Original Article
Journal of Biosystems Engineering
J. Biosyst. Eng. 43(4):410-419. (2018. 12)
https://doi.org/10.5307/JBE.2018.43.4.410
eISSN : 2234-1862
pISSN : 1738-1266

Effectiveness of Sensitivity Analysis for Parameter Selection in CLIMEX Modeling of *Metcalfa pruinosa* Distribution

Dae-hyeon Byeon[1], Sunghoon Jung[2], Changyeun Mo[3], Wang-Hee Lee[1]*

[1]*Department of Biosystems Machinery Engineering, Chungnam National University, Daejeon, 34134, Korea*
[2]*Department of Applied Biology, Chungnam National University, Daejeon, 34134, Korea*
[3]*National Institute of Agricultural Sciences, Rural Development Administration, Jeonju, Jeollabuk-do, 54875, Korea*

Received: September 18th, 2018; Revised: November 13th, 2018; Accepted: November 15th, 2018

Abstract

Purpose: CLIMEX, a species distribution modeling tool, includes various types of parameters representing climatic conditions; the estimation of these parameters directly determines the model accuracy. In this study, we investigated the sensitivity of parameters for the climatic suitability calculated by CLIMEX for *Metcalfa pruinosa* in South Korea. **Methods:** We first changed 12 parameters and identified the three significant parameters that considerably affected the CLIMEX simulation response. **Results:** The result indicated that the simulation was highly sensitive to changes in lower optimal temperatures, lower soil moisture thresholds, and cold stress accumulation rate based on the sensitivity index, suggesting that these were the fundamental parameters to be used for fitting the simulation into the actual distribution. **Conclusion:** Sensitivity analysis is effective for estimating parameter values, and selecting the most important parameters for improving model accuracy.

Keywords: CLIMEX, *Metcalfa pruinosa*, Parameter estimation, Sensitivity analysis, Species distribution modeling

Introduction

Biological invasion by alien pests has caused severe damage globally to human society and biodiversity (Gurevitch and Padilla, 2004). This problem, along with the need for the evaluation of a specific pest's potential invasion risk owing to climate change, increases the application of species distribution modeling (SDM) for predicting a species' distribution (Mainali et al., 2015). SDM is useful for identifying the suitability of a species' introduction and its survival, and consequently provides fundamental data applicable for establishing a strategy for pest management (Shabani and Kumar, 2014). Several tools therefore implement the SDM algorithm (Busby, 1991; Kriticos et al., 2015; Phillips and Dudík, 2008). CLIMEX is one of such SDM tool, which predicts potential distribution by relating climatic variables to biological characteristics and actual species occurrence (Jung et al., 2016; Kriticos et al., 2015).

***Corresponding author:** Wang-Hee Lee
Tel: +82-42-821-6720; **Fax:** +82-42-823-6246
E-mail: wanghee@cnu.ac.kr

An important and time-consuming process for modeling biological systems is parameter estimation. Because model accuracy is highly dependent on parameter values, a reliable method for parameter estimation is essential (Elith and Leathwick, 2009). The intensive study of previous publications and the collection of empirical data are necessary for this process. The source of uncertainty in the SDM is often parameter uncertainties (Van Klinken et al., 2009). When constructing a niche model, a possible habitat range is determined by the environmental suitability of a species in a location, which is defined by parameters representing the maximal and minimal tolerance of the species (Barry and Elith et al., 2006; Sabani and Kumar, 2014). This implies that the potential distribution predicted by the SDM varies with the parameter values, and the impact of some parameters on the results is significantly large (Taylor and Kumar, 2012). Hence, parameter estimation is considered to be important to generate reliable predictions (Hallgren and Pitman, 2000; Van Klinken et al., 2009; Zaehle et al., 2005).

Because a model cannot include all aspects of a system, it is necessary to appropriately select the primary variables governing species distribution. Previous studies of the CLIMEX parameter sensitivity indicated that modelers should focus on the detailed data collection for sensitive parameters, while other insensitive parameters only require small investments for data collection (Taylor and Kumar, 2012). Climate has been considered to be the primary determinant of the potential distribution of a species (Andrewartha and Birch, 1954; Shabina and Kumar, 2014) and the dominant controller of its natural distribution (Van Klinken et al., 2009). Hence, climate could be considered the most critical variable for modeling, and the parameters related to climatic conditions must be established correctly. As previously mentioned, CLIMEX uses climatic conditions as the primary variables, and it can produce a better predictive distribution of a species than other SDM tools under future climate scenarios (Sutherst and Boume, 2009; Taylor and Kumar, 2012; Webber et al., 2011,). For example, Jung et al. (2017a) reported that the effect of parametric change in implementing a climate change scenario is observable in the modeling response, resulting in different distributions of yellow crazy ants under various climate change scenarios. Therefore, it is necessary to investigate the effect of climatic parameters to appropriately select the primary parameters that affect the potential distribution of a species substantially, to ensure an effective modeling with the least investment in relatively unimportant parameter estimation (Taylor and Kumar, 2012).

The sensitivity analysis of the parameters tests the effect of parametric changes on the modeling outcome, which indicates the parameters considered to be important. Various studies have suggested that model inaccuracies associated with model parameterization can be understood using sensitivity analysis (Burgman et al., 2005; Hanspach et al., 2011; Taylor and Kumar, 2012), because it provides insight into the model parameters by identifying those most influential to model the results, and helps eliminate the effects of inaccuracy and error on the output (Barry and Elith, 2006; Burgman et al., 2005; Hamby, 1994). Because of the advantages above, sensitivity analysis has been applied for the identification of parameters significantly influencing the CLIMEX results for the distribution of *Lantana camara L.* (Taylor and Kumar, 2012) and *Phoenix dactylifera L.* (Shabani and Kumar, 2014), and to select sensitive parameters in the Global Biome Model (BIOME3) for the simulated distribution of different plant functional types (Hallgren and Pitman, 2000). It was suggested that the most cost-effective management strategies for estimating parameters and collecting data could be determined via the identification of parameters important in the SDM (Shabani and Kumar, 2014; Taylor and Kumar, 2012).

In general, the SDM is more suitable for large areas than small areas. This is because the climatic variation in a large area is significant to generate sufficient data regarding the effect of climatic variables on the species distribution, whereas small areas, having fewer stations, may not provide a representative view of the climate in that region (Bennett et al., 1998; Poutsma et al., 2007). Hence, more precise parameter estimation, along with a high-resolution climate database, is required to use the SDM in a small area. Therefore, this study investigates the effect of parametric changes on a species' distribution using CLIMEX to assess the distribution of *Metcalfa pruinosa* in South Korea. Because sensitivity analysis has not been applied to predict pest distribution using CLIMEX, and South Korea contains a small national area suffering from significant climate change, we expect that this study can provide fundamental information for the application of CLIMEX to predict insect distributions.

Materials and Methods

Target species

We targeted *Metcalfa pruinosa* to simulate the effect of changes in CLIMEX parameters on its distribution on South Korea. This species is a North American native pest globally distributed from Europe to Asia (Byeon et al., 2018), and is known to be extremely harmful to both agricultural and sanitary systems owing to its high density in nature and variety of host plants (Kim and Kil, 2014). In particular, it is reported that *M. pruinosa* is distributed in 28 sites in South Korea, and can attack 145 plant species at roadsides, and in forests and orchards (Kim and Kil, 2014). Most studies regarding *M. pruinosa* in South Korea focus on its control and current damage (Ahn et al., 2011; Kim et al., 2011); however, its potential distribution according to climate change has been studied, suggesting that CLIMEX parameters suitable for South Korea are available (Byeon et al., 2017).

Data required for CLIMEX simulation

Two types of pre-requisite datasets exist for CLIMEX simulation in addition to the biological information for *M. pruinosa*: 1) distribution data; and 2) climate data for target areas (Kriticos et al., 2015). The actual worldwide distribution record was obtained from the Global Biodiversity Information Facility website (GBIF), while the detailed distribution data in South Korea were generated in a previous study (Kim and Kil, 2014). The distribution data were used to determine the optimal parameter values, resulting in the best simulation with the least discrepancy with actual records. The reason for using both global and domestic distribution datasets was such that model accuracy could be improved by the global datasets (Mainali et al., 2015). For climate data, the same database used for predicting the potential distribution of pests in South Korea was used (Byeon et al., 2017; Jung et al., 2017a, 2017b). The climate database was constructed by averaging the historical data of temperature, precipitation, and relative humidity from 1981 to 2010, provided by the Korean Meteorological Administration, in 74 major cities in South Korea. Details regarding the 74 cities in South Korea are described elsewhere (Byeon at al., 2017).

Parameters in CLIMEX and its estimation

The parameters in CLIMEX were required to address population growth under favorable seasons and the limitations of unfavorable conditions, and were finally integrated to calculate the ecoclimatic index (EI) measuring favorableness of the location of a target species based on conditions for growing and the limiting population (Kriticos et al., 2015; Jung et al., 2016). The primary CLIMEX parameters are those for temperature and soil moisture (lower limit, lower optimal, upper optimal, and upper limit for each variable), and are related to stress accumulation, including the stress accumulation threshold and rate of stress accumulation. Moreover, growing degree days, represented by PDD, is another important parameter for the completion of at least one cycle by a species under the given climatic conditions. Most parameters in CLIMEX were determined either based on actual rearing experimentation that records population changes in response to temperature and humidity, based on previously published data, or based on a previous CLIMEX study performed on similar species. To achieve a reliable prediction, more observations and species parameter values are necessary (Poutsma et al., 2007). The definitions and background theory of the parameters have been described previously by Jung et al. (2016) and. Kriticos et al. (2015).

The basic procedure to determine the parameter values have been described elsewhere (Poutsma et al., 2007). The recommended strategy to determine the parameter values in CLIMEX for a species is to use the native distribution as a basis for estimating the model parameters, and to use the distribution outside the native areas to verify the parameter values. Moreover, the more observations and biological information necessary for parameter estimation are introduced, the more reliable is the outcome obtained.

In this study, we utilized parameter values for *M. pruinosa* from a previous study by Byeon et al. (2017). Based on the data reported by Kim and Kil (2014), it appears that *M. pruinosa* is adapted to the climate of South Korea, suggesting that parameter estimation must consider adaption using the actual distribution in South Korea, the primary target region in this study. The study by Byeon et al. (2017) employed the CLIMEX model parameters published by Strauss (2010) and modified them to fit the actual distribution in South Korea. This is consistent with the recommended process of parameter estimation, and the determined optimal parameters values for South Korea. Hence, we used these for the reference prediction to be compared with the other simulation using sensitivity analysis. All the parameter values are summarized in Table 1, while Figure 1 shows the predicted and actual distributions of *M. pruinosa* in South Korea.

Sensitivity analysis

Sensitivity analysis is a tool for a systematic analysis exploring the effects of perturbing parameters on the model responses (Lee and Okos, 2016; Tortorelli and Michaleris, 1994). In CLIMEX, many parameters affect the potential distribution, and one of these factors may act as the limiting factor (Poutsma et al., 2007). Hence, sensitivity analysis facilitates us in obtaining a factor that is the most important in model prediction and consequently, species distribution. Based on previous

Table 1. Parameter values used for *M. pruinosa* simulation[1]

Parameters	Parameter definitions	Values
Temperature parameters		
DV0	Lower temperature threshold	13℃
DV1	Lower optimal temperature	22℃
DV2	Upper optimal temperature	28℃
DV3	Upper temperature threshold	31℃
PDD	Degree-days to complete one generation	500
Moisture parameters		
SM0	Lower soil moisture threshold	0.25
SM1	Lower optimal soil moisture	0.5
SM2	Upper optimal soil moisture	1.0
SM3	Upper soil moisture threshold	1.5
Heat stress		
TTHS	Heat stress temperature threshold	31℃
THHS	Heat stress temperature rate	0.002 $week^{-1}$
Cold stress		
TTCS	Cold stress temperature threshold	-1℃
THCS	Cold stress temperature rate	-0.0001 $week^{-1}$
Dry stress		
SMDS	Dry stress threshold	0.25
HDS	Dry stress rate	-0.005 $week^{-1}$
Wet stress		
SMWS	Wet stress threshold	1.5
HWS	Wet stress rate	0.002 $week^{-1}$
Diapause parameters		
DPD0	Diapause induction day length	9h
DPT0	Diapause induction temperature	0℃
DPSW	Diapause summer or winter indicator	0

[1]The table, parameters and their values were from Byeon et al. (2017).

studies on sensitivity analysis in CLIMEX modeling (Shabina and Kumar, 2014; Taylor and Kumar, 2012), we designed two steps for sensitivity analysis on the *M. pruinosa* distribution.

To reduce the intensive computational time (Tortorelli and Michaleris, 1994), a small number of perturbation levels were first applied for 12 parameters: DV0, DV1, DV2, DV3, SM0, SM1, SM2, SM3, THCS, THHS, HDS, and HWS. The amount of perturbation was selected arbitrarily to reduce the number of parameters for further sensitivity analysis. For DVs and SMs, ±2°C and ±50% were applied, respectively, while the stress rates were changed by ±50%. The responses to changing parameter values were estimated by the changes in the EI in 74 primary cities in South Korea. We categorized the EI values into five groups: 0-2, 2-10, 10-20, 20-30, and 30-, assigned for unsuitable (U), marginally suitable (MS), suitable (S), very suitable (VS), and optimally suitable (OS), respectively. Subsequently, we counted the number of cities in the groups and recorded the change by parametric change.

From the first step, we selected three parameters from

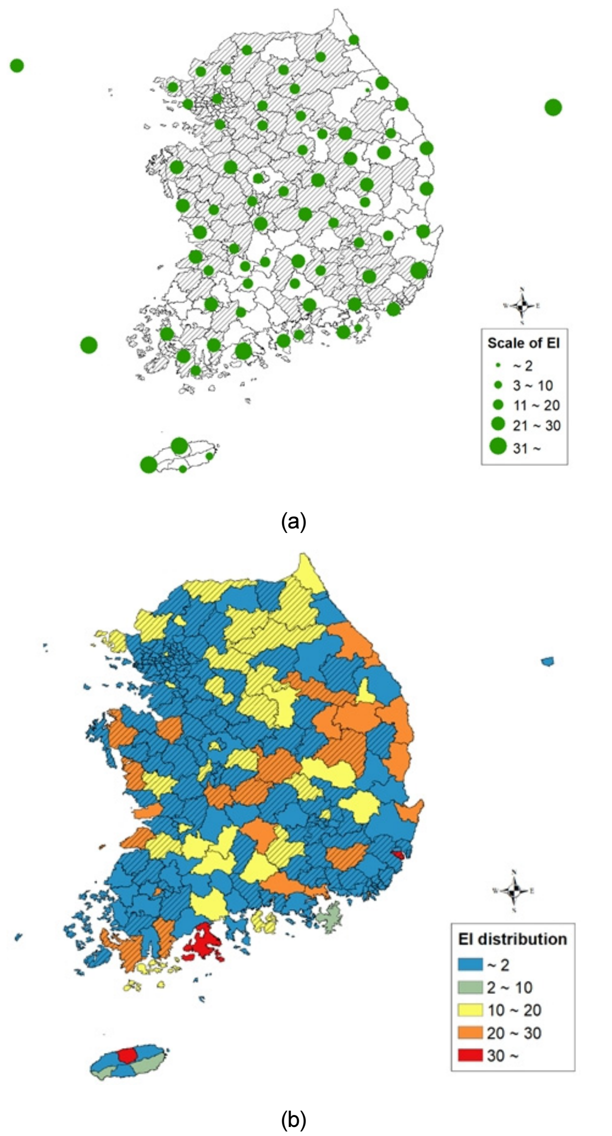

Figure 1. Potential distribution of *M. pruinosa*. (a) Potential (circles) and actual (hatched region) distribution of *M. pruinosa*, (b) EI distribution by administrative districts

each parameter type, which produced the most significant changes in the distribution of EI values. Subsequently, the selected parameters were further analyzed with a larger range of their changes and a narrow increment according to the type of parameters. Many methods can be used for testing the sensitivity of the model parameters; it has been suggested that the simplest method is to vary one parameter at a time, while maintaining the others as constant (Hamby, 1994). In this study, the units and increments of parameters were different; thus, we used a sensitivity index calculated using the output difference (Equation 1) (Hoffman and Gardner, 1983),

$$\mathrm{SI} = \frac{D_{\max} - D_{\min}}{D_{\max}} \tag{1}$$

where $D_{\max}$ and $D_{\min}$ are the max and min output values, respectively, resulting from changing the input over its entire range (Hoffman and Gardner, 1983).

Software

Species distribution modeling and sensitivity analysis were performed using CLIMEX (version 4.0, Hearne software, Melbourne, Australia).

Results and Discussion

Responses to changes in 12 parameters

For the first analysis using 12 parameters, we calculated the root of the sum of squares for the changed EI values (Table 2). In general, alterations in temperature-related parameters (DV0, DV1, DV2, and DV3) indicated the most significant change in the EI value distribution compared to those with original parameter values. Particularly, the EI distribution was most sensitive to DV2, which is the upper optimum temperature. For soil moisture, SM0 resulted in the largest change while SM1 demonstrated a comparable change to SM0, which is consistent with a previous study that reported that SM1, SM2, and SM3 demonstrated little or no effect on lantana distribution (Taylor and Kumar, 2012). The stress-related parameters did not affect the potential distribution of *M. pruinosa*, except the cold stress accumulation rate (THCS). The result was consistent with a previous study by Shabani and Kumar (2014), who reported that the parameters related to population growth were more sensitive than the stress-related parameters. However, the detailed parameters with the highest sensitivity differed slightly between this study and our study. This is because the

Table 2. Result of changes in climatic suitability by altering 12 parameters

Parameters related to temperature (DV)										
EI value	Category	Reference number[2]	No. changed by DV0		No. changed by DV1		No. changed by DV2		No. changed by DV3	
			-2℃	+2℃	-2℃	+2℃	-2℃	+2℃	-2℃	+2℃
0~2	U	1	1	0	1	0	1	1	0	0
3~10	MS	3	0	-3	0	-4	11	3	-8	0
11~20	S	35	3	-4	7	-8	43	26	-4	6
21~30	VS	29	-2	4	-4	7	17	32	9	-3
31~	OS	6	-2	3	-4	5	2	12	3	-3
	RSS[1]		4.24	7.07	9.06	12.41	16.97	11.22	13.04	7.3
	Total		11.31		21.47		28.20		20.39	
Parameters related to soil moisture (SM)										
EI value	Category	Reference number[2]	No. changed by SM0		No. changed by SM1		No. changed by SM2		No. changed by SM3	
			-0.05	+0.05	-0.05	+0.05	-0.05	+0.05	-0.05	+0.05
0~2	U	1	0	-1	0	0	0	0	0	0
3~10	MS	3	0	-1	0	-2	-1	0	-2	1
11~20	S	35	5	-5	5	-4	-2	2	1	1
21~30	VS	29	-3	7	-2	3	3	-1	1	-1
31~	OS	6	-2	0	-3	3	0	-1	0	-1
	RSS[1]		6.16	8.72	6.16	6.16	3.74	2.45	2.45	2.00
	Total		14.88		12.33		6.19		4.45	
Parameters related to stress accumulation rate										
EI value	Category	Reference number[2]	No. changed by THCS		No. changed by THHS		No. changed by HDS		No. changed by HWS	
			-0.05	+0.05	-0.05	+0.05	-0.05	+0.05	-0.05	+0.05
0~2	U	1	0	0	0	0	0	0	0	0
3~10	MS	3	0	-2	0	0	0	0	0	0
11~20	S	35	2	-3	0	0	0	0	0	0
21~30	VS	29	-2	5	0	0	0	0	0	0
31~	OS	6	0	0	0	0	0	0	0	0
	RSS[1]		2.83	6.16	0	0	0	0	0	0
	Total		8.99		0		0		0	

[1]RSS: Root sum of square calculated by taking the root of value obtained by summing square of numbers of locations changed by parameters.
[2]Reference number means that EI distribution obtained from original parameters values in Table 1.

previous study targeted a plant while the current target is an insect. Specifically, the temperature suitable for the development of *M. pruinosa* was shown to be the most important in this analysis. Compared to the parameter of soil moisture, temperature demonstrated a relatively larger effect on the potential distribution of *M. pruinosa*. No studies have directly examined the simultaneous effect of temperature and humidity on *M. pruinosa* development and distribution. However, the higher sensitivity to temperature than to soil moisture can be supported by an insect study, demonstrating that changes in soil moisture did not vary the *Diaprepes abbreviatus* (Coleoptera: Curculionidae) larvae population compared to temperatures indicating proportionality to larvae populations within optimal ranges (Lapointe and Shapiro, 1999). In addition, temperature has been proposed as the dominant factor influencing herbivorous insects by directly affecting the development, survival, range, and abundance (Bale et al., 2002). Nevertheless, the sensitivity of parameters related to soil moisture was not small, suggesting that one of the factors determining soil moisture was rainfall, which might be attributed to an increased mortality factor (Dixon, 1998; Thacker et al., 1997). Moreover, *M. pruinosa* may be indirectly influenced by soil moisture, which determines the growth of its hosts (Kriticos et al., 2015). For instance, we could deduce that a higher sensitivity to a lower soil moisture threshold than to other soil moisture-related parameters might indicate that drought, causing the death of a hosting plant, can limit the distribution of a species living on it. Based on the CLIMEX manual (Kriticos et al., 2015), it is effective to first control stress-related parameters prior to changing other parameters. However, the results indicated that the cold stress accumulation rate had a relatively low sensitivity, and other stress parameters did not affect the distribution at all. As aforementioned, this was consistent with a previous study (Shabani and Kumar, 2014), although such results may occur due to the degree of the changing parameters of stress being not as large as that of the population growth. Therefore, further analysis using a wide range with small intervals is necessary.

Sensitivity analysis for three significant parameters

Further sensitivity analysis was performed by selecting significant factors from each type of parameter based on the root of sum of squares: DV2, SM0, and THCS. For this analysis, we expanded a range of parametric changes with smaller intervals than those in the first analyses. Consequently, DV2 (originally) 28°C was changed from 23°C to 30°C by 1°C because the lower and upper limits could not pass DV1 (23°C) and DV3 (31°C). For SM0, it was changed to 0.1 to 0.45 at 0.05 intervals. THCS was altered by multiplying 0.1, 0.2, 0.5, 2, 5, 10, and 15, resulting in the range used for sensitivity analysis being -0.00001 to -0.0015. Hence, we conceived that each parameter contained eight simulations.

The sensitivity index indicated that the response of parametric changes differed by the parameters as well as by categories (Table 3). Specifically, DV2 and SM0 did not affect the number of unsuitable habitats. This might be due to the parametric characteristics of DV2, which defines the optimal lower limit, and DV0, which demonstrates a significant impact on limiting the unsuitable areas in CLIMEX modeling (Jung et al., 2016; Kriticos et al., 2015). The lower soil moisture threshold (SM0) was expected to affect the numbers for category U; however, it did not. Based on a previous study investigating the effect of soil moisture on the development of *Diaprepes abbreviatus* (Coleoptera: Curculionidae), its larvae could not survive in extreme moisture conditions (Lapointe and Shapiro, 1999). In addition, *M. pruinosa* moves by flying, suggesting that soil moisture is not the limiting factor for insect distribution, but indirectly affects it via rainfall (Dixon, 1998; Thacker et al., 1997). In contrast, a large increase in U was observed when increasing THCS to -0.0015. Because THCS defines the cold stress accumulation rate, its significant increase limits the survival of *M. pruinosa*, resulting in the increasing the number of U. Specifically, cold parts of South Korea, such as Gyunggi-do, and Gangwon-do, indicated a large decrease in EI with increasing THCS, because its cold weather accelerated the high stress accumulation rate. In contrast, relatively warm parts, such as Jeju Island and south coastal regions, indicated a lower degree of changes in EI. Interestingly, Ulleungdo was not affected by changes in THCS. This is because this island experiences relatively high winter temperatures than cities at the same latitude (Lee and Kim, 2007).

For suitable areas, including MS, S, VS, and OS, the variation in their numbers was dependent on the parameter characteristics. In contrast to category U, the value of MS indicated the overall highest sensitivity index. Increasing DV2 reduced the value of MS significantly, while

Table 3. Result of sensitivity analysis for three selected parameters (DV2, SM0 and THCS)

DV2										
	Category	23	24	25	26	27	28	29	30	Sensitivity index
0~2	U	1	1	1	1	1	1	1	1	0.000
3~10	MS	31	19	16	11	6	3	3	3	0.903
11~20	S	39	45	42	43	40	35	28	26	0.422
21~30	VS	3	8	14	17	24	29	31	32	0.906
31~	OS	0	1	1	2	3	6	11	12	1.000
Total		74	74	74	74	74	74	74	74	
SM0										
	Category	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	Sensitivity index
0~2	U	1	1	1	1	1	1	1	1	0.000
3~10	MS	3	3	3	3	5	14	17	20	0.850
11~20	S	26	29	30	35	40	34	34	34	0.350
21~30	VS	32	33	32	29	22	22	19	16	0.515
31~	OS	12	8	8	6	6	3	3	3	0.750
Total		74	74	74	74	74	74	74	74	
THCS										
	Category	-0.00001	-0.00002	-0.00005	-0.0001	-0.0002	-0.0005	-0.001	-0.0015	Sensitivity index
0~2	U	1	1	1	1	1	1	8	21	0.952
3~10	MS	3	3	3	3	5	15	19	15	0.842
11~20	S	32	33	33	35	39	32	25	19	0.513
21~30	VS	31	30	31	29	23	21	17	14	0.548
31~	OS	7	7	6	6	6	5	5	5	0.286
Total		74	74	74	74	74	74	74	74	

*Shaded parameter values were original values used for *M. pruinosa* simulation.

an increasing trend appears when increasing SM0 and THCS. This is because the large number of cities assigning S, VS, and OS was changed to MS with decreasing EI value. The suitable regions (S) indicated a lower sensitivity index than category U, but it was still high: 0.422, 0350, and 0.513 for DV2, SM0, and THCS, respectively. Very suitable regions were increased by DV2 but decreased by increasing SM0 and THCS. The number of OS indicated a high sensitivity index for DV2 and SM0, but not for THCS. Because DV2 is related to the determination of the optimal growth conditions of a target species, it is typical that DV2 exhibits a high sensitivity index for all the categories having an EI larger than 2. Moreover, an increase in DV2 indicates that the range in temperature for optimal growth is expanded, suggesting a high possibility for rapid growth. In contrast, increasing SM0 causes a reduced suitable soil moisture range, resulting in a decrease in the overall EI value. Because THCS participates in limiting the population growth, its increase causes a large reduction in the number of suitable areas and a high sensitivity index for all categories. Hence, THCS is considered to be the first parameter that must be tuned for fitting the simulation to the actual distribution of a target species (Kriticos et al., 2015). Overall, the sum of the sensitivity index was influenced by the order of DV2, THCS, and SM0, suggesting that temperature exhibits a higher impact on *M. pruinosa* distribution than soil moisture. As aforementioned, this is consistent with a previous study indicating that temperature was a dominant factor for insect distribution (Bale et al., 2002; Lapointe and Shapiro, 1999), while soil moisture was as important as temperature when simulating plant distribution (Shabina and Kumar, 2014; Taylor and Kumar, 2012).

Finally, it is noteworthy that an optimal parameter value exists that maximizes the number for each category. Highly sensitive parameters demonstrate a more significant impact on the model response than insensitive parameters; thus, sensitivity analysis evaluates the importance of parameters to be used for improving model accuracy (Merow et al., 2011; Taylor and Kumar, 2012). Hence, we can effectively select parameters that require more extensive research and data collection methods (Shabina and Kumar, 2014). To visually present the sensitivity index, we have developed a map to visualize the effect of parametric changes on the potential distribution of *M. pruinosa* (Fig. 2). Via this figure, we can confirm that DV2 and THCS led to greater changes in EI distribution than SM0.

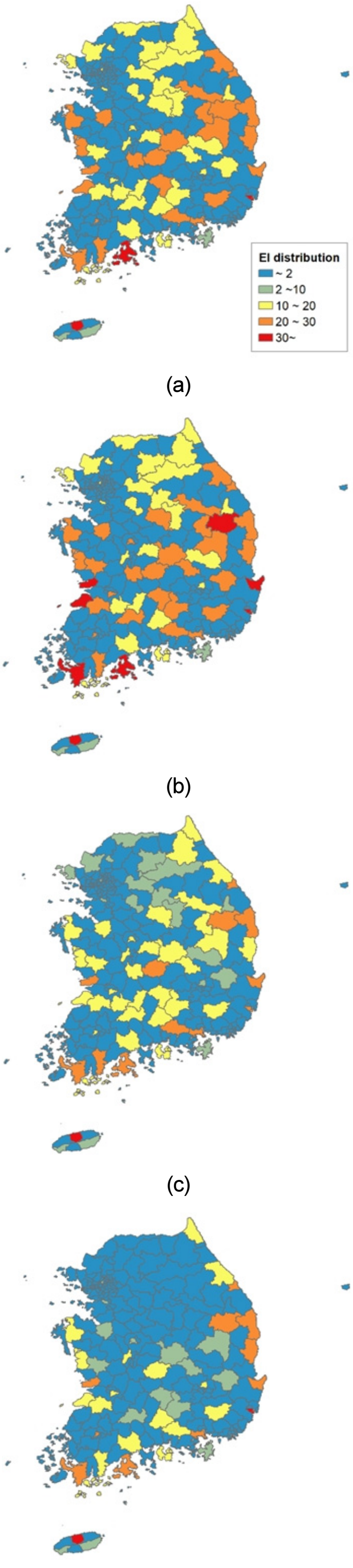

Figure 2. Effect of parametric changes on potential distribution of *M. pruinosa*. (a) original parameter value (b) change in DV2 from 28°C to 23°C , (c) change in SM0 from 0.25 to 0.45, and (d) change in THCS from -0.0001 to −0.0015.

Conclusions

Because species distribution modeling evaluates the possibility of an invasive species inhabiting a specific area, it has been considered to be a useful tool for providing the fundamentals for the control and management of alien species. In this study, we analyzed the sensitivity of parameters in CLIMEX, a popular species distribution modeling software, and reported the most important parameters affecting *M. pruinosa* distribution in South Korea. Even though climate is the most critical factor determining the distribution of plants and insects, CLIMEX does not consider other environmental factors, implying that its accuracy is limited (Pattison and Mack, 2008). Hence, parameter estimation must be as precise as possible, and field data, which requires money and labor, is necessary. In this context, sensitivity analysis can provide insight into which parameter is necessary for emphasis thus allowing for limited experimental investments. Moreover, sensitivity analysis has been used to identify the optimal values for unknown parameters whose information is limited

Conflict of Interest

The authors have no conflicting financial or other interests.

Acknowledgement

This study was supported by research funds provided by the Chungnam National University in 2017.

References

Ahn, K. S., G. S. Lee, K. H. Lee, M. K. Song, S. C. Lim and G. H. Kim. 2011. Susceptibility of North American planthopper, *Metcalfa pruinosa* to commercially registered insecticides in Korea. The Korean Journal of Pesticide Science 15(3): 329-334 (In Korean, with English abstract).

Andrewartha, H. G. and L. C. Birch. 1954. *The Distribution and Abundance of Animals*, Chicago, IL, USA: University of Chicago Press.
https://doi.org/10.1086/401497

Bale, J. S., G. J. Masters, I. D. Hodkinson, C. Awmack, T. M. Bezemer, V. K. Brown, J. Butterfield, A. Buse, J. C. Coulson, J. Farrar, J. E. Good, R. Harrington, S. Hartley, T. H. Jones, R. L. Lindroth, M. C. Press, I. Symrnioudis, A. D. Watt and J. B. Whittaker. 2002. Herbivory in global climate change research: direct effects of rising temperature on insect herbivores. Global Change Biology 8(1): 1-16.
https://doi.org/10.1046/j.1365-2486.2002.00451.x

Barry, S. and J. Elith. 2006. Error and uncertainty in habitat models. Journal of Applied Ecology 43(3): 413-423.
https://doi.org/10.1111/j.1365-2664.2006.01136.x

Bennett, S. J., N. Said and D. Enneking. 1998. Modelling climatic similarities in Mediterranean areas: a potential tool for genetic resources and breeding programmes. Agriculture, Ecosystems & Environment 70(2-3): 129-143.
https://doi.org/10.1016/s0167-8809(98)00121-2

Burgman, M. A., D. B. Lindenmayer and J. Elith. 2005. Managing landscapes for conservation under uncertainty. Ecology 86(8): 2007-2017.
https://doi.org/10.1890/04-0906

Busby, J. R. 1991. BIOCLIM-a bioclimate analysis and prediction system. Plant Protection Quarterly 6: 8-9.

Byeon, D. H., J. M. Jung, S. Jung and W. H. Lee. 2018. Prediction of global geographic distribution of *Metcalfa pruinosa* using CLIMEX. Entomological Research 48(2): 99-107.
https://doi.org/10.1111/1748-5967.12253

Byeon, D. H., J. M. Jung, S. Lohumi, B. K. Cho, S. Jung and W. H. Lee. 2017. Predictive analysis of *Metcalfa pruinosa* (Hemiptera: Flatidae) distribution in South Korea using CLIMEX software. Journal of Asia-Pacific Biodiversity 10(3): 379-384.
https://doi.org/10.1016/j.japb.2017.06.004

Dixon, A. F. G. 1998. *Aphid Ecology*, 2nd edn., London., UK: Chapman & Hall.

Elith, J. and J. R. Leathwick. 2009. Species distribution models: ecological explanation and prediction across space and time. Annual Review of Ecology, Evolution, and Systematics 40(1): 677-697.
https://doi.org/10.1146/annurev.ecolsys.110308.120159

GBIF.org (29th February 2016) GBIF Occurrence Download
https://doi.org/10.15468/dl.ywhpmz

Gurevitch, J. and D. K. Padilla. 2004. Are invasive species a major cause of extinctions?. Trends in Ecology & Evolution 19(9): 470-474.
https://doi.org/10.1016/j.tree.2004.07.005

Hallgren, W. S. and A. J. Pitman. 2000. The uncertainty in simulations by a Global Biome Model (BIOME3) to alternative parameter values. Global Change Biology 6(5): 483-495.
https://doi.org/10.1046/j.1365-2486.2000.00325.x

Hamby, D. M. 1994. A review of techniques for parameter sensitivity analysis of environmental models. Environmental Monitoring & Assessment 32(2): 135-154.
https://doi.org/10.1007/bf00547132

Hanspach, J., I. Ku¨hn, O. Schweiger, S. Pompe and S. Klotz. 2011. Geographical patterns in prediction errors of species distribution models. Global Ecology and Biogeography 20(5): 779-788.
https://doi.org/10.1111/j.1466-8238.2011.00649.x

Hoffman, E. O. and R. H. Gardner. 1983. Evaluation of Uncertainties in Environmental Radiological Assessment Models. In: *Radiological Assessments: A Textbook on Environmental Dose Assessment*, eds. J. E. Till and H. R Meyer, 11.1-11.47. Washington, DC, USA: Nuclear Regulatory Commission.

Jung, J. M., S. Jung, M. R. Ahmed, B. K. Cho and W. H. Lee. 2017a. Invasion risk of the yellow crazy ant (*Anoplolepis gracilipes*) under the Representative Concentration Pathways 8.5 climate change scenario in South Korea. Journal of Asia-Pacific Biodiversity 10(4): 548-554.
https://doi.org/10.1016/j.japb.2017.08.004

Jung, J. M., J. W. Lee, C. J. Kim, S. Jung and W.H. Lee. 2017b. CLIMEX-based Analysis of Potential Geographical Distribution of *Aedes albopictus* and *Aedes aegypti* in South Korea. Journal of Biosystems Engineering 42(3): 217-226.
https://doi.org/10.5307/JBE.2017.42.3.217

Jung, J. M., W. H. Lee and S. Jung. 2016. Insect distribution in response to climate change based on a model: Review of function and use of CLIMEX. Entomological Research 46(4): 223-235.
https://doi.org/10.1111/1748-5967.12171

Kim, D. E. and J. Kil. 2014. Occurrence and host plant of *Metcalfa pruinosa* (Say) (Hemiptera: Flatidae) in Korea. Journal of Environmental Science International 23(8): 1385-1394.
https://doi.org/10.5322/jesi.2014.23.8.1385

Kim, Y. E., M. Y. Kim, K. J. Hong and S. H. Lee. 2011. Outbreak of an exotic flatid, *Metcalfa pruinosa* (Say) (Hemiptera: Flatidae), in the capital region of Korea.

Journal of Asia-Pacific Entomology 14(4): 473-478. https://doi.org/10.1016/j.aspen.2011.06.002

Kriticos, D. J., G. F. Maywald, T. Yonow, E. J. Zurcher, N. I. Herrmann and R. W. Sutherst. 2015. *CLIMEX Version 4: Exploring The Effects of Climate on Plants, Animals and Diseases*. Canberra, Australia: CSIRO.

Lapointe, S. L. and J. P. Shapiro. 1999. Effect of soil moisture on development of *Diaprepes abbreviatus* (Coleoptera: Curculionidae). Florida Entomologist 82(2): 291-299. https://doi.org/10.2307/3496582

Lee, C. B. and J. C. Kim. 2007. Aspect and cause of long term trend of climate in Ulleungdo and Dokdo Area. Korean Journal of Nature Conservation 1(1): 19-28 (In Korean, with English abstract).

Lee, W.-H. and M. R. Okos. 2016. Model-based analysis of IGF-1 effect on osteoblast and osteoclast regulation in bone turnover. Journal of Biological Systems 24(1): 63-89. https://doi.org/10.1142/s0218339016500042

Mainali, K. P., D. L. Warren, K. Dhileepan, A. McConnachie, L. Strathie, G. Hassan, D. Karki, B. B. Shrestha and C. Parmesan. 2015. Projecting future expansion of invasive species: comparing and improving methodologies for species distribution modeling. Global Change Biology 21(12): 4464-4480. https://doi.org/10.1111/gcb.13038

Merow, C., N. LaFleur, J. A. Silander Jr, A. M. Wilson and M. Rubega. 2011. Developing dynamic mechanistic species distribution models: predicting bird-mediated spread of invasive plants acrosss Northeastern North America. The American Naturalist 178(1): 30-43. https://doi.org/10.1086/660295

Pattison, R. R. and R. N. Mack. 2008. Potential distribution of the invasive tree *Triadica sebifera* (Euphorbiaceae) in the United States: evaluating CLIMEX predictions with field trials. Global Change Biology 14(4): 813-826. https://doi.org/10.1111/j.1365-2486.2007.01528.x

Phillips, S. J. and M. Dudík. 2008. Modeling of species distributions with Maxent: new extensions and a comprehensive evaluation. Ecography 31(2): 161-175. https://doi.org/10.1111/j.0906-7590.2008.5203.x

Poutsma, J., A. J. M. Loomans, B. Aukema and T. Heijerman. 2007. Predicting The Potential Geographical Distribution of The Harlequin Ladybird, *Harmonia axyridis*, Using The CLIMEX Model. In: *From Biological Control to Invasion: The Ladybird Harmonia Axyridis as A Model Species*, eds. H. E. Roy and E. Wajnberg, 103-125. Berlin/Heidelberg, Germany: Springer https://doi.org/10.1007/978-1-4020-6939-0_8

Shabani, F. and L. Kumar. 2014. Sensitivity analysis of CLIMEX parameters in modeling potential distribution of *Phoenix dactylifera* L.. PLoS ONE 9(4): e94867. https://doi.org/10.1371/journal.pone.0094867

Strauss, G. 2010. Pest risk analysis of *Metcalfa pruinosa* in Austria. Journal of Pest Science 83(4): 381-390. https://doi.org/10.1007/s10340-010-0308-3

Sutherst, R. W. and A. S. Bourne. 2009. Modelling non-equilibrium distributions of invasive species: a tale of two modelling paradigms. Biological Invasions 11(6): 1231-1237. https://doi.org/10.1007/s10530-008-9335-x

Taylor, S. and L. Kumar. 2012. Sensitivity analysis of CLIMEX parameters in modelling potential distribution of *Lantana camara* L., PLoS ONE 7(7): e40969. https://doi.org/10.1371/journal.pone.0040969

Thacker, J. I., T. Thieme and A.F.G. Dixon. 1997. Forecasting of periodic fluctuations in annual abundance of the bean aphid: the role of density dependence and weather. Journal of Applied Entomology 121(1-5): 137-145. https://doi.org/10.1111/j.1439-0418.1997.tb01383.x

Tortorelli, D. A. and P. Michaleris. 1994. Design sensitivity analysis: overview and review. Inverse Problems in Engineering 1(1): 71-105. https://doi.org/10.1080/174159794088027573

Van Klinken, R. D., B. E. Lawson and M. P. Zalucki. 2009. Predicting invasions in Australia by a Neotropical shrub under climate change: the challenge of novel climates and parameter estimation. Global Ecology and Biogeography 18(6): 688-700. https://doi.org/10.1111/j.1466-8238.2009.00483.x

Webber, B. L., C. J. Yates, D. C. Le Maitre, J. K. Scott, D. J. Kriticos, N. Ota, A. McNeill, J. J. Le Roux and G. F. Midgley. 2011. Modelling horses for novel climate courses: insights from projecting potential distributions of native and alien Australian acacias with correlative and mechanistic models. Diversity and Distributions 17(5): 978-1000. https://doi.org/10.1111/j.1472-4642.2011.00811.x

Zaehle, S., S. Sitch, B. Smith and F. Hatterman. 2005. Effects of parameter uncertainties on the modeling of terrestrial bio-sphere dynamics. Global Biogeochemical Cycles 19(3): GB3020. https://doi.org/10.1029/2004gb002395