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Original Article

Effect of types of meteorological data on species distribution predicted by the CLIMEX model using an example of *Lycorma delicatula* (Hemiptera: Fulgoridae)

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ABSTRACT

Climate has been used as a main variable in species distribution model, suggesting that the type of meteorological data can affect the predictive range of a target species. This study was to investigate the effect of meteorological data on the prediction of the potential distribution of a species in the CLIMEX model. We constructed three different types of meteorological data to be inserted into the CLIMEX model to predict the climatic suitability of the spotted lanternfly [*Lycorma delicatula* (Hemiptera: Fulgoridae)] in South Korea: (1) minimum–maximum data (Y-data), (2) annual average data (AY-data), and (3) 30-year long-term average data (A-data). As a result, the climatic suitability represented by the Ecoclimatic Index (EI) was significantly different in the Y-data compared with the other data sets because of the extreme winter condition in which they were recorded. In contrast, the AY- and A-data sets showed similar climatic suitability, but the AY-data showed slightly higher Ecoclimatic Index values than the A-data. It is conclusive that the AY- and A-data sets were suitable for evaluating annual variations by the years of data collection and current potential distribution, respectively, whereas the Y-data could be used for simulation under extreme climate conditions for a conservative assessment.

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Introduction

Recent increases in pest invasions due to climate change have expedited the use of species distribution modeling (SDM) to evaluate the possible occurrences of species in a specific area (Guisan and Thuiller 2005; Hijmans and Graham 2006). To produce a reliable result, SDM requires various types of information, such as, climate, geography, host plant distribution, species occurrence data, and biological characteristics of a target species for estimating model variables (Byeon et al 2018a; Elith et al 2006; Kéry et al 2010; Václavík and Meentemeyer 2009). For this reason, not only does a type of required information determine the result but also it should be chosen in accordance with the study objective. For example, the climate change scenario has been used to predict future potential distribution of a few notorious pests (Byeon et al 2018b; Iverson et al 1999; Jung et al 2017a), whereas the effect of altitude or host distribution has been inserted to determine its effect on species distribution (Jiménez-Valverde et al 2008; Kriticos et al 2013).

Among the factors determining species distribution, climate is known to be dominant in establishing insect habitat because temperature and soil moisture greatly influence the development of insects (Andrewartha and Birch 1954; Shabani and Kumar 2014; Van Klinken et al 2009). In this regard, CLIMEX is one of the most advanced tools that use climate as the main variable with consideration of the biological characteristics of a target species (Kriticos et al 2015). For operating CLIMEX, a specific type of information is required, and meteorological data are one of the key information sources used in developing a reliable model (Jung et al 2016; Kriticos and Leriche 2010). In other words, the type of meteorological data has significantly large impact on predicting the potential distribution of a target insect in the CLIMEX model. With an appropriate format to be inserted in CLIMEX, a few types of meteorological data can be used. In most CLIMEX-based studies, the average climate data for a specific duration have been used to remove the noise that might lead to biased analysis in predicting the current potential distribution of a target species (Lanoiselet et al 2002). The insect species *Metcalfa pruinosa*

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(Hemiptera: Flatidae) (Byeon et al 2017) and *Lycorma delicatula* (Hemiptera: Fulgoridae) (Jung et al 2017b) have been simulated to investigate their possible occurrence in 74 cities of South Korea by using the average climate data for 30 years (from 1981 to 2010). For predicting future distribution and dispersion patterns, climate change scenarios, such as Representative Concentration Pathway (RCP) and Special Report on Emission Scenarios, have been applied (Bosso et al 2016; Ramirez-Cabral et al 2017). In South Korea, *Aedes albopictus* and *Aedes aegypti* were simulated by inserting the climate change scenario RCP 8.5 to evaluate the risk of disease transfer between the two species (Jung et al 2017a). Moreover, the potential distributions of *Anoplolepis gracilipes* were compared after applying different types of climate changes scenarios (RCP 8.5 and Special Report on Emission Scenarios) (Jung et al 2017c). Finally, the annual climate data might be applicable to simulate the occurrence of a species in the year of interest. For example, *Leptoglossus occidentalis* Heidemann (Heteroptera: Coreidae) suddenly dispersed in South Korea in 2007 (Ahn et al 2013), and a study investigating the climate effect on its distribution needs to use the climate data of 2007.

Despite its large impact on the CLIMEX model, studies investigating how different types of climatic data affect model prediction and which data type would be adequate for achieving the study objectives have rarely been conducted. Therefore, in this study, we used three different types of meteorological data sets to predict the potential distribution of spotted lanternfly: (1) monthly average climate data of 30 years, (2) annual monthly average data, and (3) minimum and maximum annual monthly climate data. Subsequently, the CLIMEX results were compared to determine the difference in potential distributions and to identify the adequate type of meteorological data.

Material and methods

CLIMEX indices

CLIMEX simulates the climatic suitability of a species in a specific area by calculating the Ecoclimatic Index (EI) (Jung et al 2016; Kriticos et al 2015). Its value ranges from 0 to 100, representing climatically impossible and optimal species distribution, respectively. In general, the EI value larger than 20 indicates that an area has favorable climate for species inhabitation. The EI value is calculated by taking population growth under a favorable season and stress that exerted under harsh climates into account. In other words, growth index (GI) and stress index are calculated by exposing the biological characteristics of a target species to the climate of an area. These two indices are then combined to produce the EI value. The details of CLIMEX indices are well described elsewhere (Jung et al 2016; Kriticos et al 2015). In this study, we focused on the changes in EI values that resulted from implementing different types of meteorological data sets.

Target species

Spotted lanternfly (*Lycorma delicatula*) is a global pest causing severe domestic damages in wide variety of agricultural crops (Han et al 2008; Lee et al 2009; Park et al 2009; Shin et al 2010). It is originally native to countries with relatively hot climates, such as China, India, and Vietnam (Xiao 1991), and its distribution range has expanded to East Asia, probably because of global warming (Jung et al 2017a). In South Korea, its first occurrence was reported in 2006, and it dispersed into several South Korean cities, including Cheonan, Kongju, Jungeup, and Sang-Ju (Lee et al 2011; Park et al 2009). Now, it is considered to be distributed all over the country, causing severe agricultural and societal damages (KFRI 2009). Because this study focused on the effect of climate data, a previously simulated species was targeted to minimize the labor and cost associated with estimating the CLIMEX model parameters. In addition, to show the effect of climate data, a species that distributed throughout the country is necessary because it can make the difference of prediction by data type significant. For this reason, *L. delicatula* was selected because its model parameters were well estimated based on the biological characteristics and climates of its distributional regions (Jung et al 2017b).

Meteorological data

Three types of meteorological data sets were constructed and formatted as a data format required for the CLIMEX operation. The basic data consisting of the average daily maximum and minimum temperatures, precipitation, and relative humidity at 9:00 am and 3:00 pm were obtained for 73 cities from the Korea Meteorological Administration (KMA) in South Korea (Jung et al 2017b). The starting point for constructing the climate database suitable for the CLIMEX model was the collection of daily meteorological data, followed by its integration into monthly data. At this point, the monthly data in which the maximum and minimum temperatures and precipitation values were recorded comprised one of the meteorological data sets used in this study. Subsequently, the maximum and minimum values in meteorology were averaged to produce the average data for a month and for a year. These data were used as the annual average data in this study. Finally, the average monthly data for a year were constructed for 30 years (from 1981 to 2010) to construct a 30-year average database (Byeon et al 2017; Jung et al 2017a, b, d). In fact, we obtained all types of meteorological data sets directly from Korea Meteorological Administration and converted them into the format (mm file) available for CLIMEX. The types of meteorological data sets used in this study and their abbreviations are as follows:

1) Climate data averaged for 30 years (1981 to 2010): A-data
2) Annual monthly average data from 2006 to 2010: AY-data
3) Minimum and maximum annual monthly climate data from 2006 to 2010: minimum–maximum data (Y-data)

Process of analysis

To analyze the EI values differing in accordance with the types of meteorological data, we selected three different years—2005, 2007, and 2010. The years 2005 and 2010 were selected because they were the starting and ending years of collecting meteorological data in our climate database, whereas 2007 was the year when spotted lanternfly started to be observed in various sites in South Korea because its population increased in 2006 (Han et al 2008; Park et al 2009). For the selected years, we first statistically compared the average EI values differing in accordance with the types of meteorological data to determine EI variations at the national level. Subsequently, we tracked the number of areas as per the EI categories ($EI = 0$: unsuitable, $0 < EI \leq 10$: marginally suitable, $10 < EI \leq 20$: suitable, $EI > 20$: optimal) to investigate how climatic suitability changed (Hill et al 2016). In addition, we selected six representative cities to investigate EI variations based on the types of meteorological data and compared climatic conditions and CLIMEX indices for these cities. Finally, we concluded the best meteorological data set for predicting the potential distribution of a species in accordance with the study purpose.

Software

CLIMEX (CLIMEX, version 4.0, Hearne software, Melbourne, Australia) was the main software to calculate the EI values by

embedding different meteorological data, and the maps projecting EI values were constructed by ArcMap (version 10.4.1, ESRI, Redland, CA, USA). A statistical analysis was performed using the SAS software package (version 9.4, SAS Institute Inc., Cary, NC, USA), and the p-values less than 0.05 were considered statistically significant.

Results and discussion

First, the average EI values differing in accordance with the year and types of meteorological data sets were compared. Practically, the average EI value is not meaningful in SDM because it focuses only on the area-specific possibility of distribution. However, it can provide an insight into the effect of meteorological data on the CLIMEX result. Our results showed high EI values in the order of AY-data, A-data, and Y-data (Table 1). This met our expectation as A-data, the averaged data for 30 years that was developed to remove the abnormally high or low noise values in climate data (Byeon et al 2017; Jung et al 2017a, b, d). It has been reported that the average daily minimum temperature during the winter for 15 years was approximately $-1.0\ ^{\circ}C$ from 1986–1987 to 2000–2001, and it has gradually increased because of global warming (Ryoo et al 2004). Thus, the averaged winter temperature is likely to be more than $-3.4\ ^{\circ}C$, at which the complete egg mortality was observed (Lee et al 2011). In contrast, the minimum winter temperatures generally exceeded the biologically endurable temperature, causing significantly high cold stress with Y-data. The spotted lanternfly is known to overwinter with egg (Dara et al 2015), but the area showing larger than 100 cold stress had a daily minimum temperature less than $-3.4\ ^{\circ}C$ in the Y-data, greatly limiting the distribution of spotted lanternfly and showing the lowest average EI value. When comparing the average EI values by years at the same type of meteorological data, both AY-data and Y-data in 2007 produced the highest average EI values, consistent with a report that the occurrence of the spotted lanternfly was abnormally high in this year (Han et al 2008; Park et al 2009). In contrast, the average EI values were the lowest in 2005, even though they were not statistically significant. Because the population of spotted lantern fly was reported to increase from 2006, and the EI value is determined based on the climate data, it is deducible that the climate condition might be a factor underlying the activation of spotted lanternfly in 2006 (Park et al 2009). For example, we might think that the temperature range recorded in the AY-data in 2007 matched with the optimal temperature range, which was estimated to be 16 to 30 °C, for a long period (Jung et al 2017b). We will specifically investigate the climate data by years and cities later.

Second, we counted the number of areas based on their EI categories (Figure 1). As a result, the numbers of areas with an EI value of 0 were the largest in the Y-data, showing 50, 35, and 50 cities in 2005, 2007, and 2010, respectively. In contrast, the areas having the EI values higher than 20 were the largest in the AY-data (56, 70, and 63 in 2005, 2007, and 2010, respectively), whereas 52 cities showed the EI value to be more than 20 in the A-data. This result indicated that the predicted distribution of spotted lanternfly was limited

Table 1. Comparison of the Ecoclimatic Index values based on the types of meteorological data and years of data collection (mean ± standard deviation).

Type of data	2005	2007	2010
Y-data	4.6 ± 9.9^{a}	9.3 ± 14.6^{a}	5.6 ± 13.0^{a}
AY-data	32.1 ± 16.5^{b}	42.1 ± 12.9^{bc}	34.9 ± 14.5^{c}
A-data	30.3 ± 13.8^{c}		

*Different alphabets in superscript indicates that the values are statistically significant ($p<0.05$).
AY-data = annual average data; A-data = average data for 30 years; Y-data = minimum–maximum data.

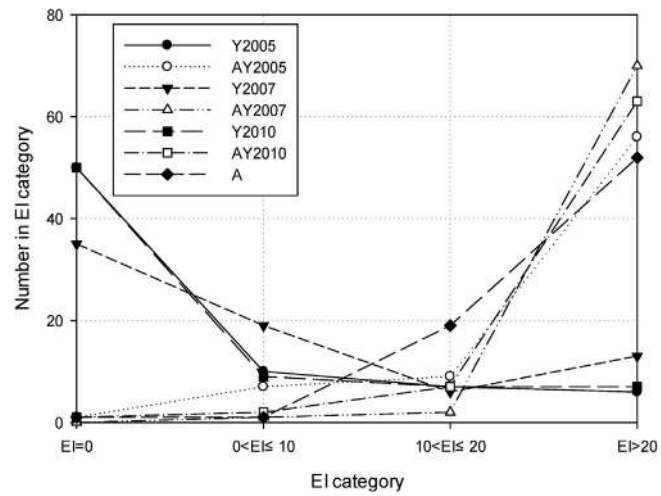

Figure 1. Number of areas in all Ecoclimatic Index categories counted according to the types of meteorological data and years of data collection. A-, AY-, and Y-data sets indicate the climate data averaged for 30 years (1981 to 2010), annual monthly average data (2006 to 2010), and minimum and maximum annual monthly climate data (2006 to 2010), respectively. A-data = average data for 30 years; AY-data = annual average data; Y-data = minimum–maximum data.

because the extreme climate conditions recoded in the Y-data were beyond the favorable condition for the spotted lanternfly, whereas the climate conditions recorded in the AY-data and A-data agreed with its limited predicted distribution because of the neutralization of extreme data by averaging. When considering regions, the difference of EI values between Y-data and AY-data was smaller in southern areas because of their moderate climate during winter than that in northern areas where the monthly minimum winter temperature in the Y-data was lower than the average winter temperature in the AY-data. As mentioned previously, the minimum temperature recorded in the Y-data was below the low threshold temperature in the CLIMEX model, leading to high cold stress and limited EI values. As expected, the A-data showed less numbers of the areas having EI values higher than 20 than the AY-data because of the alleviation caused by averaging; consequently, the number of areas with $10 < EI \leq 20$ was increased in the A-data than in the AY-data. In addition, we performed the same analyses on *Metcalfa pruinosa* and *Anoplolepis gracilipes* based on the parameters in Byeon et al (2017) and Jung et al (2017), respectively. As expected, *M. pruinosa* showed the same pattern of climatic suitability as shown in the simulation of *L. delicatula* because it was considered to be distributed throughout the country. That is, Y-data showed the largest number of areas having the EI value of zero, whereas either A-data or AY-data showed climatic possibility in all the cities with generally larger values in A-data than in AY-data. For *A. gracilipes*, all the data types showed the EI value of zero in almost all cities (only 3 cities showed the EI value larger than zero in AY- and A-data, whereas Y-data showed all zero values), meaning that the types of climatic data did not affect prediction for a species that is not living in South Korea.

To scrutinize the effect of climate data on the spotted lanternfly distribution, we selected six cities, among which Seoul, Cheonan, and Jeongeup showed actual occurrence (Park et al 2009), and Daegwallyeong, Bonghwa, and Seogwipo showed interesting EI variations by data type (Table 2). In Daegwallyeong, the EI values were zero in most cases except for the 2007 AY-data, suggesting unsuitable climate for the spotted lanternfly because of the high altitude and coldness of this area. In contrast, the EI values in Seogwipo were the highest in all investigated years and similar by the type of meteorological data. Because Seogwipo is one of the

Table 2. Representative six cities of South Korea and their Ecoclimatic Index values based on the types of meteorological data and year of data collection.

Cities	Longitude	Latitude	Y 2005	AY 2005	Y 2007	AY 2007	Y 2010	AY 2010	A
Daegwallyeong	128.71	37.66	0	0	0	7	0	0	0
Seoul	126.95	37.56	0	37	2	52	0	30	31
Bongwhoa	128.9	36.93	0	3	0	22	0	5	35
Cheonan	127.11	36.76	0	22	0	37	0	27	20
Jeongeup	126.85	35.55	0	30	7	44	0	39	26
Seogwipo	126.55	33.23	49	68	55	63	60	60	60

AY = annual average; A = average; Y = minimum–maximum.

southernmost cities in South Korea, both minimum and average temperatures would be above the low threshold temperature for the spotted lanternfly (Jung et al 2017b; Lee et al 2011). The EI values in the Y-data were zero in Seoul, Cheonan, and Jeongeup in most years except 2007, whereas they were above 20 when the AY-data and A-data were used, regardless of year. In addition, the A-data showed relatively lower EI values than the AY-data. Interestingly, the EI values in Bonghwa were lower in the AY-data than in the A-data, and the difference of EI values by years was the largest in the AY-data. This might be because that the climate conditions in Bonghwa before 2005 would be more suitable than the current conditions, and the climate was more suitable in 2007 than in 2005 and 2010, consistent with the occurrence records of the spotted lanternfly (Han et al 2008; Park et al 2009). In addition, we graphically produced the climate data of temperature and precipitation used in modeling and GI from the CLIMEX simulation for the A-, AY-, and A-data sets in 2007 for the previously mentioned cities. In Figure 2, the overall patterns of temperature and precipitation were smoothed in the A-data compared with other data sets because this data set averaged the temperature and precipitation values for 30 years. The shapes of the GI and temperature index (TI) curves were different between the A-data and AY-data. Except for Seogwipo, all cities showed large fluctuations in GI showed along with TI variations and reached the zero value, indicating that growth was not sustained because of the low temperature recorded in the Y-data. In contrast, all indices were maintained for approximately 9 months because the average temperature was above the low threshold temperature for the spotted lanternfly (Jung et al 2017b). Recorded precipitations were the same in the Y-data and AY-data, but moisture index was different because of its interaction with TI. Along with the limited EI values in the Y-data because of the use of minimum temperature, temperature would be the most important factor affecting the spatial range of the spotted lanternfly (Kriticos et al 2007; Lee et al 2011). Nevertheless, the GI decreased during the summer season with high precipitation, suggesting that too much rainfall might be unfavorable for the spotted lanternfly (Choi et al 2012).

The current distribution data provided by public databases, such as Global Biodiversity Information Facility and Centre for Agricsulture and Bioscience International, are long-term accumulated

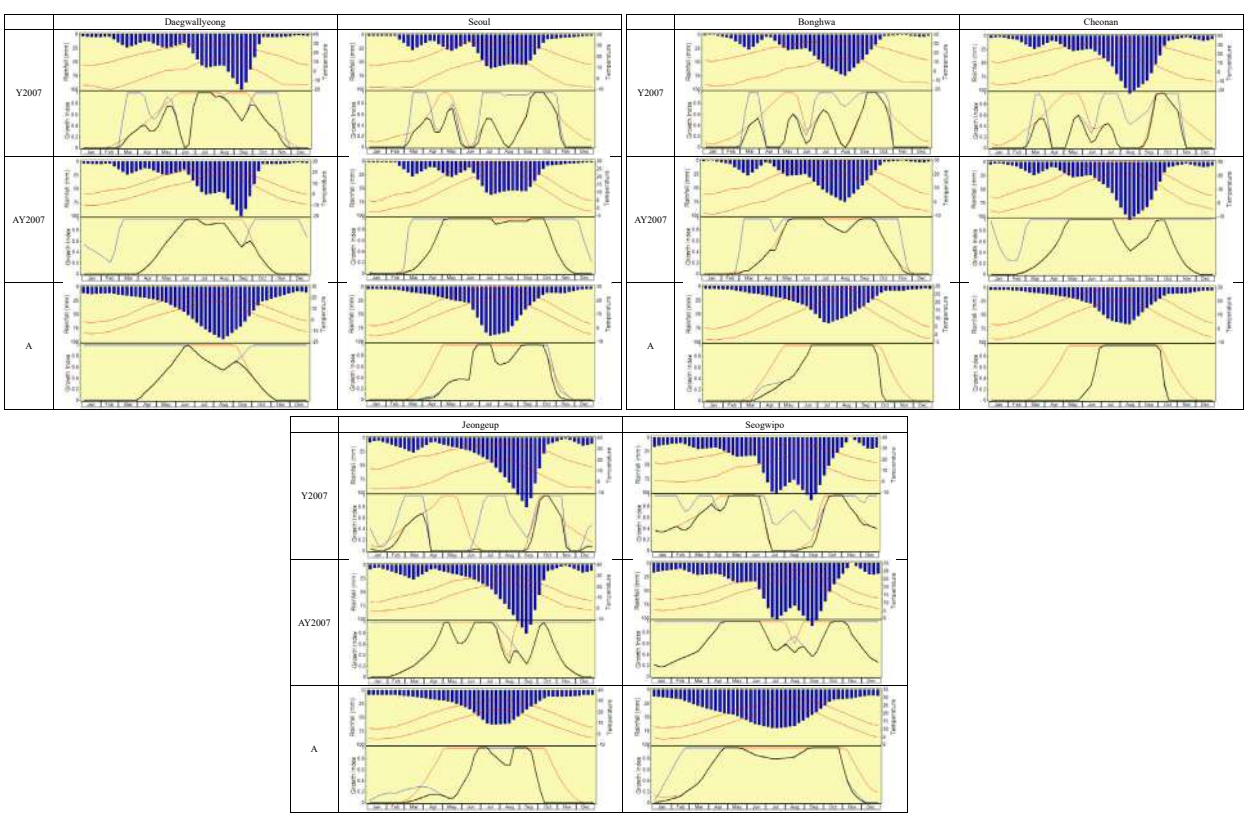

Figure 2. Climatic conditions (temperature and precipitation) and CLIMEX indices (growth index, temperature index, and moisture index) for six cities of South Korea in 2007. *D = Daegwallyeong, S = Seoul, B = Bonghwa, C = Cheonan, J = Jeongeup, and SE = Seogwipo. **Upper and lower led lines in upper panel indicate maximum and minimum temperatures, respectively, while blue bars indicate monthly precipitation. In lower panel, black, red and blue lines are growth, temperature and moisture indices, respectively.

records (CABI 2019; GBIF 2019). For this reason, when predicting the current distribution and to validate the model by comparing simulation with actual distribution, it would be better to use the long-term averaged climate data, e.g. the A-data in this study (Macfadyen and Kriticos 2012; Zheng et al 2012). In contrast, the AY climate data are suitable for analyzing the year-specific occurrence of a species (Ward et al 2015). For example, the spotted lanternfly occurred drastically in 2007–2008 in South Korea; thus, the AY-data could be used to identify the climatic factors affecting its active occurrence. When analyzing the data in Seoul in 2005 (EI = 37) and 2007 (EI =52), the moisture index peaked earlier in 2007 than in 2005, whereas the GI and TI values increased faster in 2007 than in 2005. Thus, it is conclusive that climates became more suitable in 2007 than in 2005, and this might be due to increased winter temperature (Lee et al 2011). However, it should be noted that the spotted lanternfly was first recorded in 2006; thus, the first reason for its occurrence would be artificial migration by trade and tourism from China, where the spotted lanternfly was originated (Han et al 2008; Xiao 1991). A climate record of extreme conditions (herein, Y-data) might not be applicable for general SDM as it predicts the potential distribution that needs to fit the actual distribution under the current climate. It might be useful when considering a target species under extreme climate, but it is not the general approach in SDM. For instance, conservative evaluation is necessary for a few notorious species that cause huge irreversible damage in local agriculture and biodiversity (e.g. fire ants) (Vinson 1997; Wheeler 1910). Thus, to consider the worst situation, extreme conditions need to be applicable for SDM.

Conclusion

The objective of SDM is generally determined by a target species that is dominantly affected by climate. In particular, recent climate change has altered spatial ranges of species inhabitation with time. This study investigated the effect of different types of meteorological data (long-term average data, annual average data, and extreme data) on predicting the climatic suitability of a species by using CLIMEX with an example of the spotted lanternfly. We compared the climatic suitability represented by the EI values differing in accordance with the years and data types and climate conditions with the CLIMEX index, suggesting that effective analysis would be possible by applying different types of climate data in accordance with the study objectives. Finally, it was noted that constructing climate data suitable for the software implanting SDM is a time- and labor-consuming process. However, upon construction, it can be widely used for various species.

Conflict of interest

The authors declare that there is no conflict of interest.

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