). First, we established two different spatial removal scenarios, namely Inside-out and Outside-in, using occurrence point data, the input data for model analysis. We examined a standard scenario to compare the different effects of each scenario. Second, based on input data set for each scenario, we used the species distribution model MaxEnt to determine the potential distribution of common ragweed. Third, we performed assessment analyses for each scenario in comparison with the results of the standard scenario.

3.1. Invasive species management strategy

In the present study, we established spatial removal scenarios based on the concept of density and assessed the removal effects of each scenario based on the aforementioned theory (Fig. 2).

3.1.1. Spatial removal scenarios

We designated spatial removal strategies based on the Outside-in and Inside-out strategies (Menz et al., 1980). The former entails removal commencing from the low-density outliers and progressing toward the high-density center of the colonized area, whereas the latter proceeds in the opposite direction. Given that the rate of removal of invasive species can influence the effects of each strategy (Research

[1] http://www.worldclim.org/bioclim.org
[2] http://www.cgiar-csi.org
[3] http://egis.me.go.kr
[4] http://nodelink.its.go.kr

Institute of Gangwon, 2017), the spatial removal strategies were subdivided according to the removal rate.

The objective of this study was to validate the efficacy of different strategies (Outside-in and Inside-out). The effect of each strategy can be precisely determined when removal is conducted in spatially distinct regions in which the densities of target species are clearly defined.

3.1.1.1. Density analysis. Before applying each scenario, we classified the spatial region for each scenario, prioritizing removal thorough density analysis. To define the density of common ragweed stands, we conducted kernel density analysis using ArcGIS 10.3 (ESRI, Redlands, CA, USA). The tool calculates a magnitude per unit area from a point or polyline features using a kernel function to fit a smoothly tapered surface to each point or polyline (ArcGIS 10.3). The results were then classified into 5 density levels based on quantile classification, with level 1 indicating low density and level 5 indicating high density (level 1: 0–20 %, level 2: 20–40 %, level 3: 40–60 %, level 4: 60–80 %, level 5: 80–100 %). Consequently, for each scenario, the region prioritized for removal was determined based on the level of ragweed density. For example, scenario [In-1] entailed the removal of 5% of the total occurrence points from high-density areas, starting from density level 5; in scenario [Out-1], the same percentage of ragweed was removed from low-density areas, starting from density level 1 (Table 2).

To distinguish the removal effects of the Outside-in and Inside-out strategies, we set minimum and maximum values for the rate of removal. In other words, the appropriate removal rate was set to proceed at different density levels for different strategies. Given that there were considerably fewer occurrence points at high density levels, minimum and maximum removal rates were calculated based on the ratio of the occurrence points at level 5 ($(18/328) \times 100 = 5.4$ %) to that at level 4 ($((18 + 39)/328) \times 100 = 17$ %) over the total number of occurrence points, excluding level 3, which was not suitable to reflect the density difference between the two strategies. Minimum and maximum removal rates were set as 5% and 15 %, respectively; an additional rate of 10 % was included to represent moderate removal.

Consequently, we established a total of six spatial scenarios: three Inside-out scenarios (In-1, In-2, and In-3) with removal rates of 5 %, 10 %, and 15 %, respectively, and three Outside-in scenarios (Out-1, Out-2, and Out-3) with removal rates of 5 %, 10 %, and 15 %, respectively.

3.1.1.2. Application of spatial removal scenarios. To determine a representative value for the removal effect under each scenario, it was necessary to produce generalized results. Generalization was performed by randomly selecting removal occurrence sites 100 times for each scenario, using R version 3.3.4 (R Foundation for Statistical Computing, Vienna, Austria) [i.e., (In-1), (In-2), and (In-3): start by removing 5% (= 16 points), 10 % (= 32 points), and 15 % (= 49 points) of the total occurrence points at random from density level 5; (Out-1), (Out-2), and (Out-3): start by removing 5% (= 16 points), 10 % (= 32 points), and 15 %(= 49 points) of the total occurrence points at random from density level 1]. Consequently, for each scenario, we applied the distribution results of 100 random samples of occurrence points as input data for MaxEnt.

Given that the 328 occurrence records were obtained by removing duplicate points based on a spatial resolution of approximately 1 km^2, we assumed that a single point occurrence is representative of an area of 1 km^2. As it is known that common ragweed has a survival strategy that maintains high coverage, the removal is conducted for a nearby area (e.g. within 10 m), including a certain radius based on the location where the species is found (Kang, 2009; Ministry of Environment of Korea and National Institute of Ecology, 2016). Thus, this study intended to reflect the methods of the ongoing projects, and as the minimum spatial variable resolution was 1 km^2, we assumed the removal of a single occurrence point to be interpreted as the removal of a 1 km^2 area, which is equivalent to the total extermination of common ragweed within this area. Accordingly, each removal rate value could be converted into an area by multiplying the value by 1 km^2 (Table 2).

The analysis of the removal effect of different scenarios necessitates a standard result, which represents the potential distribution of common ragweed with no removal applied. For this purpose, all 328 occurrence points were used as input data for MaxEnt.

3.2. Species distribution model

A large number of statistical models are currently used to simulate the spatial distribution of plant species (Kumar and Stohlgren, 2009; Adhikari et al., 2012), spread of invasive species (Anderson et al., 2003; Thuiller et al., 2009), spatial patterns of species diversity (Graham and Hijmans, 2006), and effects of climate change (Thomas et al., 2004; Saran et al., 2010). Among traditional models that use presence/absence data, the maximum-entropy (MaxEnt) method (Phillips et al., 2006), which is based on statistical mechanic techniques (Jaynes, 1957) and can be applied to presence-only data, is acknowledged to show superior performance (Qin et al., 2014; Elith et al., 2006), even when dealing with small sample sizes (Hernandez et al., 2006; Pearson et al., 2007; Papeş and Gaubert, 2007; Wisz et al., 2008; Benito et al., 2009). The model generates an estimate of the probability distribution (ranging from 0 [lowest] to 1 [highest]) for the occurrence of a species based on environmental constraints (Phillips et al., 2006; Kumar and Stohlgren, 2009).

We used 10-fold cross-validation to test model performance (Lee et al., 2016); here, 10 random partitions were made, with each partition including training data generated by randomly selecting 80 % of the species occurrence records and test data comprising the remaining 20 % (Ward, 2007). The maximum number of background points was 10,000, and other values were maintained as default values. The final results represent the average of 10 replicate outputs.

We used the area under the receiving operator curve (AUC) to evaluate model performance, because this provides a measure of model performance that varies from 0 to 1 (Fielding and Bell, 1997), with an AUC value higher than 0.7 indicating acceptable model performance (Park et al., 2017). We used the jackknife procedure to assess the importance of different variables.

3.3. Assessment analysis

To assess the different scenarios, we developed a dedicated index, the "removal effect index" (REI), which can be used to represent a reduction in the distribution area of an invasive species under different scenarios relative to that of the standard. Analysis for reductions in areal distribution were limited to the region stated as the "removal management priority spatial range" (RMPSR), which was defined based on the high-probability spatial range of the occurrence of the species determined using MaxEnt. In this regard, we introduced the parameter "appearance level" obtained by classifying the results of potential distribution derived from MaxEnt into 5 different levels, with level 1 indicating low probability and level 5 indicating high probability (level 1: 0–20 %, level 2: 20–40 %, level 3: 40–60 %, level 4: 60–80 %, level 5: 80–100 %). Levels 4 and 5 were selected as the RMPSR, which represents a priority region for the removal of the invasive species.

We used the following formula to calculate the REI:

$$\text{Removal Effect Index} = \frac{\textit{Number of Samples with Reduced Area Distribution Result in Removal Management Priority Spatial Range}}{\textit{Total Random Samples of Occurrence Points}} \quad (1)$$

where the ratio is calculated as the number of samples that show a reduction in the area of distribution of an invasive species within an RMPSR over the total random samples of occurrence points.

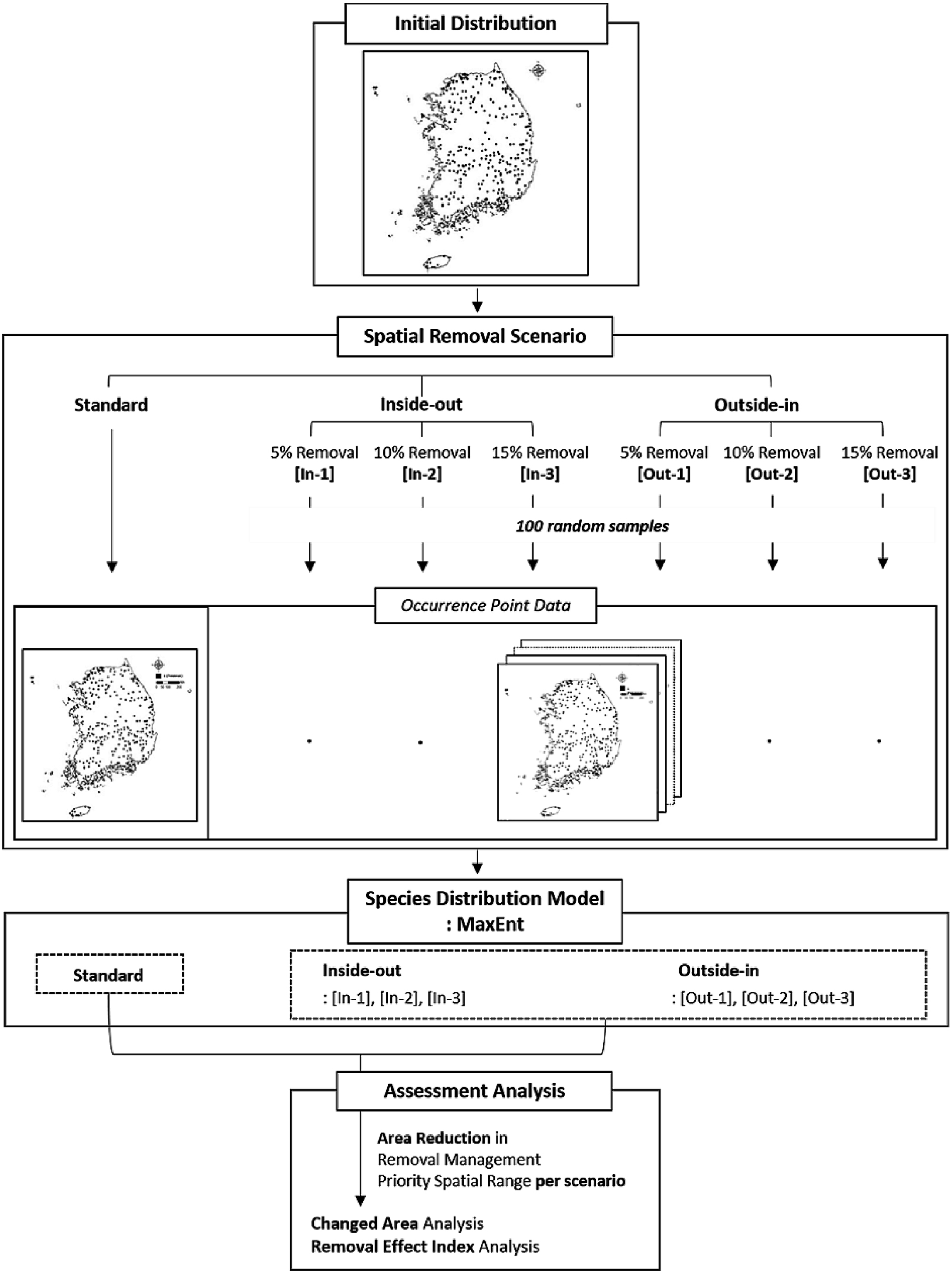
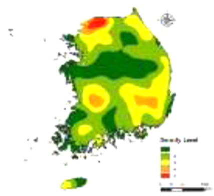


Fig. 2. Research flow chart.

Table 2
Number of final occurrence points for each density level.

Density Level		Number of Occurrence Points (Area)
Density Level Map	Level	
	1	30 (30 km^2)
	2	109 (109 km^2)
	3	132 (132 km^2)
	4	39 (39 km^2)
	5	18 (18 km^2)

4. Results and discussion

4.1. Standard result

The MaxEnt internal jackknife test of variable importance showed that PET, Slope, DEM, and Road were the most important predictors that contained the largest amount of information to predict the potential distribution of common ragweed (Fig. A1).

Furthermore, PET, DEM, and Road were identified as the most influential variables measured by percentage contribution, accounting for over 50 % of its variable contribution (Table A1). Both metrics consistently identified PET, DEM, and Road as the most important predictor variables, so the analysis was conducted based on this result.

The response curves of the predictor variables show the numerical section in which the occurrence probability reacts (Fig. 3). We found that occurrence probability increased markedly as the value of PET increased up to 900 mm y^{-1}. In contrast, a substantial decrease was observed following this peak value. For DEM, locations with an elevation above 600 m were unlikely to be suitable as habitats for the common ragweed. Considering that low temperature functions as a strong ecological barrier for the survival of the common ragweed, the noticeable decrease in occurrence probability above 600 m was expected. The response curve for distance from roadsides indicated that habitats within a distance of approximately 2 km are conducive to common ragweed colonization, which is consistent with the estimated minimum and maximum distances (500 m to 5 km) of spread via transportation (Vittoz and Engler, 2007).

The MaxEnt model results for all scenarios indicated a high accuracy of performance with an average AUC value exceeding 0.7 (Table A2). The results of the standard also showed high accuracy, with an AUC value of 0.763.

4.2. Scenario results

4.2.1. Changed area analysis

Different trends were observed in the change of spatial distribution for each of the different scenarios (Fig. 4), with broad-scale and localized changes being observed for the Outside-in and Inside-out strategies, respectively.

Compared with the standard result, changes in the spatial distribution within the RMPSR in response to the Outside-in strategy appeared wide, including the surroundings of the spatial range in which the scenario was applied (e.g., density level 1). We also observed that the reduction in the area of the RMPSR increased gradually, concomitant with the increase in the removal rate. For the Inside-out strategy, we observed a similar increase in the reduction in the area of the RMPSR, dependent on the removal rate, but the spatial distribution of the change was concentrated within the spatial range in which the scenario was applied (e.g., density level 5).

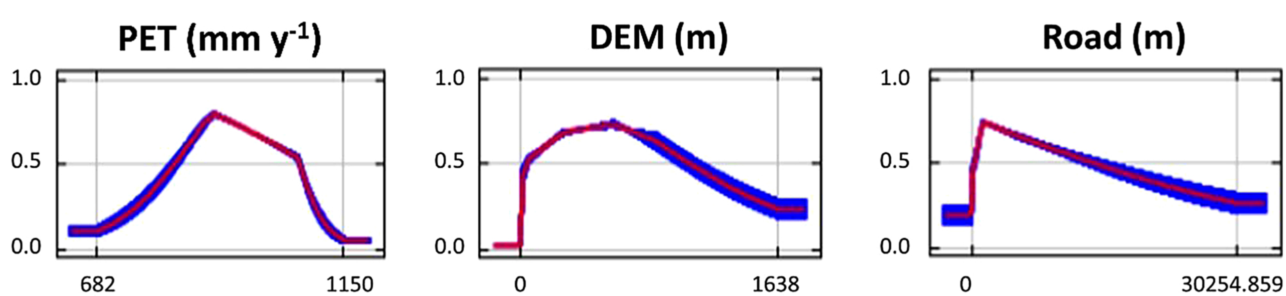


Fig. 3. Response curves showing the relationships between the most important predictor variables of common ragweed, and the probability of the presence of the species. Values shown are averages over 10 replicate runs; blue margins show ± 1 SD calculated for the 10 replicates.

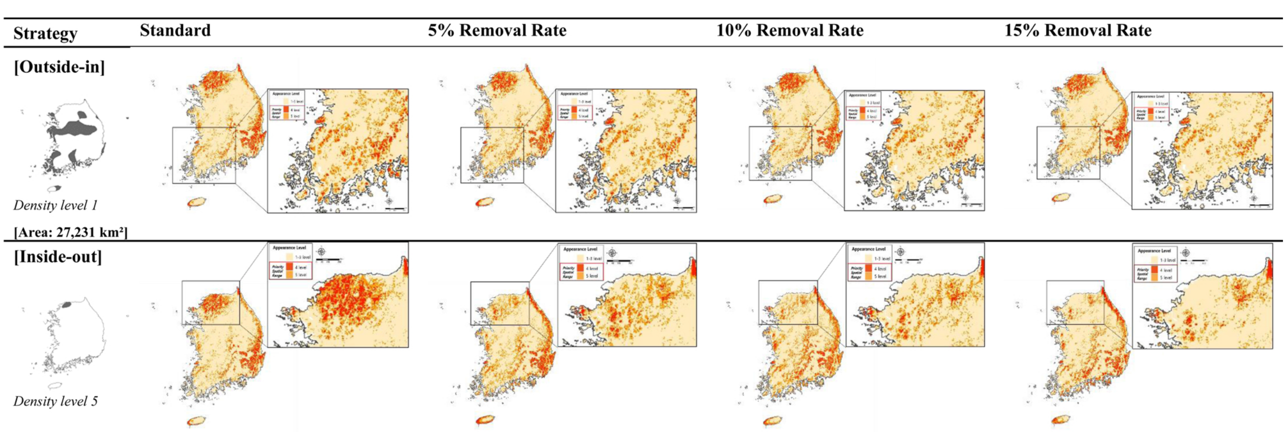
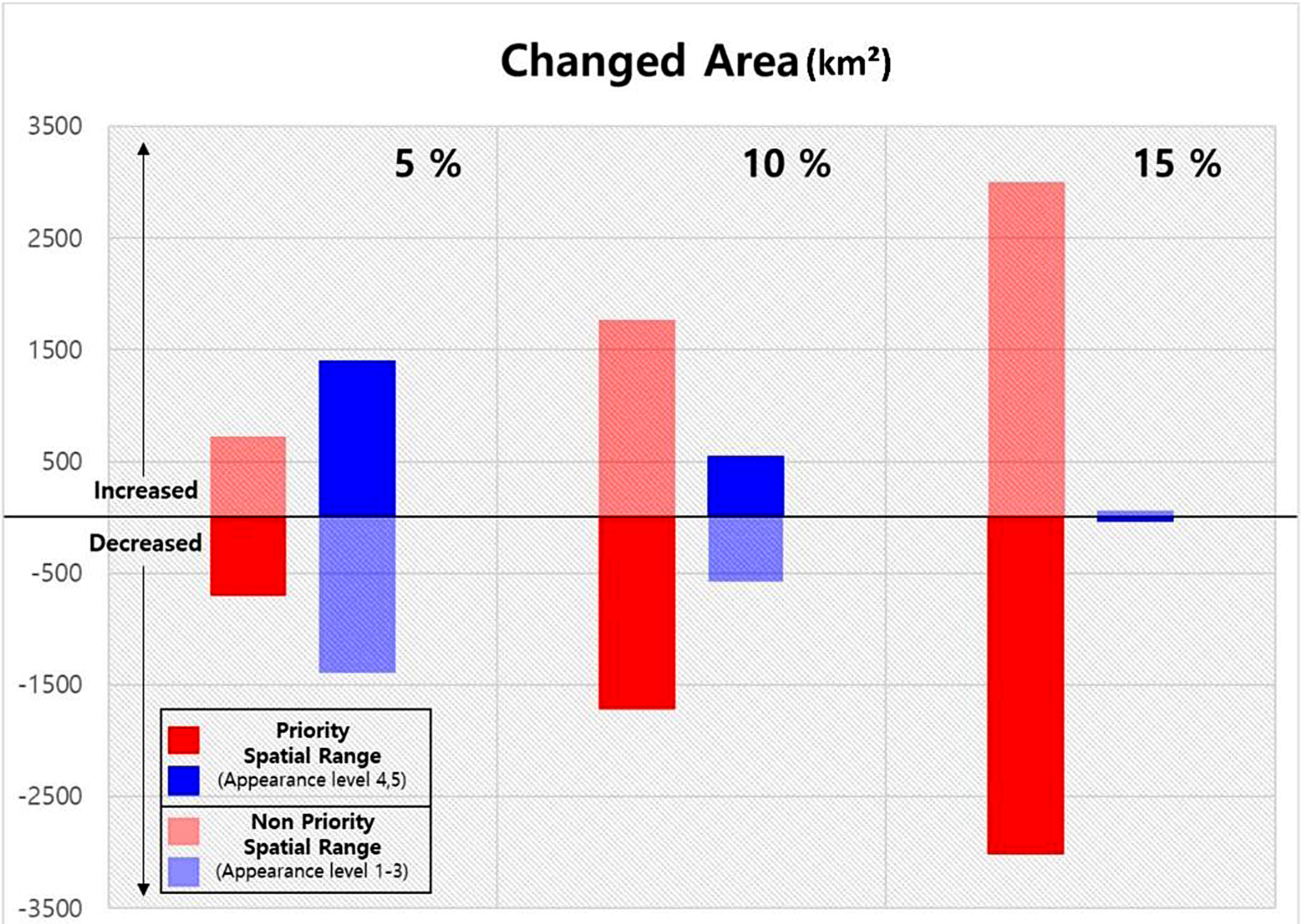


Fig. 4. Example of an appearance-level result for each common ragweed removal scenario.



Priority Spatial Range	5 %	10 %	15 %
[Outside-in]	*33,816(St)* → 33,112 **(-704)**	*33,816(St)* → 32,097 **(-1,719)**	*33,816(St)* → 30,802 **(-3,014)**
[Inside-out]	*33,816(St)* → 35,223 **(+1,407)**	*33,816(St)* → 34,362 **(+546)**	*33,816(St)* → 33,777 **(-39)**

Fig. 5. Average values of the changed area compared with the standard result (St) for each common ragweed removal scenario, in both the removal management priority spatial range and the remainder of the spatial range (unit = 1 km^2).

.For the quantitative assessment of the removal effect of each scenario, we performed numerical analysis by determining the average value of the changed area compared with the standard result for each scenario (Fig. 5). In the case of the Outside-in strategy, the removal effect was successfully focused on the RMPSR, and compared with the standard result, we observed an increase in area reduction in response to the increase in the removal rate. In contrast, the removal effect of the Inside-out strategy appeared to have a limited effect with regard to the RMPSR and, instead, was reflected to a greater extent in the remainder of the spatial range. Nevertheless, the effect of removal was gradually detected in the RMPSR, as indicated by a decrease in the amount of increased area in response to an increase in removal rate to 10 %, and finally showed a reduction in the changed area at 15 %. For each scenario, the reduction of area in the RMPSR in response to the Outside-in strategy exceeded that obtained by applying the Inside-out strategy. For both strategies, the reduction in the changed area accelerated in response to the increase in removal rate.

Our analysis of the different extents of the changed area clearly indicated that from both spatial and quantitative perspectives, the Outside-in strategy would have a better removal effect than the Inside-out strategy. The spatial range of the removal effect obtained using the Outside-in approach was observed to be considerably wider, comfortably encompassing the RMPSR. The absolute value of the changed area in the RMPSR also substantially exceeded that obtained in response to the Inside-out strategy.

4.2.2. REI analysis

For the assessment analysis of the REI of the two strategies, we calculated the areal difference in the RMPSR compared with the values obtained for the standard condition. For this purpose, we determined the values of changed area per random sample (Table A3) and obtained the final number of random samples that showed a negative value (i.e.,

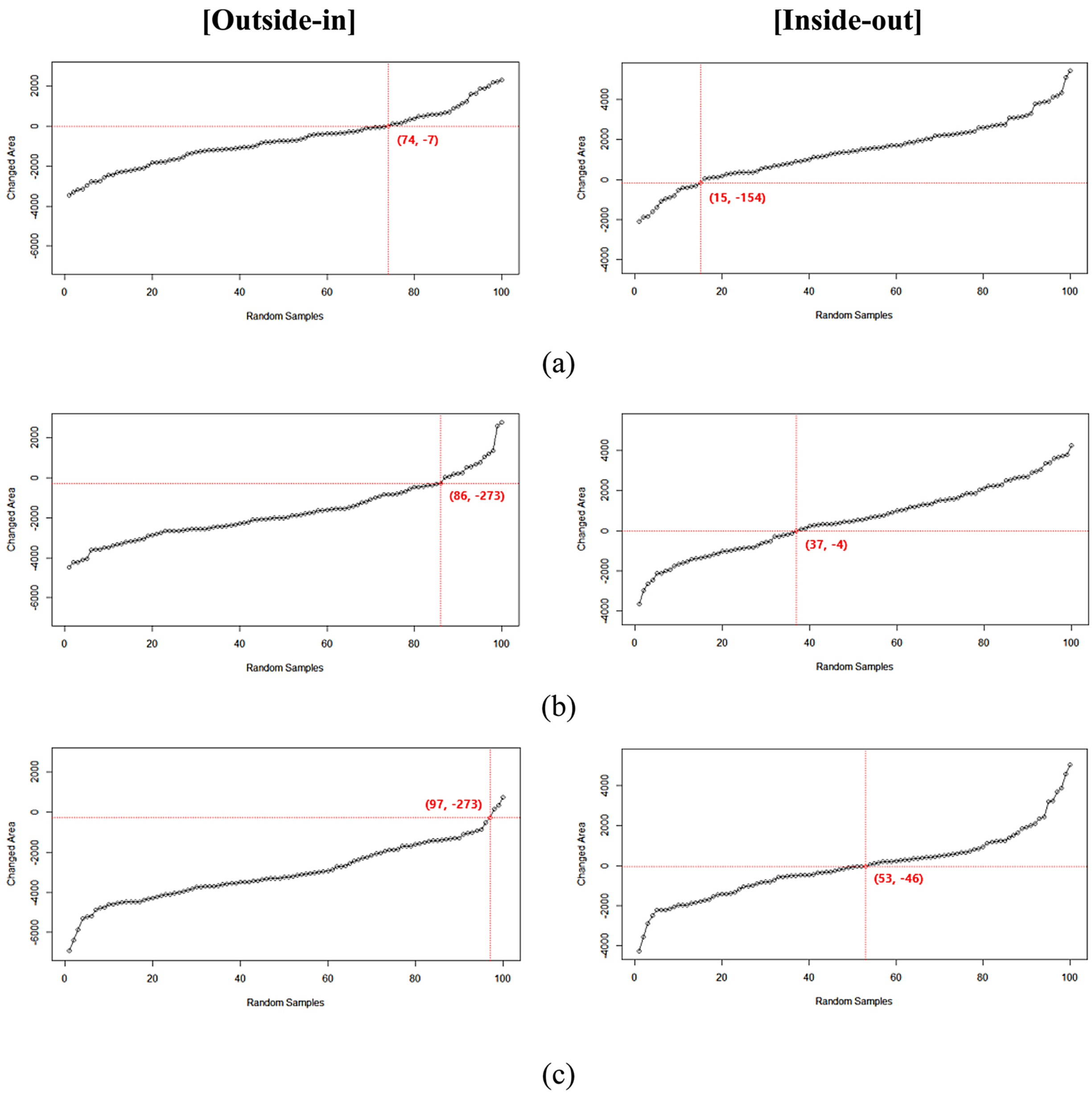


Fig. 6. Graphs of the changed area value per random sample set with the threshold point represented as (number of samples vs. value of changed area): (**a**) 5% removal scenario; (**b**) 10 % removal scenario; (**c**) 15 % removal scenario (unit = 1 km^2).

an areal reduction). We adopted this value as the threshold point (Fig. 6). For example, as shown in Fig. 6(a), 74 was set as the threshold point for the Outside-in strategy; among all 100 random samples of the occurrence point data, 74 samples showed a negative value of changed area (-7 km^2) in the RMPSR. On the basis of the same principle, 15 was set as the threshold point for the Inside-out strategy.

The REI was calculated based on the derived threshold points (e.g., REI for Fig. 6 (a) is calculated as 0.74). The removal effect of both strategies increased with an increase in removal rate, indicating that both spatial strategies operate more effectively as the rate of removal increases. However, for each assessed scenario, we found that the removal effect of the Outside-in strategy exceeded that of the Inside-out strategy (Table A4). Therefore, we confirm that from a spatial perspective, the Outside-in strategy would be the optimal strategy for controlling the spread of common ragweed.

5. Conclusions

For the effective control of the expansion of invasive species, it is necessary to apply a removal strategy with an optimal impact. Our results suggest that eradicating from the outliers is the most efficient strategy.

We successfully formed a general validation methodology and derived both spatial and statistical results for the efficacy of the invasive species management strategies. In order to set representative management strategies, we incorporated a density-based spatial concept into the assessment of invasive species strategies and applied a species distribution model to assess both the spatial and quantitative dimensions of the removal effect. This methodology should be applicable to any invasive species with various spatial characteristics (e.g., distribution form, different types of ecosystems and landscapes) that have occurrence data, as it is conducted through density analysis. Moreover, as this methodology can provide fundamental feedbacks on the efficacy of applied management strategies, the evaluation of the EDRR policy can be processed much more effectively, resulting in an increase of its substantial utility. In addition, because various climate change scenarios can be applied to species distribution models, this methodology can help identify monitoring sites and locations for appropriate removal management strategies.

Our approach has some limitations. For example, the MaxEnt model cannot be used to assess the ecological characteristics of target species, such as its expansion rate, germination rate, and ecological cycles. Given that we did not conduct an economic analysis, we were limited in our ability to identify the optimal removal rate for each strategy. Although our results indicate that the removal effect increases with an increase in the rate of removal, the associated management costs can be included to establish the optimum removal rate in actual practice. Because the analysis was not conducted in the same location for all scenarios owing to differences in density, a more specific methodology should be applied to conduct assessment analyses for the same location. In future studies, models that consider the overall ecological characteristics of target species can be applied in conjunction with an assessment of the economics of invasive species control. Different climate change scenarios in different time series can be processed to support environmental decision making for managing invasive species and to facilitate the practical use of these strategies.

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CRediT authorship contribution statement

Hye In Chung: Methodology, Software, Formal analysis. **Yuyoung Choi:** Software, Investigation. **Jieun Ryu:** Validation, Resources. **Seong Woo Jeon:** Conceptualization, Supervision, Project administration.

Declaration of Competing Interest

None.

Appendix A

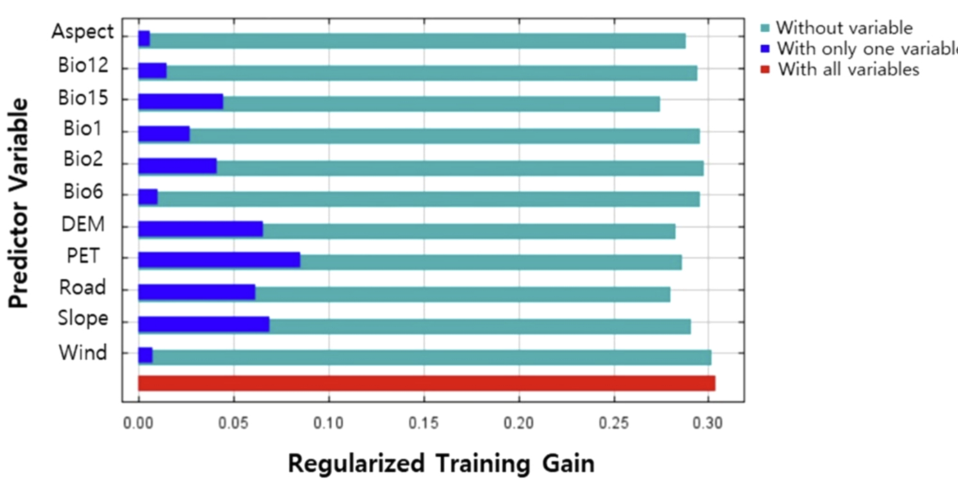

Fig. A1. Results of jackknife evaluations of the relative importance of predictor variables for the common ragweed MaxEnt model.

Table A1
Average AUC values for different common ragweed removal scenarios.

Strategy	5 %	10 %	15 %
[Inside-out]	0.728	0.720	0.712
[Outside-in]	0.740	0.736	0.737

Table A2
Percentage contribution of predictor variables.

	Bio1	Bio2	Bio6	Bio12	Bio15	PET	DEM	Slope	Aspect	Wind	Road
Con	6.0	3.1	11.4	2.7	11.8	20.3	17.1	9.4	3.1	0.2	14.4

Notes: Abbreviations are Con, Percentage contribution; PET, Potential Evapo-Transpiration; DEM, Digital Elevation Model; Road, Distance from Roadsides.

Table A3
The final results of changes in the invasive species area within the removal management priority spatial range for each of the assessed removal scenarios (unit = 1 km^2).

Random Sample	[Out-1]	[Out-2]	[Out-3]	[In-1]	[In-2]	[In-3]
1	119	−671	−3084	3911	1302	118
2	561	−4224	−1937	1692	535	−2052
3	−370	−460	−2390	359	−2131	412
4	−276	−1208	−1413	3153	2616	−49
5	−1185	−1805	−1326	119	746	1240
6	−724	−573	−1524	5441	−1168	−474
7	−2177	−2898	144	691	−1668	441
8	−753	−2417	−2258	2700	−1998	−1848
9	−3290	−2455	−4758	2243	−142	−1185
10	−2105	−2062	−3715	2356	2960	−3559
11	977	−2067	−529	−800	−278	−1801
12	−2785	504	−1900	−412	1007	484
13	501	−1366	−1044	1274	1853	5037
14	−1061	210	−3162	−304	−1939	602
15	−723	−1883	−4120	2602	1036	1126
16	−1253	−3056	−4224	2300	−1409	−535
17	108	−4094	−4465	48	−3000	−2231
18	−2437	−2645	−3415	1526	388	193
19	−1069	−1872	345	−1849	−1035	−1427
20	−819	1189	−1867	1136	−2460	664
21	−2138	−1426	−6921	1592	460	394
22	2295	−1850	−2052	365	3405	3221
23	229	−3338	−3665	899	2029	−458
24	−2276	−2094	−3237	4120	1171	−717
25	1864	−3582	−2959	−904	−1002	−2204
26	−195	−2017	−3339	1938	668	356
27	−1661	−2889	−3227	1113	608	−912
28	−389	−435	−2724	179	3662	2433
29	−1292	−1535	−3888	−348	707	3871
30	−1985	−2623	−4471	2033	2105	−2906
31	−473	−3487	−2062	84	3369	2339
32	−83	757	−4489	1804	1518	842
33	−1352	−836	−273	598	3602	−72
34	−2321	1046	−3375	3873	−1033	817
35	−2236	1364	−2700	787	1058	−181
36	1859	−2214	−3040	2195	458	245
37	−1538	19	−4169	1380	852	−470
38	2179	−1590	−1436	−1097	3745	−1316
39	−2557	−2251	−4019	2626	−1298	211
40	−1211	−2570	−4496	−2085	−1155	−51
41	346	−2645	742	3221	−4	−501
42	−579	554	−1392	−1396	352	−311
43	−425	−3572	−3949	3822	1240	189
44	−747	−3501	−4034	123	3063	1239
45	485	−1546	−4537	1938	−1261	−90
46	578	−1720	−946	−526	474	49
47	−412	−2738	−4372	1307	−852	−335
48	714	−2118	−3489	2032	1769	−2217
50	−382	−2609	−1296	−154	1854	422
51	−7	−3085	−1122	1518	1450	−1388
52	−2969	−2664	−4485	1190	2264	−1014
53	−2265	−1074	−2578	1847	−280	−4265
54	−357	−1656	−1310	3119	4260	−436
55	−1709	−3183	−1890	3082	896	1391
56	−815	−4238	−5852	2711	−616	941
57	−1206	−3307	−1688	−1613	−219	−1450
58	−1815	−830	−5171	612	328	4575
59	1146	−2547	−3545	1846	2300	1196
60	−1826	676	−3718	3088	−1539	−2165
61	−1380	−2559	−1442	−1894	−1768	−986
62	−3156	−3224	−2860	2424	1178	1529
63	624	−842	−2273	−972	2521	−1729
64	−76	−2367	−3538	2393	729	−1042
65	−105	−2440	−4793	2330	2896	−811
66	−2447	−2347	−1697	2734	−1355	−1894
67	−1083	−745	−3433	4348	−2118	1920
68	−1191	−2014	−3612	1331	1648	541
69	664	−4479	−6378	802	−902	−1976
70	−1158	2779	−4586	341	−2646	−1555
71	891	−2050	−1013	418	1326	2106
72	−281	−2574	−3305	2237	553	3250
73	−1807	−3405	−3046	1428	2238	575
74	−1279	57	−4314	682	−862	−555

(*continued on next page*)

Table A3 (*continued*)

Random Sample	[Out-1]	[Out-2]	[Out-3]	[In-1]	[In-2]	[In-3]
75	−1102	−1243	−5207	2752	283	−1967
76	−2763	−2566	−1619	1625	−738	−1693
77	1221	−374	−4279	4182	317	278
78	2212	−2477	−4595	1148	−830	361
79	138	−273	−3299	357	68	1650
80	1613	−2274	−3133	2190	−208	−1965
81	−1647	−2022	−1573	268	243	1847
82	−748	−935	−3487	2596	1586	306
83	−3192	−1627	−3243	3777	2703	2018
84	−969	2573	−2986	−420	2650	710
85	1995	−321	−3296	289	1857	−513
86	1596	−1483	−859	5116	1529	−359
87	−1010	187	−3729	534	2239	−571
88	−248	−4037	−3493	986	1578	−2492
89	−847	−2812	−4889	1435	−519	307
90	−2770	−1622	−2171	895	−3655	−811
91	−408	235	−2927	1711	109	−853
92	369	−472	−3719	1543	1306	678
93	−771	−1991	−3597	1371	2489	496
94	−38	−3157	−2436	1581	2678	−46
95	−336	−998	−4118	352	3796	3703
96	−113	−3614	−1708	743	250	148
97	580	−1765	−2733	971	−561	−330
98	−656	−1556	−5294	3310	−940	−150
99	−1794	−2662	−3729	1696	324	−1433
100	−1137	−804	−1364	2256	−1610	−264

Table A4
Final result of the removal effect for all scenarios of different ragweed removal strategies.

Strategy	Removal rate	Removal effect index
	5 % (16 km^2)	0.74
[Outside-in]	10 % (32 km^2	0.86
	15 % (49 $km^{2)}$	0.97
	5 % (16 km^2)	0.15
[Inside-out]	10 % (32 km^2	0.37
	15 % (49 km^2)	0.53

Average AUC values for different common ragweed removal scenarios

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