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## Full Length Article

Risk map for the range expansion of *Thrips palmi* in Korea under climate change: Combining species distribution models with land-use changeJinsol Hong<sup>a</sup>, Gwan-Seok Lee<sup>b</sup>, Jung-Joon Park<sup>c</sup>, Hyung-ho Mo<sup>d</sup>, Kijong Cho<sup>a,\*</sup><sup>a</sup> Department of Environmental Science and Ecological Engineering, Korea University, Seoul 02841, Republic of Korea<sup>b</sup> Crop Protection Division, National Institute of Agricultural Sciences, Wanju 55365, Republic of Korea<sup>c</sup> Department of Plant Medicine, Institute of Agriculture and Science, Gyeongsang National University, Jinju 52828, Republic of Korea<sup>d</sup> Jungbu Regional Office, Animal and Plant Quarantine Agency, Incheon 22133, Republic of Korea

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## ABSTRACT

Climate change and land-use change are the most powerful drivers for the invasion of alien species. To understand the integrated effects of these two drivers on pest invasion risk in the future, this study assessed how they impact the invasion risk of *Thrips palmi* Karny, which is the most serious invasive species in the Korean peninsula. The potential distribution of *T. palmi* was projected with a MaxEnt model for current and future climate change scenarios (RCP 4.5 and 8.5) based on occurrence records. The potential distribution extends to the north over time, except the eastern high mountainous area, for both RCPs in 2075. The MaxEnt outputs were filtered with agricultural area using data from three land-use change scenarios derived from the Shared Socio-economic Pathways (SSPs), because *T. palmi* populations can only be sustained in agricultural areas. The potential risk of *T. palmi*, based on the potential distribution probability in the future agricultural area, increased over time under all RCPs-SSPs combinations. The total area of *T. palmi* occurrence increased under RCPs-SSP1 and -SSP2 but decreased under RCPs-SSP3, due to agricultural areas being converted to urban areas. In conclusion, based on future climate change scenarios, *T. palmi* could be distributed throughout the Korean peninsula in the future. The invasion risk in agricultural areas will increase substantially; thus, intensive control measures for *T. palmi* are required in the future. Our research suggests that using both climate change and land-use change in pest risk mapping study can provide informative data for management strategy.

## Introduction

Invasive species are a well-recognized component of global environmental change (Hellmann et al., 2008; Bellard et al., 2013), and may be favored by climate change. Especially, many invasive insect species are pests for various fields and may be parasites or vectors of diseases; however, their economic, social, and environmental impacts are less known, compared to the impacts of introduced plant species. Yet, it is clear that the ecological changes caused by invasive insects influence resources and the functioning of ecosystems in regions where they are introduced, resulting in economic losses (Cook et al., 2007).

Because invasive insect species are able to sustain their populations over generations in introduced areas, they have the potential to disperse over the new territory (Andersen et al., 2004). Therefore, preemptive identification of accessible and suitable areas is required to establish management strategies to identify and mitigate future invasion risks. To prevent and manage future invasion risks in agricultural systems, spatio-

temporal distribution assessments of invasive insect pests in introduced environments must be performed. Various pest risk mapping techniques have been developed to identify and geographically visualize areas at risk of invasion (Venette et al., 2010; Jiménez-Valverde et al., 2011). Species distribution models (SDMs), also known as ecological niche models, are often used to estimate the potential invasion risk of invasive species under climate change (Venette et al., 2010; Jiménez-Valverde et al., 2011). Maximum entropy (MaxEnt) is one of the most popular correlative niche modeling method that has been widely used to predict potential distribution (Elith et al., 2011). The MaxEnt model uses a machine learning algorithm, and only requires species' presence only occurrence data and environmental variables to predict the geographic distribution of the target species. The MaxEnt model is superior to other algorithms in various comparative studies that showed greater statistical performance (Elith et al., 2006). Also, the MaxEnt model can successively predict distributions of target species from small numbers of occurrence records (Pearson et al., 2007).

\* Corresponding author.

E-mail address: [kjcho@korea.ac.kr](mailto:kjcho@korea.ac.kr) (K. Cho).<https://doi.org/10.1016/j.aspen.2019.04.013>

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Climate, especially temperature, has a strong and direct influence on insect development, reproduction, and survival (Bale et al., 2002). Climate change is expected to mediate the range expansion/contraction of insects, affect phenology, and alter the rates of growth and development. Therefore, to assess the future invasion risk of insect pests, climate change scenarios are considered as one of the most important future scenarios in risk mapping studies (Jeschke and Strayer, 2008). Representative Concentration Pathways (RCPs) are the latest emission scenarios that simulate four pathways developed for climate change modeling experiments (Van Vuuren et al., 2011). However, distributions also depend on factors other than climate, such as land-cover and land-use, as colonization performance and dispersal success vary with the landscape structures (With, 2002; Stanton et al., 2012). Even if the climatic conditions for a certain space are suitable, the invasion risk might not be valid when non-climatic environmental factors do not meet their requirements. Land-use change is the most representative dynamic and non-climatic environmental variable, and should be included to improve SDM performance (Pearson et al., 2004). Land-use change is typically used to assess the future anthropogenic impact on natural ecosystems or natural resources (Reidsma et al., 2006). From both logical and technical perspectives, modeling future invasion risk without considering land-use change could result in faulty predictions.

Applying land-use change to pest risk maps has the advantage of including human activity, which alters landscape structure and land-use simultaneously (Ficetola et al., 2010). Moreover, land-use change and variability are also critical drivers of climate change (Kalnay and Cai, 2003). The Shared Socioeconomic Pathways (SSPs) are socioeconomic pathways that are described with two different axes, *i.e.*, the mitigation and adaptation challenge of climate change (O'Neill et al., 2014). Thus, land-use change scenarios derived from SSPs could be implemented in insect pest risk maps, because agricultural pests mainly sustain their populations in the agricultural areas, and disperse to agricultural areas for future establishment.

To demonstrate the combined effect of climate change and land-use change on future invasion risk of invasive insect pest species, *Thrips palmi* Karny was selected as the target insect species in this study. This species is a polyphagous pest, that has devastating effects on Cucurbitaceae and Solanaceae crop species by causing both direct damage (to foliage) and indirect damage (by transmitting plant virus pathogens) (Jones, 2005). *T. palmi* originates from Sumatra and Java in Indonesia, but its geographical range has expanded to Southeast Asia, East Asia, Australia, North America, South America, and West Africa (Palmer, 1992; CABI/EPPPO, 1998; Cannon et al., 2007; CABI, 2016). This species is considered to be the most destructive invasive species, after its first observation in the 1970s in Japan (NIES, 2017). In Korea, *T. palmi* was first reported in 1993 on Jeju Island, located at the southernmost of the Korean peninsula (Ahn et al., 1994). The current distribution of this species on the mainland is limited to the southern coastal area (Hong et al., 1998). Park et al. (2014) simulated the potential distribution of *T. palmi* in Korea using the CLIMEX system under an RCP 8.5 climate change scenario and reported that the marginal future geographic range of this species will continue to expand northward and will be distributed throughout the Korean peninsula in 2100. The CLIMEX system is based on mechanistic niche modeling approach to estimate the ecoclimatic suitability and biophysical limitations of target species using various life history parameters (Sutherst et al., 2007). Because inherent differences in each modeling algorithms result in different projections, there are many case studies of the CLIMEX and the MaxEnt models used together to predict the potential distribution of insect pest species (Kumar et al., 2015; Wu et al., 2018).

This study aimed to: 1) model the potential distribution of *T. palmi* in the Korean peninsula using MaxEnt under two climate change scenarios (RCP 4.5 and RCP 8.5), 2) project the distribution of this species in the agricultural area under three future land-use change scenarios (SSP1, SSP2, and SSP3), and 3) calculate and compare the potential invasion risks of this species for all combinations of the RCPs-SSPs

scenarios. Our results are expected to demonstrate the importance of considering both climate change and land-use change when predicting future invasion risks of insect pests.

## Materials and methods

### *Climatic and geographical conditions of the Korean peninsula*

This study covers the southern part of the Korean peninsula, which is currently experiencing abrupt changes to climate conditions, with particularly unbalanced patterns of dry and wet seasons. Annual mean temperature and precipitation from 1981 to 2010 was 6.6–16.6 °C and 825.6–2007.3 mm, respectively (KMA, 2012). When comparing climate data from the last 30 years before 2000 (from 1970 to 2000) with the 10 years after 2000 (from 2001 to 2010), the annual mean, maximum, and minimum temperatures have increased by at least 0.5 °C (Lee et al., 2011). The annual precipitation from 1906 to 2002 also increased by 259 mm (Chung et al., 2004).

The land surface characteristics of the Korean peninsula are very distinctive, with mountainous areas covering about 70% of the total area, with heterogeneous vegetation components (Baik and Choi, 2015). The major land-use/land-cover classes are mixed forest and cropland area. The western and southern regions have relatively flat terrain and are mainly agricultural areas, mosaics of rice paddy and vegetable field. The eastern region is formed of mountainous terrain, with steep slopes and mixed forest cover, thus agricultural activities in this region are very limited.

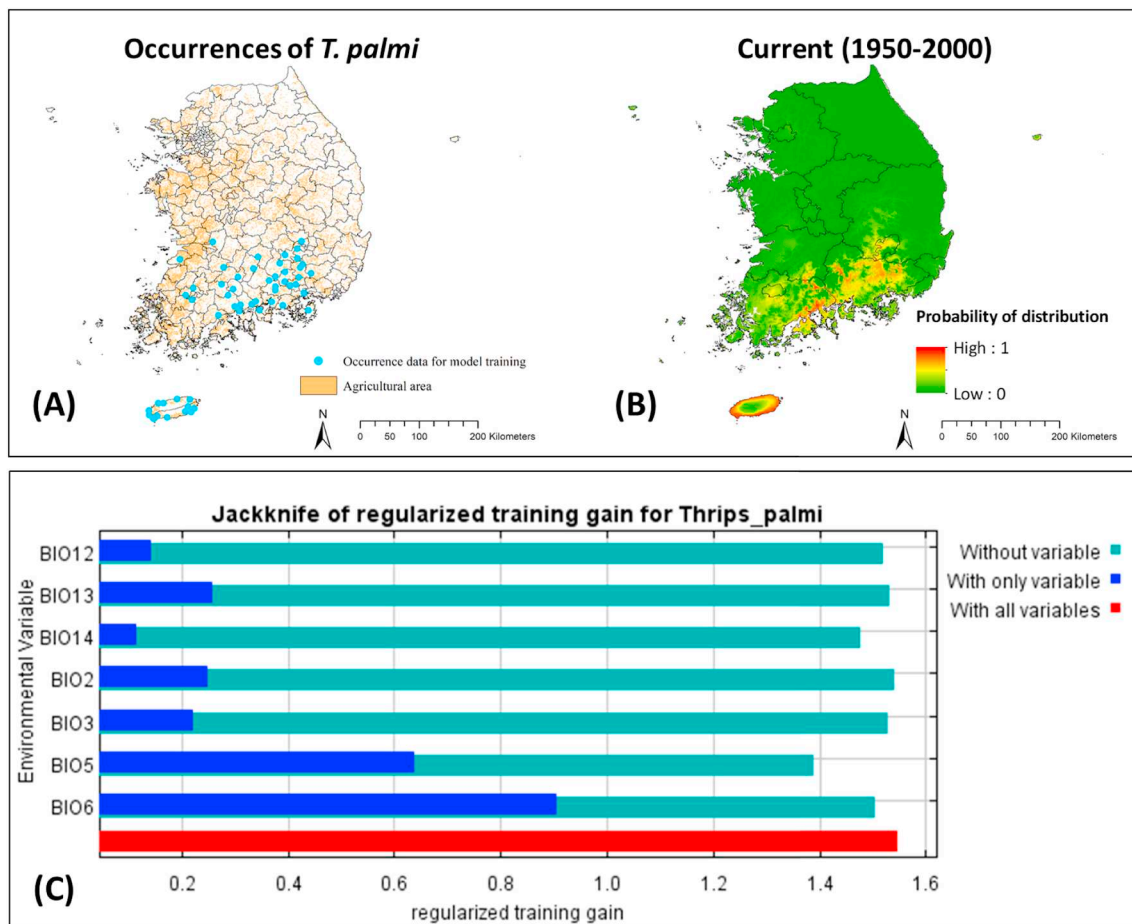
### *T. palmi* occurrence data in Korea

The occurrence data of *T. palmi* in Korea were collected from national scale monitoring reports conducted in 1995 and 1996 (Hong et al., 1998). Unpublished observations conducted in 1997 were also included in this study (Fig. 1A). After collecting all occurrence records, repeated records were rarefied into 5 km distances to reduce spatial autocorrelation, and a total of 53 occurrence records were included in the MaxEnt model.

### *Climate data*

To model and predict correlative SDMs, the same list of environmental variables is needed in each target year. Current climate conditions (1950–2000) were represented by 19 bioclimatic variables acquired from the WORLDCLIM database v1.4 (Hijmans et al., 2005; www.worldclim.org). These data are available in  $\approx 1 \text{ km}^2$  resolution. The WORLDCLIM dataset uses altitude, temperature, and precipitation to derive monthly, quarterly, and annual climate indices to represent trends (*e.g.*, mean diurnal temperature range), seasonalities (*e.g.*, temperature seasonality), and extremes (*e.g.*, maximum temperature of the warmest month) that are biologically relevant. For future climate data, two different RCP climate change scenarios, HadGEM3 RCP 4.5 and RCP 8.5, were obtained from the Korea Metrological Administration (KMA) website (www.kma.go.kr). RCP 4.5 is a moderate climate change scenario that radiative forcing increase to 4.5 W/m<sup>2</sup> by 2100. RCP 8.5 assumes the most dramatic increase in carbon dioxide emission that radiative forcing increase to 8.5 W/m<sup>2</sup> by 2100. All annual climate datasets in RCP 4.5 and 8.5 were transformed to 19 bioclimatic variables using 'biovars' function in R 'dismo' package (Hijmans et al., 2017).

Although the 19 bioclimatic variables have diverse and distinctive characteristics, many variables could be highly correlated because they are derived from just three meteorological elements, *i.e.*, precipitation, maximum temperature, and minimum temperature (Table 1S). To avoid multicollinearity in the model, variables that were highly correlated with each other (*i.e.*, showed more than |0.8| Pearson's correlation coefficient) were removed using the 'Remove Highly Correlated



**Fig. 1.** Occurrence data of *Thrips palmi* in the Korean peninsula using MaxEnt modeling (A), the predicted potential distribution under current climate conditions (B), and Jackknife test results of the environmental variables used in this study (C). The bars with deep blue, teal, and red color represent the relative information of each variable when the model was created using each variable in isolation, the remaining variables with an exclusion, and all variables, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Variables’ tool in SDM Toolbox v1.1c (Brown, 2014). Seven bioclimatic variables were selected from the WORLDCLIM database and were used in the model system (Table 1). Each selected bioclimatic variable was averaged over 10 years for each target year for the Korean peninsula; namely, 2030 (2026–2035) and 2075 (2071–2080).

*MaxEnt analysis*

The MaxEnt model was used to analyze and predict the geographic distribution of *T. palmi* (3.3.3 k stand-alone version software; Phillips et al., 2006) for current and future climates. The MaxEnt is the most appropriate tool for our analysis because it requires presence-only occurrence data. This model is also the most capable modeling method in producing useful results with a small sample size (Pearson et al., 2007).

Seven bioclimatic variables selected in this study (Table 1) were incorporated into the MaxEnt model, along with the *T. palmi* occurrence data, as projection layers for the current climate, 2030, and 2075. MaxEnt requires the user to specify a background for the study area from which the algorithm will select random points that are assumed as ‘pseudo-absences’. Because *T. palmi* was intensively observed over the whole nation, we set MaxEnt to select 10,000 random background points from the entire Korean peninsula. The model classifies areas that have conditions most similar to the current known occurrences of the target species and ranks them from 0 (unsuitable or most dissimilar) to 1 (most suitable or most similar).

MaxEnt generates a set of feature classes using environmental variables. In this study, the auto feature function and logistic output options were set as defaults. The model uses a regularization multiplier

**Table 1**  
Climate variables and their relative contribution in the MaxEnt model.

Code	Bioclimatic variable	Contribution (%)
BIO2	Mean Diurnal Range (Mean of monthly (T <sub>max</sub> -T <sub>min</sub> ))	0.1
BIO3	Isothermality (Mean Diurnal Range/Temperature Annual Range)	9.3
BIO5	Maximum Temperature of Warmest Month	32.3
BIO6	Minimum Temperature of Coldest Month	50.2
BIO12	Annual Precipitation	4.5
BIO13	Precipitation of Wettest Month	0.4
BIO14	Precipitation of Driest Month	3.1

(RM) to reduce the number of parameters and, thus, automatically controls model complexity (Phillips and Dudík, 2008; Elith et al., 2011). The default RM value is 1; a smaller value of RM ( $\leq 1$ ) may potentially overfit the model and produce a more restricted distribution, whereas a higher value ( $> 1$ ) would result in simpler models with less discriminating power and broader species potential distribution (Phillips et al., 2006).

To evaluate the final MaxEnt model with seven variables compared to random expectations, the AUC (Area Under receiver operating characteristic Curve) was calculated. AUC values vary from 0 to 1; 0.5 shows model performance not better than random, values  $< 0.5$  worse than random; 0.5–0.7 indicate poor performance; 0.7–0.9 indicate

reasonable or moderate performance; and 0.9 indicates high performance (Swets, 1988). The 10-fold cross-validation ( $n = 53$ ) in MaxEnt with 5000 iterations was used, along with the averaged test AUC values across the 10 replicated being reported for each target year. The presence was classified using the 10th percentile training presence logistic threshold ( $= 0.21$ ) produced by the MaxEnt model (Table 2S).

The final MaxEnt model was also validated using independent datasets observed in Japan (Fig. 2). Occurrence records of *T. palmi* in Japan during 1978–1994 were obtained from the published literature and web data (Kawai, 2001; Murai, 2002; NIES, 2017). Because no exact sampling locations were available for these monitoring data, occurrences were summarized to the prefecture levels ( $n = 41$ ). The

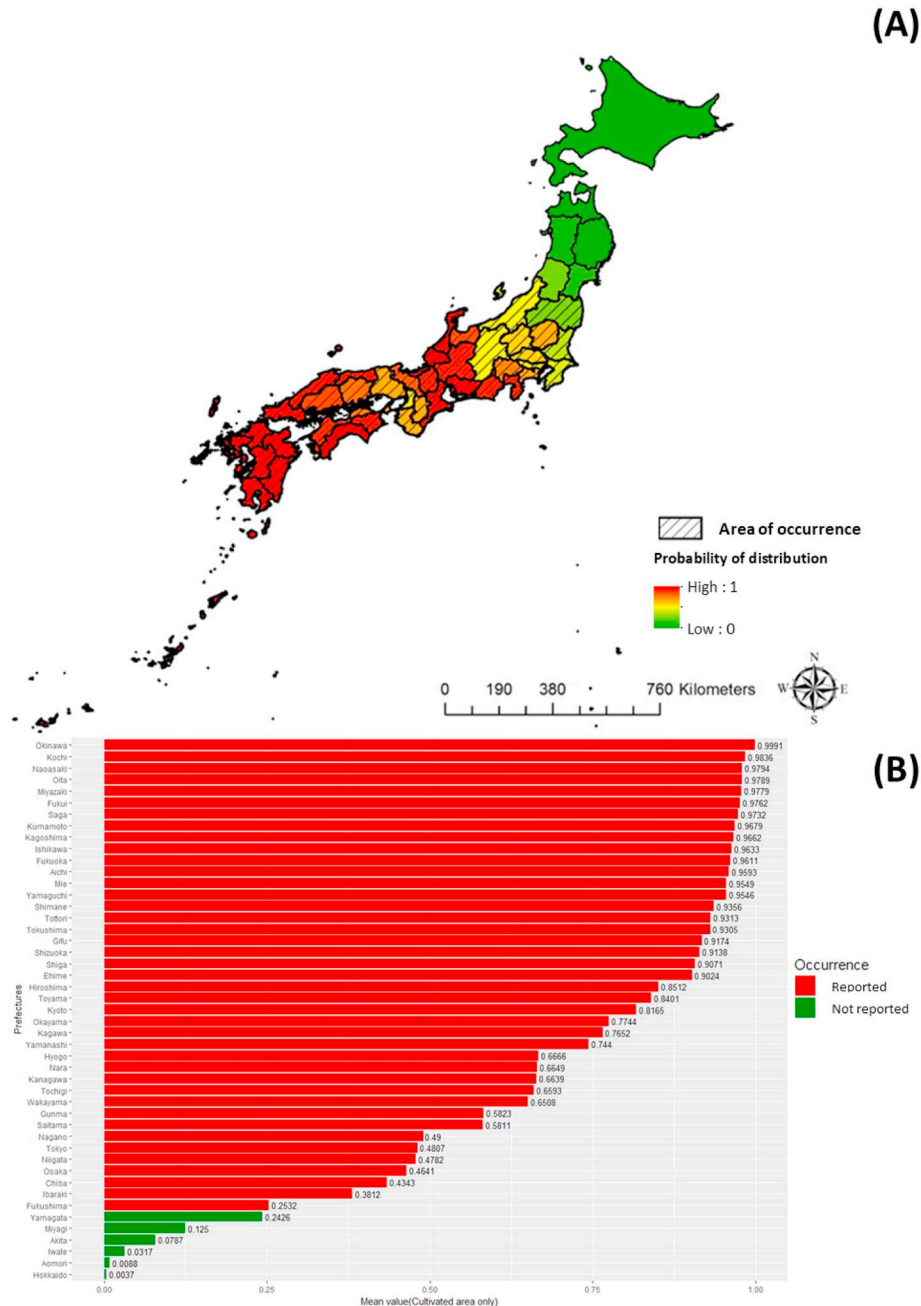


Fig. 2. Predicted potential distribution of *Thrips palmi* at the prefecture level in Japan using the MaxEnt model. The hatched area denotes the prefectures where *T. palmi* was observed during 1978–1994 (A). The mean values for the probability of distribution of *T. palmi* in the agricultural areas of each prefecture using the final MaxEnt model (B). The prefectures where *T. palmi* occurrence was reported (according to Kawai, 2001; Murai, 2002; NIES, 2017) are plotted with red bars. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

weather data observed at each meteorological station for 17 years were obtained from the Japan Meteorological Agency (JMA) and were interpolated using the inverse distance weighting method (IDW) to transform point-based observation data to 1 km<sup>2</sup> scale ASCII format raster data with ArcGIS v10 software (ESRI, 2011). Using the rasterized climate data, bioclimatic variables were also produced using the same methodology to produce bioclimatic variables in Korea. Each bioclimatic variable was averaged over 17 years (1978–1994). After the predicting the distributions of *T. palmi* in Japan, agricultural areas where this species was expected to be distributed were extracted with The Global Land Cover for the Year 2000 (Bartholomé and Belward, 2005) dataset, and the mean presence threshold of *T. palmi* was calculated.

*Land-use change with the Shared Socio-economic Pathways (SSPs) scenario*

Three SSPs for the Korean peninsula have been developed for future socioeconomic developments, as they might unfold in the absence of explicit additional policies and measures to limit climate forcing or to enhance adaptive capacities (Kim, 2016). These SSPs represent low (SSP1), medium (SSP2), and high (SSP3) adaptation and mitigation challenges. The four projected components in the scenarios are: 1)

demographic projection and preference for urban areas, 2) economic growth, 3) land-use change, and 4) energy consumption. Under SSP1, sustainable development successfully progresses. Population decline eases, urbanization is suppressed, successful climate change adaptation derives economic growth, and energy is consumed efficiently. In contrast, dramatically decreased and old future population, poor economic growth, indiscreet urbanization, and inefficient energy consumption are predicted under SSP3. SSP2 is a moderate scenario of SSP1 and SSP3.

Changes in land-use were implemented through cellular automata modeling based on SSP scenarios (Kim, 2016). Future land-use change maps for each SSP were resampled to the 1 km<sup>2</sup> scale to match the spatial extent and resolution of the climate data. There were four classes of land-use in the SSPs: 1) urban, 2) agriculture, 3) forest, and 4) other.

*Integrating the MaxEnt outputs to land-use change*

The agricultural area for each land-use change from the three scenarios (SSP1, SSP2, and SSP3) was overlaid on each predicted distribution map of *T. palmi* under two climate change scenarios (RCP 4.5 and 8.5) in 2030 and 2075. Although *T. palmi* has a wide host range, the known host plants are mainly agricultural crops. Therefore, it was

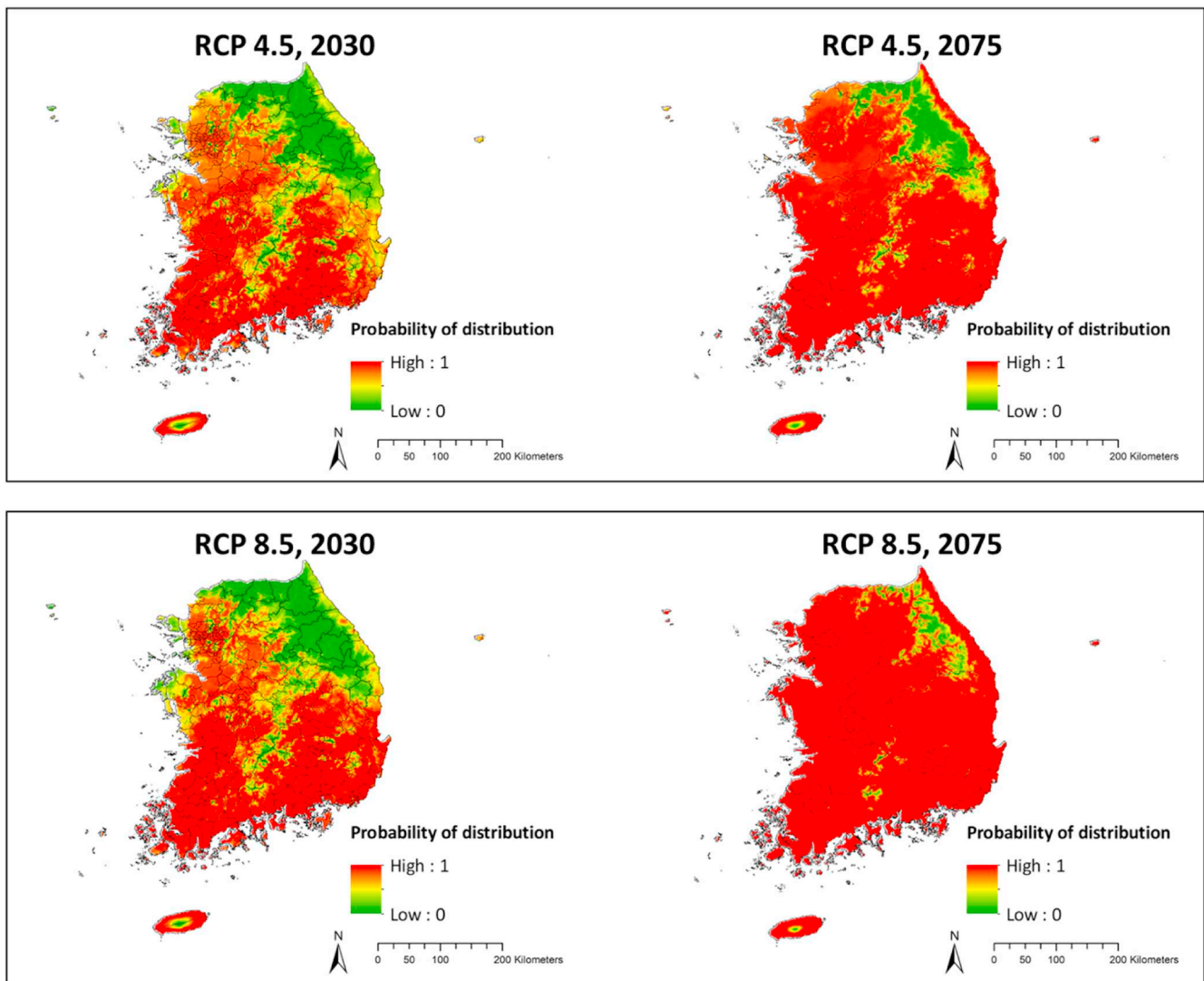


Fig. 3. The predicted potential distribution of *Thrips palmi* in Korea in 2030 and 2075 under RCP 4.5 and RCP 8.5 scenarios.

assumed that *T. palmi* is only present in the agricultural area (CABI, 2016). Using these overlaid datasets, two indices were calculated: total risk of occurrence (TRO) and risk intensity of occurrence (RIO). The TRO was defined as the projected agricultural area with a 10th percentile training presence logistic threshold value > 0.21 (see Table 2S). The RIO was the mean value of the potential distribution probability in the projected agricultural area.

**Results**

*Climate variable correlation and final MaxEnt model*

Out of 19 bioclimatic variables, seven were not correlated ( $|r| < 0.80$ ) (Table 1) and were used in the final MaxEnt model. The average AUC value in the training was 0.93, indicating the MaxEnt algorithm performed well at describing the occurrence of *T. palmi* in the Korean peninsula (Fig. 1B, and Table 2S). The average test AUC value was also high (0.92), but it was slightly smaller than the training AUC.

The simulation showed that the minimum temperature of the coldest month (BIO6) contributed the most to the model (50.2%), followed by the maximum temperatures of the warmest month (BIO5) (32.3%) (Table 1). Isothermality (BIO3), annual precipitation (BIO12), and precipitation of the driest month (BIO14) contributed 9.3%, 4.5%, and 3.1% to the model, respectively (Table 1). Model response to the top predictor variable (i.e., BIO6) indicated that the probability of *T. palmi* presence in a given cell was > 50% when winter temperature is suitable for overwintering at a given area. Jackknife output confirmed the importance of BIO6 to the final model (i.e., higher training gain and test AUC value; Table 2S). BIO5 was the most unique variable to explain the distribution of *T. palmi* because ‘the regularized training gain’ which is the quantity of information, dropped the most without it (Fig. 1C).

The final MaxEnt model was also validated with independent occurrence data collected in Japan, indicating that the final MaxEnt explained the current occurrence records very well in Japan (Fig. 2A). *T. palmi* occurred in 41 out of 47 prefectures during 1978–1994. Of the prefectures in which *T. palmi* was observed, Fukushima Prefecture had the lowest model prediction value of 0.25 (Fig. 2B). This value was comparable with the value (0.21) observed in the final MaxEnt model estimated using the 10% training presence logistic threshold, which is one of the commonly used methods in MaxEnt studies to produce presence/absence data from logistic outputs. When the training threshold was applied to the records in Japan, the final MaxEnt model prediction was valid in all prefectures where *T. palmi* was observed, except for Yamagata Prefecture where the predicted potential distribution was 0.24. These results demonstrate that the final MaxEnt model performed well, and correctly predicted most currently known occurrences of *T. palmi* in both in the Korean peninsula and Japan.

*Current and future distribution of T. palmi under RCP climate change scenarios*

The projected potential distribution conformed well to the current known distribution of *T. palmi* in the Korean peninsula (Fig. 1B). No significant commission errors (false presence) in the current prediction were observed. The main potential distribution was observed in the southern area, and the northernmost distribution was approximately at 36°N. Given that *T. palmi* is not distributed in the western coastal plains area, physical barriers, such as mountains, are not the greatest limitation of the range limit. The highest predicted distribution probability occurred in the lowlands of Jeju Island (0.92).

In the future prediction, the potential distribution extended to the north over time, with *T. palmi* being distributed throughout the Korean peninsula, except the eastern high mountainous area, for both RCP 4.5 and RCP 8.5 scenarios (Fig. 3). The average probability of distribution value under the current climate was 0.10, but this value increased to

0.84 for RCP 4.5 and 0.95 for RCP 8.5 in 2075.

*Generating the risk map by integrating MaxEnt and land-use change models*

After overlaying land-use changes with the predicted potential distribution of *T. palmi*, total risk of occurrence (TRO) and risk intensity of occurrence (RIO) were calculated for each combination of RCP-SSP scenario sets (Table 2). The agricultural area in both SSP1 and SSP2 did not change from 2030 to 2075, but the area in the SSP1 was slightly larger than that in SSP2 (18.18% and 17.8%, respectively). However, in SSP3, the total agricultural area in the Korean peninsula decreased gradually from 14.35% in 2030 to 13.45% in 2075 (Table 2; Figs. 1S and 2S). This decline was attributed to the large agricultural area located in the southwestern part being transformed into an urban area in SSP3 (Fig. 4).

The TRO gradually increased over time in SSP1 and SSP2 for the two climate scenarios (Table 2). When accounting for the fact that the agricultural area does not change in all combinations, the invasion risk of *T. palmi* constantly increased. The transformed TRO value to percentile scale (TRO% = agricultural area of *T. palmi* occupied/total agricultural area x 100) clearly showed this trend. For all SSP and RCP combinations, the TRO% in 2030 was at least 94%, with the value increasing to > 99% in 2075 (Table 2). RIO also changed in a similar way to that observed for TRO, from > 0.79 in 2035 to > 0.98 in 2075 (Table 2). These results indicate that nearly the entire agricultural area will become more favorable for invasion by *T. palmi* and that the intensity of occurrence will increase as climate change progresses.

**Table 2**

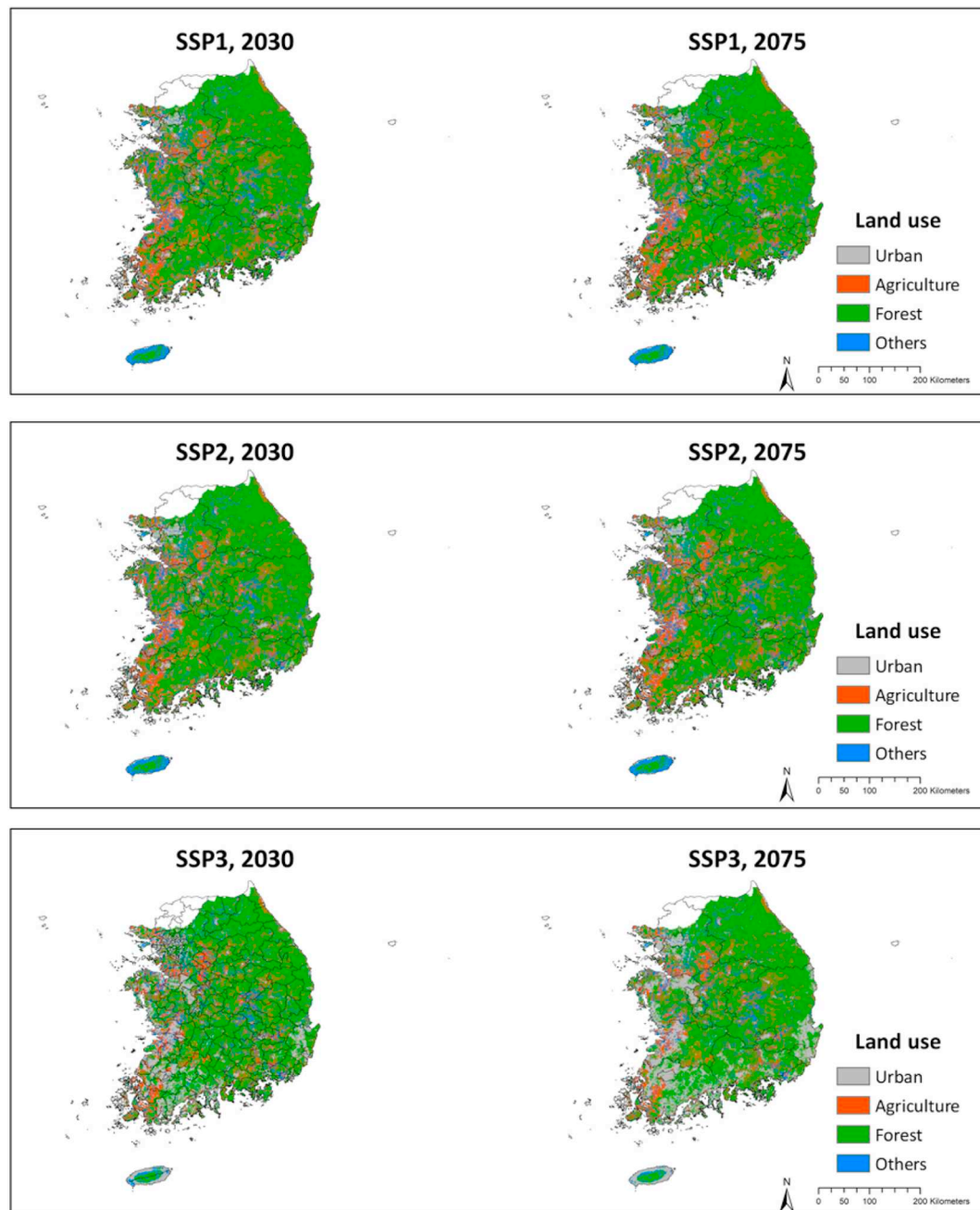
Changes in agricultural areas under two climate change scenarios (RCP4.5 and 8.5) and three socioeconomic scenarios (SSP1, SSP2, and SSP3). Total area of occurrence (TRO) and risk intensity of occurrence (RIO) of *Thrips palmi* were calculated based on the agricultural area.

SSP	RCP	Year	Agricultural area (km <sup>2</sup> )	TRO (km <sup>2</sup> )	RIO	
SSP1	RCP 4.5	2020	16,960 (18.18%) <sup>a</sup>	15,605 (92.01%) <sup>b</sup>	0.72	
		2030	16,960 (18.18%)	16,205 (95.55%)	0.81	
		2040	16,960 (18.18%)	16,579 (97.75%)	0.93	
		2050	16,960 (18.18%)	16,565 (97.67%)	0.93	
		2075	16,960 (18.18%)	16,647 (98.15%)	0.93	
	RCP 8.5	2020	16,960 (18.18%)	15,893 (93.71%)	0.75	
		2030	16,960 (18.18%)	16,186 (95.44%)	0.83	
		2040	16,960 (18.18%)	16,595 (97.85%)	0.92	
		2050	16,960 (18.18%)	16,656 (98.21%)	0.93	
		2075	16,960 (18.18%)	16,927 (99.81%)	0.98	
	SSP2	RCP 4.5	2020	16,611 (17.80%)	15,265 (91.90%)	0.72
			2030	16,611 (17.80%)	15,862 (95.49%)	0.81
			2040	16,611 (17.80%)	16,232 (97.72%)	0.93
			2050	16,611 (17.80%)	16,219 (97.64%)	0.93
			2075	16,611 (17.80%)	16,299 (98.12%)	0.93
RCP 8.5		2020	16,611 (17.80%)	15,554 (93.64%)	0.75	
		2030	16,611 (17.80%)	15,843 (95.38%)	0.83	
		2040	16,611 (17.80%)	16,248 (97.81%)	0.92	
		2050	16,611 (17.80%)	16,309 (98.18%)	0.93	
		2075	16,611 (17.80%)	16,578 (99.80%)	0.98	
SSP3		RCP 4.5	2020	13,993 (15.00%)	12,679 (90.61%)	0.69
			2030	13,387 (14.35%)	12,637 (94.40%)	0.79
			2040	13,036 (13.97%)	12,655 (97.08%)	0.92
			2050	12,840 (13.76%)	12,444 (96.92%)	0.91
			2075	12,551 (13.45%)	12,238 (97.51%)	0.92
	RCP 8.5	2020	13,993 (15.00%)	12,965 (92.65%)	0.73	
		2030	13,387 (14.35%)	12,623 (94.29%)	0.81	
		2040	13,036 (13.97%)	12,670 (97.19%)	0.91	
		2050	12,840 (13.76%)	12,536 (97.63%)	0.92	
		2075	12,551 (13.45%)	12,518 (99.74%)	0.98	

TRO is the projected agricultural area with the threshold value > 0.21, and RIO is the mean value of the distribution probability in the projected agricultural area.

<sup>a</sup> Agricultural area/total land area x 100.

<sup>b</sup> TRO/total agricultural area x 100.



**Fig. 4.** Land-use predictions in 2030 and 2075 under three SSP scenarios (SSP1, SSP2, and SSP3) in the Korean peninsula. Each scenario represents low, medium, and high socioeconomic challenges with respect to the mitigation and adaptation of climate change. Data were obtained from Kim (2016), and the resolution of data was modified to the 1km<sup>2</sup> scale.

## Discussion

Ongoing changes to the climate in the Korean peninsula might facilitate the chance for the introduction, establishment, and geographical expansion of exotic insect pests, especially those from tropical regions (Hellmann et al., 2008). Together with the changing climate, changes to future agricultural areas could have a major impact on the success of invasive insect species. This study clearly demonstrated that climate change and land-use change should be considered simultaneously when mapping pest risk. While the MaxEnt model showed all potential geographical distributions of *T. palmi* as climate change progressed, land-use change indicated the realistic areas where *T. palmi* could establish and develop populations.

The final MaxEnt model developed in this study describes well the

current and future range expansion of *T. palmi* under climate change in Korea. Validation using independent data observed from Japan confirmed the suitability of the MaxEnt model at explaining changes to the distribution of *T. palmi*. Moreover, our results supported a previous study performed with a mechanistic niche model (CLIMEX model) (Park et al., 2014). To improve our understanding of the risk of tropic insect pests, like *T. palmi*, invading temperate regions, overwintering ability might be the most critical factor to determine whether species survive and establish in introduced areas. The high contribution (50.2%) of the BIO6 variable, which is highly related to overwintering, to the final model demonstrates the importance of winter temperatures for the future geographical distributions of *T. palmi* in Korea. As the winter temperature increases due to climate change, the opportunity for overwintering increases, increasing population size during the crop

growing seasons. Laboratory experiments have demonstrated that no stage of *T. palmi* grows below 10.1 °C, with relatively greater mortality occurring under chronic cold conditions than *Frankliniella occidentalis* Pergande (McDonald et al., 1999, 2000). A field survey in Korea showed that low numbers of *T. palmi* can survive in the lowlands of Jeju Island (Lee et al., 2001). Considering the geographic and meteorological features of the survey area (such as low elevation and high winter temperature), the area where *T. palmi* can overwinter on the mainland of the Korean peninsula will rapidly extend northwards because most agricultural lands are located at low elevations.

The summer temperature could be another meteorological feature to consider. *T. palmi* has a short lifecycle that net reproductive rate reached a maximum at 25 °C and the generation time is < 25 days (Murai, 2002). That is, at a suitable condition, there is a potential that *T. palmi* can reproduce another generation only in a month. The results in this study showed that summer temperature is also important to understand the potential distribution of *T. palmi*. The BIO5 ranked the second greatest contribution rate (32.3%) and the most unique variable also. Therefore, summer temperature will be an important factor in predicting the distribution of *T. palmi* along with the overwintering potential.

Many studies have assessed the impact of land-use changes on biodiversity and invasive species (Charles and Dukes, 2008; Dukes et al., 2009), but very few studies have considered climate change and land-use change in parallel. This study is the first to show how the distribution and risk of introduced insect pests vary with climate change and land-use changes. Even if climate change drives the expansion of an invasive species, the magnitude of invasion risk could be limited by land-use change. TRO in 2075 declined by 399 km<sup>2</sup> and 105 km<sup>2</sup> under RCP4.5-SSP3 and RCP8.5-SSP3, respectively (Table 2); thus, land-use change has a greater impact on change to invasion under RCPs-SSP3. The land-use change scenario in SSP3 predicted that over 800 km<sup>2</sup> of agricultural areas in the southwestern region will be converted to urban areas from 2030 to 2075 (Fig. 4). Kim (2016) explained that this conversion is the result of 'low level urban planning'. However, compared with a global case study, the trend of changes in agricultural land areas under SSP3 in Korea seems to be a unique and rare case. From the global perspective, SSP3 assumed high population demands and high food production, resulting in increasing agricultural area (Popp et al., 2017). Thus, region-specific land-use change might determine the overall invasion risk of a given area. Although the potential distribution area of *T. palmi* is expanding rapidly based on future climate change scenarios, the actual distribution should be limited to the existing agricultural area (Fig. 3, and Figs. 1S and 2S). The risk intensity in the agricultural areas increased greatly (Table 2), indicating that agricultural areas in Korea will shift to a climate zone where *T. palmi* can establish. Intensive management and proper monitoring strategies of current agricultural lands are needed in the future.

Although the integration of climate change and land-use change generated meaningful outcomes in this study, further studies are needed to produce more meaningful results. There is a limited consideration of invasion risks of *T. palmi* depending on the type of agricultural land. Agricultural lands consist of paddy fields, vegetable fields, and orchards in Korea; however, the agricultural area used in the current SSP scenarios did not reflect these subclasses of land. The host range of *T. palmi* is very broad, but the main hosts are vegetables and ornamental crops (Hong et al., 1998; CABI, 2016). Excluding paddy fields and orchards could improve predictions of the invasion risk of *T. palmi*; thus, subclasses of agricultural land should be considered in future studies.

Our results suggest that, if land-use change is not taken into consideration in pest risk mapping study, the risk is exaggerated, providing insufficient information to develop pest management strategies for the future. The pest risk mapping process in the current study provides the potential future range of a pest species that needs managing, along with the magnitude of invasion risk at the national level. Risk maps were

generated by integrating future climate change and land-use change, confirming that the intensive management of current agricultural lands will be needed in the future. Climate change will increase the ability of *T. palmi* to survive during winter in Korea; however, there will be no noticeable new croplands, as the coverage of agricultural lands will not significantly change under SSP1 and SSP2, and will even reduce under SSP3 in Korea. In conclusion, both future range shifts of invasive species and changes to agricultural land coverage must be considered when planning pest management strategies.

## Declarations of interest

The authors certify that they have NO affiliations with or involvement in any organization or entity with any financial interest.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.aspen.2019.04.013>.

## References

- Ahn, S.B., Han, M.J., Choi, J.Y., Choi, K.M., 1994. First record of *Thrips palmi* and its geographical distributions in Korea. *Korean J. Appl. Entomol.* 33, 127–128 (In Korean with English abstract).
- Andersen, M.C., Adams, H., Hope, B., Powell, M., 2004. Risk assessment for invasive species. *Risk Anal.* 24, 787–793.
- Baik, J., Choi, M., 2015. Evaluation of remotely sensed actual evapotranspiration products from COMS and MODIS at two different flux tower sites in Korea. *Int. J. Remote Sens.* 36, 375–402.
- Bale, J.S., Masters, G.J., Hodkinson, I.D., Awmack, C., Bezemer, T.M., Brown, V.K., Butterfield, J., Buse, A., Coulson, J.C., Farrar, J., Good, J.E.G., Harrington, R., Hartley, S., Jones, H.T., Lindroth, R.L., Press, M.C., Symrnioudis, I., Watt, A.D., Whittaker, J.B., 2002. Herbivory in global climate change research: direct effects of rising temperature on insect herbivores. *Glob. Change Biol.* 8, 1–16.
- Bartholomé, E., Belward, A.S., 2005. GLC2000: a new approach to global land cover mapping from Earth observation data. *Int. J. Remote Sens.* 26, 1959–1977.
- Bellard, C., Thuiller, W., Leroy, B., Genovesi, P., Bakkenes, M., Courchamp, F., 2013. Will climate change promote future invasions? *Glob. Change Biol.* 19, 3740–3748.
- Brown, J.L., 2014. SDMtoolbox: a python-based GIS toolkit for landscape genetic, biogeographic and species distribution model analyses. *Methods Ecol. Evol.* 5, 694–700.
- CABI, 2016. Invasive Species Compendium. CAB International, Wallingford, UK. [www.cabi.org/isc](http://www.cabi.org/isc).
- CABI/EPPO, 1998. *Thrips palmi*, map 149. In: Smith, I.M., Charles, L.M.F. (Eds.), Distribution Maps of Quarantine Pests for Europe: Distribution Maps of Quarantine Pests for the European Union and for the European and Mediterranean Plant Protection Organization. CAB International, Wallingford.
- Cannon, R.J.C., Matthews, L., Collins, D.W., 2007. A review of the pest status and control options for *Thrips palmi*. *Crop Prot.* 26, 1089–1098.
- Charles, H., Dukes, J.S., 2008. Impacts of invasive species on ecosystem services. In: Nentwig, W. (Ed.), *Biological Invasions. Ecological Studies.* vol. 193. Springer, Berlin, New York, pp. 217–237.
- Chung, Y.S., Yoon, M.B., Kim, H.S., 2004. On climate variations and changes observed in South Korea. *Clim. Chang.* 66, 151–161.
- Cook, D.C., Thomas, M.B., Cunningham, S.A., Anderson, D.L., De Barro, P.J., 2007. Predicting the economic impact of an invasive species on an ecosystem service. *Ecol. Appl.* 17, 1832–1840.
- Dukes, F.S., Pontius, J., Orwig, D., Garnas, J.R., Rodgers, V.L., Brazee, N., Cooke, B., Theoharides, K.A., Stange, E.E., Harrington, R., Ehrenfeld, J., Gurevitch, J., Lerdau, M., Stinson, K., Wick, R., Ayres, M., 2009. Responses of insect pests, pathogens, and invasive plant species to climate change in the forests of northeastern North America: what can we predict? *Can. J. For. Res.* 39, 231–248.
- Eliith, J., Graham, C.H., Anderson, R.P., 2006. Novel methods improve prediction of species' distributions from occurrence data. *Ecography* 29, 129–151.
- Eliith, J., Phillips, S.J., Hastie, T., Dudík, M., Chee, Y.E., Yates, C.J., 2011. A statistical explanation of MaxEnt for ecologists. *Divers. Distrib.* 17, 43–57.
- ESRI, 2011. ArcGIS Desktop: Release. 10 Environmental Systems Research Institute, Redlands, CA.



- Ficetola, G.F., Maiorano, L., Falcucci, A., Dendoncker, N., Boitani, L., Padoa-Schioppa, E., Thuiller, W., 2010. Knowing the past to predict the future: land-use change and the distribution of invasive bullfrogs. *Glob. Change Biol.* 16, 528–537.
- Hellmann, J.J., Byers, J.E., Bierwagen, B.G., Dukes, J.S., 2008. Five potential consequences of climate change for invasive species. *Conserv. Biol.* 22, 534–543.
- Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G., Jarvis, A., 2005. Very high resolution interpolated climate surfaces for global land areas. *Int. J. Climatol.* 25, 1965–1978.
- Hijmans, R.J., Phillips, S., Leathwick, J., Elith, J., 2017. *dismo: Species Distribution Modeling*. R Package Version 1.1–4. <https://CRAN.R-project.org/package=dismo>.
- Hong, K.J., Lee, M.L., Han, M.J., Ahn, S.B., Kim, I.S., Lee, G.H., Ku, D.S., 1998. Distribution and host plants of recently introduced palm thrips, *Thrips palmi* Karny (Thysanoptera: Thripidae) in Korea. *RDA. J. Crop. Protec.* 40, 89–95 (In Korean with English abstract).
- Jeschke, J.M., Strayer, D.L., 2008. Usefulness of bioclimatic models for studying climate change and invasive species. *Ann. NY Acad. Sci.* 1134, 1–24.
- Jiménez-Valverde, A., Peterson, A.T., Soberón, J., Overton, J.M., Aragón, P., Lobo, J.M., 2011. Use of niche models in invasive species risk assessments. *Biol. Invasions* 13, 2785–2797.
- Jones, D.R., 2005. Plant viruses transmitted by thrips. *Eur. J. Plant Pathol.* 113, 119–157.
- Kalnay, E., Cai, M., 2003. Impact of urbanization and land-use change on climate. *Nature* 423, 528.
- Kawai, A., 2001. Population management of *Thrips palmi* Karny. *Jpn. J. Appl. Entomol. Zool.* 45, 39–59 (In Japanese with English abstract).
- Kim, H.Y., 2016. Simulation of land use change by storylines of shared socio-economic reference pathways. *J. Korean Assoc. Geogr. Inf. Stud.* 19, 1–13 (In Korean with English abstract).
- Korea Meteorological Administration, 2012. *The Climate Atlas of Korea*. Korea Meteorological Administration, Seoul, pp. 1–20.
- Kumar, S., Neven, L.G., Zhu, H., Zhang, R., 2015. Assessing the global risk of establishment of *Cydia pomonella* (Lepidoptera: Tortricidae) using CLIMEX and MaxEnt niche models. *J. Econ. Entomol.* 108, 1708–1719.
- Lee, G.S., Lee, J.H., Song, J.H., 2001. Overwintering of *Thrips palmi* Karny (Thysanoptera: Thripidae) on Jeju Island, Korea. *J. Asia Pac. Entomol.* 4, 45–50.
- Lee, K., Baek, H.J., Cho, C., Kwon, W.T., 2011. The recent (2001–2010) changes on temperature and precipitation related to normal (1971–2000) in Korea. *Geogr. J. Korea* 45, 237–248 (In Korean with English abstract).
- McDonald, J.R., Bale, J.S., Walters, K.F., 1999. Temperature, development and establishment potential of *Thrips palmi* (Thysanoptera: Thripidae) in the United Kingdom. *Eur. J. Entomol.* 96, 169–174.
- McDonald, J.R., Head, J., Bale, J.S., Walters, K.F., 2000. Cold tolerance, overwintering and establishment potential of *Thrips palmi*. *Physiol. Entomol.* 25, 159–166.
- Murai, T., 2002. The pest and vector from the East: *Thrips palmi*. In: Marullo, R., Mound, L. (Eds.), *Thrips and Tospoviruses: Proceedings of the 7th International Symposium on Thysanoptera*, Reggio Calabria, Italy, 2–7 July 2001, pp. 19–32.
- National Institute for Environmental Studies, 2017, July 31. *Invasive Species of Japan*. Retrieved from: <https://www.nies.go.jp/biodiversity/invasive/DB/detail/60180e.html>.
- O'Neill, B.C., Krieglner, E., Riahi, K., Ebi, K.L., Hallegatte, S., Carter, T.R., Mathur, R., Van Vuuren, D.P., 2014. A new scenario framework for climate change research: the concept of shared socioeconomic pathways. *Clim. Chang.* 122, 387–400.
- Palmer, J.M., 1992. Thrips (Thysanoptera) from Pakistan to the Pacific: a review. *Bull. Br. Mus. Nat. Hist. Entomol.* 61, 1–76.
- Park, J.J., Mo, H.H., Lee, G.S., Lee, S.E., Lee, J.H., Cho, K., 2014. Predicting the potential geographic distribution of Thrips palmi in Korea, using the CLIMEX model. *Entomol. Res.* 44, 47–57.
- Pearson, R.G., Dawson, T.P., Liu, C., 2004. Modelling species distributions in Britain: a hierarchical integration of climate and land-cover data. *Ecography* 27, 285–298.
- Pearson, R.G., Raxworthy, C.J., Nakamura, M., Peterson, A.T., 2007. Predicting species distributions from small numbers of occurrence records: a test case using cryptic geckos in Madagascar. *J. Biogeogr.* 34, 102–117.
- Phillips, S.J., Dudík, M., 2008. Modeling of species distributions with Maxent: new extensions and a comprehensive evaluation. *Ecography* 31, 161–175.
- Phillips, S.J., Anderson, R.P., Schapire, R.E., 2006. Maximum entropy modelling of species geographic distributions. *Ecol. Model.* 190, 231–259.
- Popp, A., Calvin, K., Fujimori, S., Havlik, P., Humpenöder, F., Stehfest, E., Bodirsky, B.L., Dietrich, J.P., Doelmann, J.C., Gusti, M., Hasegawa, T., Kyle, P., Obersteiner, M., Tabeau, A., Takahashi, K., Valin, H., Waldhoff, S., Weindl, I., Wise, M., Krieglner, E., Lotze-Campen, H., Fricko, O., Riahi, K., Van Vuuren, D.P., 2017. Land-use futures in the shared socio-economic pathways. *Glob. Environ. Change-Human Policy Dimens.* 42, 331–345.
- Reidsma, P., Tekelenburg, T., Van den Berg, M., Alkemade, R., 2006. Impacts of land-use change on biodiversity: an assessment of agricultural biodiversity in the European Union. *Agric. Ecosyst. Environ.* 114, 86–102.
- Stanton, J.C., Pearson, R.G., Horning, N., Ersts, P., Reşit Akçakaya, H., 2012. Combining static and dynamic variables in species distribution models under climate change. *Methods Ecol. Evol.* 3, 349–357.
- Sutherst, R.W., Maywald, G.F., Kriticos, D., 2007. *CLIMEX Version 3 User's Guide*. CSIRO, Australia.
- Swets, J.A., 1988. Measuring the accuracy of diagnostic systems. *Science* 240, 1285–1293.
- Van Vuuren, D.P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., Hurtt, G.C., Kram, T., Krey, V., Lamarque, J.-F., Masui, T., Meinshausen, M., Nakicenovic, N., Smith, S.J., Rose, S.K., 2011. The representative concentration pathways: an overview. *Clim. Chang.* 109, 5–31.
- Venette, R.C., Kriticos, D.J., Magarey, R., Koch, F., Baker, R.H.A., Worner, S., Gómez, N.N., McKenney, D., Dobesberger, E., Yemshanov, D., De Barro, P., Hutchison, W.D., Fowler, G., Kalaris, T., Pedlar, J., 2010. Pest risk maps for invasive alien species: a roadmap for improvement. *Bioscience* 80, 349–362.
- With, K.A., 2002. The landscape ecology of invasive spread. *Conserv. Biol.* 16, 1192–1203.
- Wu, L.H., Hill, M.P., Thomson, L.J., Hoffmann, A.A., 2018. Assessing the current and future biological control potential of *Trichogramma ostrinae* on its hosts *Ostrinia furnacalis* and *Ostrinia nubilalis*. *Pest Manag. Sci.* 74, 1513–1523.