Pest distribution model comparisons in integrated management of key crop pests: empirical studies of Taiwan and Southeastern Asia

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ABSTRACT

Wide ranges of pests affect crop production and cause considerable yield losses. Several conceptual modelling frameworks have been proposed, and the choice of an approach depends largely on the objective of the model and the availability of data. Existing challenges on the modelling of insects are listed. Difficulties reside on the development and adaptation of adequate strategies to predict insect pests for their management to ensure enhanced agricultural production. This paper presents a summary of advances in insect population distribution and pest mapping around Asia. Following the step-wise modelling comparisons innovations, we evaluate the distributions of *Trichogramma ostriniae* and native host, *Ostrinia furnacalis* in southeastern Asia, and target host, *Ostrinia nubilalis* in North America, using a combination of MAXENT and CLIMEX modelling approaches. These correlative and process-based niche models led to similar predictions about the expected distribution of the two species in Asia, and enabled the emphasis of likely mismatches between the host and its natural enemy. Records of successful inundative releases involving the introduction of *T. ostriniae* in North America were modelled and used to adjust parameters in the CLIMEX model. Releases took place outside in the suitable climate areas identified from the native range of this species, suggesting that permanent wasp populations might only establish based on changes in temperature-related life history parameters.

Keywords: biocontrol, model comparison, environmental niche model, adaptation

INTRODUCTION

Global warming caused by the over-exploitation of petroleum and tropical rainforest seemed to get worse and worse in recent decades with the clear evidence of increasing frequency and intensity of the extreme climate events. The extreme weather-related events increase globally, as predicted by the latest IPCC report [(1)], such as massive floods in Pakistan (2010) and Thailand (2012); the ongoing crippling droughts across sub-Saharan Africa, Amazonian Brazil (2005 and 2010) and in the central United States; record heat waves, as in the United States (2012), Russia (2010), western Europe (2003) which took tens of thousands of human lives.

The natural and agricultural ecosystems and the species in them will have to adapt to these changes, which are probably unprecedented in recent evolutionary history. Parmesan and Yohe [(2)] predicted that climate change would be a major factor contributing to a significant increase in extinction rates of all species. Since agricultural productivity depends on a wide array of biotic interaction involving mutualists (e.g. pollinators, natural enemies) and antagonists (e.g. herbivores and pathogens), thus studies exploring the effects of extreme weather related events on multitrophic interactions will shed more light on the consequences of these events on primary production in cropping systems and on interactions with these important mutualists and antagonists [(3)]. Researchers even claim that extreme climate change will facilitate the coextinction rates of endangered species, parasites, and mutualists [(4)], which in turn can affect the production of crop simultaneously. For example, pollination and biocontrol using natural enemies on crops largely depend upon its interactions between different trophic levels that are highly vulnerable to extreme climate events, which may break down the trophic network and lead to food shortages in modern society.

Population interactions between pests and their natural enemies are inevitably complex, involving many components among diverse scales. To reveal issues that are related to the impacts of extreme climate on the interaction level, the most crucial but difficult approach is to build up a long-term and large-scale database that enables further comparisons and analysis focusing on certain species or time series. However, given the variability in how studies are conducted and the often-sparse sampling durations, it is almost impossible to reveal the general pattern and impacts simply by comparing and analyzing [(5)]. While the influence of climate on range boundaries may be mediated through species interactions, species distribution models (SDMs) driven

by bioclimatic data are increasingly being applied to deal with the large scale and long-term issue with distribution shift and population dynamics.

There are two prevalent approaches in modeling the risk establishment and expansion of an insect pest. The "inductive" approach uses pattern-matching functions that chase down the potential exploitation of a non-indigenous invasive species to new areas by comparing the long-term meteorological data for each selected location where the species is absent to the location of origin or locations where the species prevails [6, 7]. To apply this approach, computer-aided tools, such as CLIMEX and MAXENT, have been developed and used to predict species' demography for pest management and potential climate change effects [6]. It uses minimal data sets and simple functions to describe the species' response to temperature and other climatic factors and shows advantages where detailed life cycle parameters for the species are limited; however, it failed to consider the biological characteristics in the modeling framework, hence, could only provide the potential establishment risk maps of the targeted species but not the further information about its population dynamics within a growing season or year in a given region [8].

By contrast, the "deductive" approaches adopt process-based climatic response model for targeting pest species (phenology model): the main advantage is that the rule they use are based upon causation, not correlation. This kind of model packages, e.g., Dymex and Insect Life Cycle Modeling (ILCYM), are based on detailed laboratory assessment for deriving life-table parameters and simulated population dynamics according to long-term temperature data for a given region and time [9]. The development of insects, as in other ectothermic organisms, depends on the ambient temperature. This temperature dependency can be applied in a process-oriented framework; forecasting the potential distribution of insect species is totally independent of observed occurrence, and this approach is therefore referred to as "deductive" [8]. Degree-day (DD) models, employing linear models using accumulation of temperature above the minimum temperature threshold [10] have been established to describe the development of different insect pests. However, due to the non-linearity of the development curve, especially deviation from the intrinsic optimal temperature of the species, these models become poor predictors of insect development. DD models work well for intermediate temperatures, but produce errors when daily temperature fluctuates to extremes [11]. For better evaluation, more sophisticated and progressive

models were developed by using non-linear models of higher biological significance [12], and by including stochastic function for variability in development times within a population among individuals [13].

Simulation models were further developed as a powerful means for representing the dynamic of organisms responding to a series of external factors. Dymex package enables the user to deal with a class of ecological models referred to as mechanistic or process-based models, without the need to be familiar with a computer programming language [14]. ILCYM software calculates the life table population parameters based on within-the-day temperature variability and use these to evaluate the potential effect of certain pest management strategies. Moreover, ILCYM includes a sub-module for the development of a two-species interaction model for linking the parasitoid and its host phenology models through a deterministic simulation procedure under constant and fluctuating temperature conditions. This process uses the predicted temperature-dependent development times and parasitoid fertility rates for simulations of the host population growth and development [8]. To make predictions of species distributions precisely, different types of niche models are increasingly used both in biodiversity conservation and in applied ecology at the same time [15, 16]. The choice of the model type is typically determined by the type of data that is available for the species.

CASE STUDY

The Asian corn borer (ACB), Ostrinia furnacalis Guenée (1854), is a serious pest of corn causing more than 9 million tons of yield loss per year. The geographic range of *O. furnacalis* extends from eastern and southeastern Asia to western Pacific islands [17]. The egg parasitoid Trichogramma ostriniae Pang & Chen (1974), the predominant species, parasitizes *O. furnacalis* across the native range of most corn growing regions of southeastern Asia [18, 19]. In China, using *Trichogramma osatriniae* for biocontrol of Asian corn borer has been conducted since early 1950s. Because of its success in China, T. ostriniae has been introduced to control the closely related European corn borer Ostrinia nubilalis Hübner (1917) in northeastern USA (New York, Massachusetts, Delaware and other locations) and Canada (southern Quebec) since the early 1990s [20, 21]. Early inoculative releases showed promising results, with up to 80% of parasitism achieved in cornfields at those locations [20]. These novel range data offer an

opportunity to test how well our modeled responses trained by native range can capture them.

By using a correlative ENM approach in conjunction with the semi-mechanistic approach (CLIMEX), we aim to identify suitable areas for effective inundative releases of T. ostriniae. The specific aims of the current study are: (1) using complementary modelling methods, to reveal the efficacy of T. ostriniae and ACB in current climates and (2) to understand the climate suitability for T. ostriniae in North America for control of European corn borer.

Distribution data

Occurrence locality data were obtained from published references [22] (n = 111 for Trichogramma ostriniae, n = 149 for Ostrinia furnacalis), field surveys in 2014 and 2015 (n = 9 for T. ostriniae, n = 28 for O. furnacalis) and Global Biodiversity Information Facility (GBIF) database (*n* = 1091 for O. nubilalis) (Fig. 1). The listed North American distribution of T. ostriniae was not used in model training, rather we adopted them to test the validity of our modeled responses, because all these data were obtained from successful inundative releases in biological control programs, and it is not clear if permanent populations have established at these release points [23].

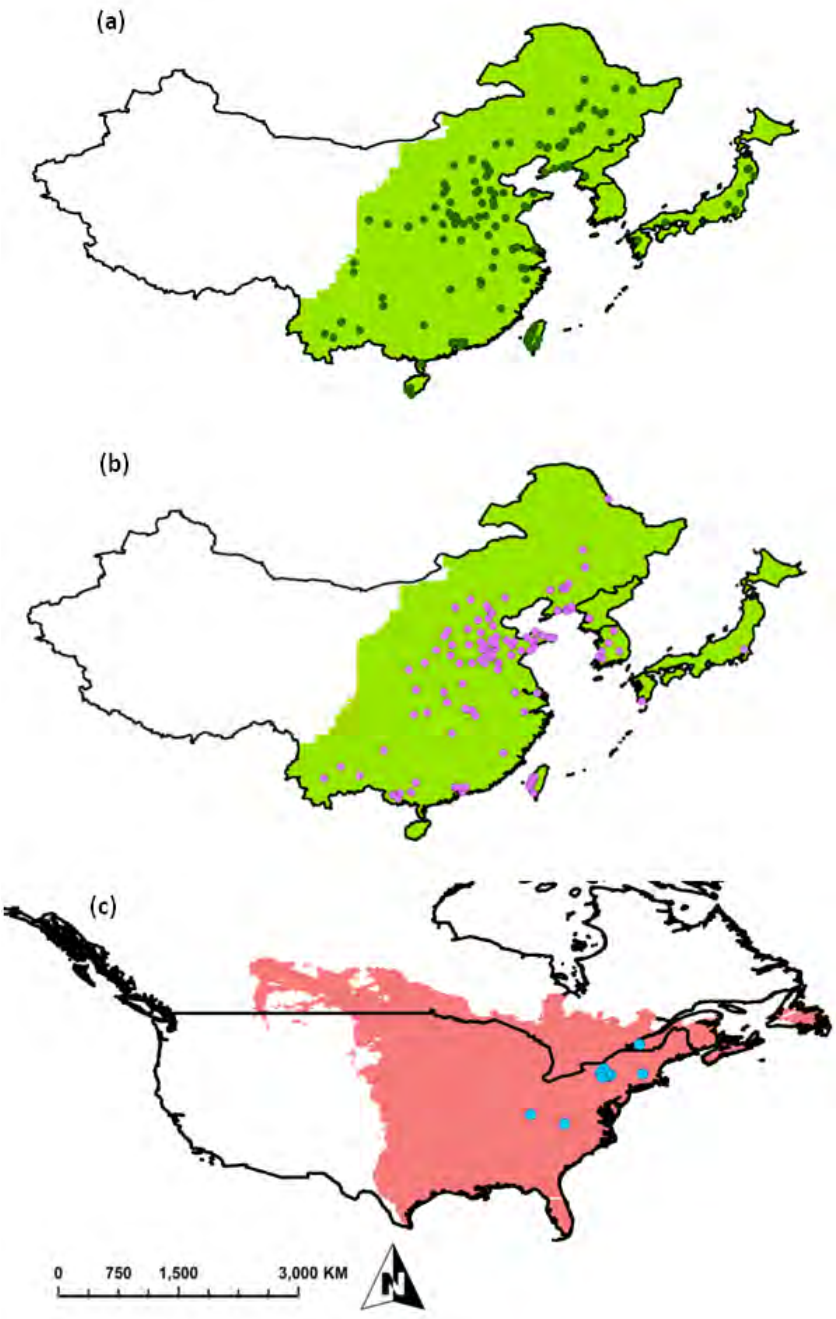


Figure 1 Native distributions of (a) Ostrinia furnacalis and (b) Trichogramma ostriniae. Sources are published references and field surveys were performed in 2014 and 2015 in China, Japan, Korea and Taiwan. (c) Inoculative releases locations of T. ostriniae undertaken in North America were obtained from published references. Colored areas represents backgrounds used in Environmental Niche Model (ENMs) construction based on the modified Köppen-Geiger classifications (Green = Asia-trained model; Pink = America-trained model) [(22)].

Environmental data and model projections

We obtained environmental data from CliMond [24], data formats suitable for both correlative ENMs and CLIMEX models. For ENM model construction, CliMond provides 35 bioclimatic variables describing means, seasonality and trends for temperature, precipitation, solar radiation and soil moisture. We used a grid cell resolution of 10′, which is approximately 20 x 20 km at the equator. Model details were indicated in Wu *et al.* (2018) [22].

To explore relative abundance in distribution under climate change for T. ostriniae and O. furnacalis in southeastern Asia, we adopted the CSIRO Mk. 3.0 models (available from CliMond, [24]) for the current time. American occurrence data surveyed in the current study were all inundative release points, so we only adopted response curves of the North American model to adjust our CLIMEX parameters to modify projections of North American data (Table 1).

Table 1 CLIMEX parameter values for the final model for *Trichogramma ostriniae* determined by iteratively changing parameter values until the performance best fit known native distributions (see Fig. 1)

Index	Parameter	Value[a]	
		T. ostriniae (Asia)	*T. ostriniae* (adjusted for America)
Temperature	DV0 = Lower threshold	13 °C	10 °C
	DV1 = Lower optimum temperature	20 °C	15 °C
	DV2 = Upper optimum temperature	29 °C	25 °C
	DV3 = Upper threshold	35 °C	30 °C
Moisture	SM0 = Lower soil moisture threshold	0.15	
	SM1 = Lower optimum soil moisture	0.35	
	SM2 = Upper optimum soil moisture	0.80	

	SM3 = Upper soil moisture threshold	1.50	
Cold stress	TTCS = Cold stress Temperature threshold	1 °C	0.5 °C
	THCS = Cold Stress accumulation rate	-0.00013 week^{-1}	-0.00005 week^{-1}
Heat stress	TTHS = Heat stress Temperature threshold	35 °C	
	THHS = Heat Stress accumulation rate	0.02 week^{-1}	
Dry stress	SMDS = Dry stress threshold	0.1	
	HDS = Dry stress rate	-0.02 week^{-1}	
Wet stress	SMWS = Wet stress threshold	1.5	
	HWS = Wet stress rate		

Adjusted values are underlined. [a]Values without units are dimensionless proportions.

Distribution comparison

Subtracting the output of *T. ostriniae* from *O. furnacalis* highlights areas likely to be particularly suitable for conducting *T. ostriniae* releases (Figs 2a & 2b). These areas were mostly distributed across Hebei, Shandon, Henan, Anhui and Shananxi provinces of China, and Korea. The maps of preference difference present only relative values for suitable habitat, and these would need to be refined through empirical studies.

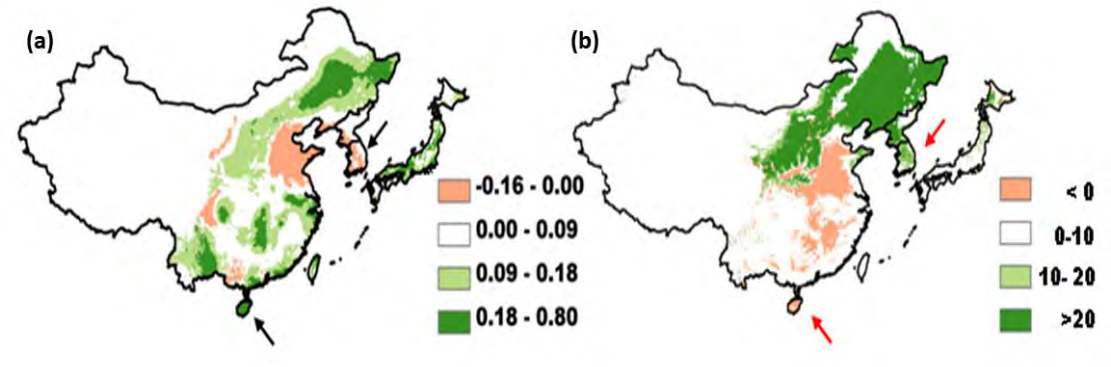


Figure 2 Distribution fitting models between *Ostrinia furnacalis* and *Trichogramma ostriniae* built on CliMond data sets. (a) *T. ostriniae* logistic MAXENT output subtracted from *O. furnacalis* logistic MAXENT output. Pink areas indicate where

more suitable climate space was predicted in the *T. ostriniae* model than the *O. furnacalis* one; (b) *T. ostriniae* CLIMEX output subtracted from *O. furnacalis* CLIMEX output. Pink areas indicate where more suitable climate space was predicted in the *T. ostriniae* model than the *O. furnacalis* one. Green areas indicate where more suitable climate space was predicted in the *O. furnacalis* model than for *T. ostriniae*. Arrows indicate different fitting performances (black: better; red: worse) between MAXENT and CLIMEX models.

Model projections

The variance of climate variables between Asia and North America also lowered the performance of CLIMEX projections (AUC = 0.404, Fig. 3a). To deal with the constraints, response curves of the America-trained MAXENT models were adopted to modify CLIMEX parameters and acquire a new North American projection (Table 1) and massively improved the power of the latest model ($AUC_{adjusted}$ = 0.772, Fig. 3b) to predict where inundative releases occurred.

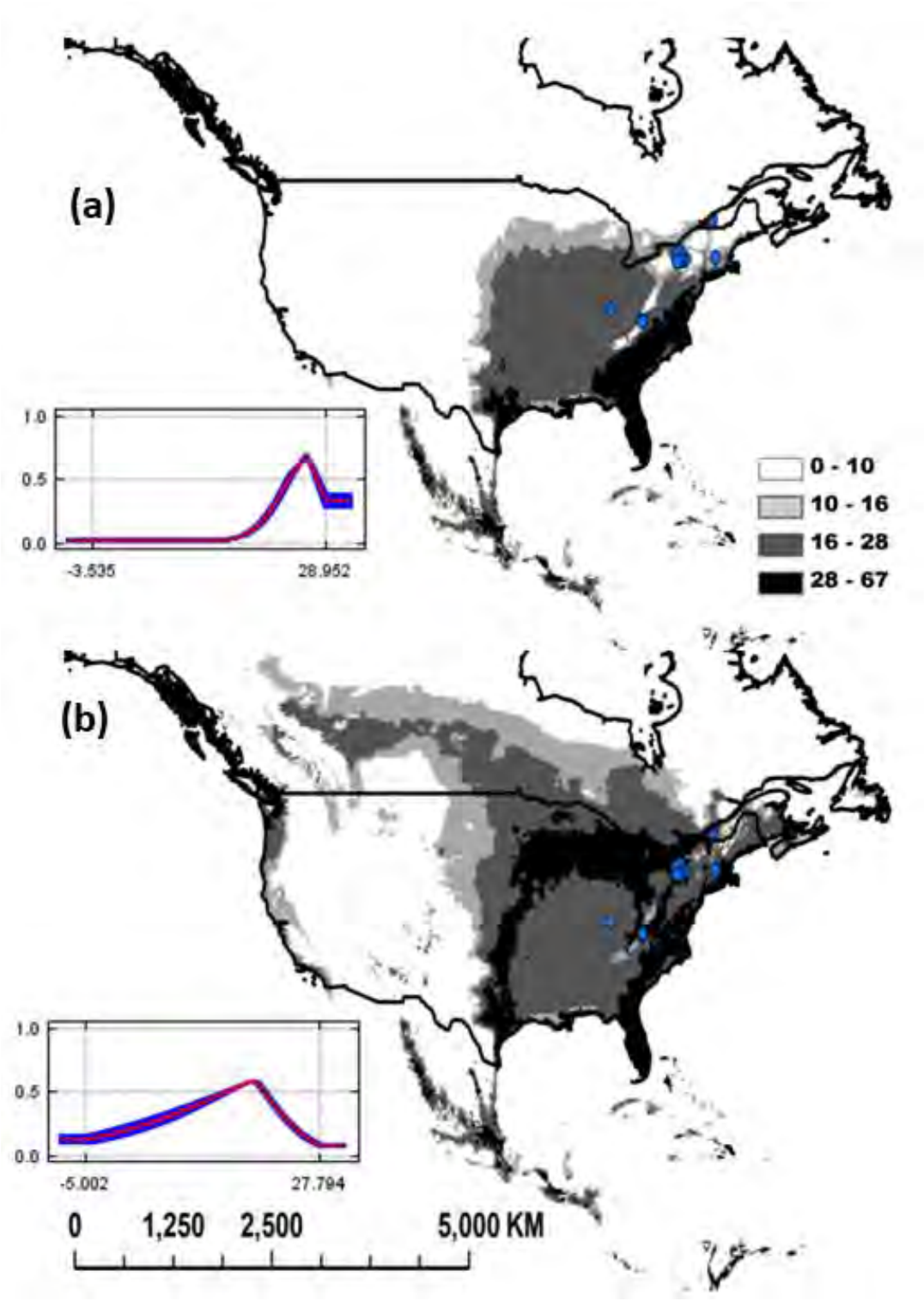


Figure 3 (a) 'original' and (b) 'adjusted' projections (lowered temperature index and cold stress parameters based on response curves of mean temperature of wettest quarter listed). Shading reflects Ecoclimatic Index (EI). Projections for North America are Miroc-H A1B SRES projections.

DISCUSSION

The projection of the Asia-trained model on the North American areas highlights the potential limit of MAXENT (inherent issues of extrapolation) [25]. These projections could be integrated and could supply adjustments for parameter tuning in the CLIMEX model. To sum up, the inundative occurrence data and CLIMEX projections suggested that T. ostriniae presented different temperature-related life history parameters (lowered cold threshold and cold stress accumulation rate). Such differences in life history traits may reflect the fact that T. ostriniae populations have not become permanently established. However evolutionary changes among T. ostriniae populations might also provide an explanation. Wang et al. [23] have previously suggested that individuals from North American populations grow faster than Chinese populations (9 days at 24°C for America; 10 to 11 days at 25°C for China). These possibilities remain to be tested.

It is worth highlighting some limitations in our SDMs fitting process. Distributional data for both T. ostriniae and O. furnacalis were limited due to recent survey efforts being restricted and a lack of precise locality data associated with most published records [26, 27]. Meta-analyses have suggested for competing natural enemy species that antagonism may result in effects on the target being less than additive, and this deleterious outcome is most obvious when the same life stage of a host is attacked [28]. Our model approaches overlook the influence of other Trichogramma species present across the predicted distributions. Therefore, any inference regarding areas suitable for T. ostriniae ought to be made with caution and requires empirical studies that include molecular identification of potential competing Trichogramma species given by the cryptic nature of species in this group [19].

In conclusion, two different modelling comparisons provided insights into factors controlling the distribution of a pest host and a parasitoid that is important for its control. In predicting inundative release areas of T. ostriniae in a novel area, we had to change parameters and this led to an alternative hypothesis. Areas where successful parasitism might be expected were identified, but additional data are required to determine whether T. ostriniae may have become established in its novel range outside these areas, which might reflect adaptation to local climate conditions.

ACKNOWLEDGMENTS

Current study was supported by the grants from (MOST 106-2313-B-020 -014 - MY2). We are grateful to the scientists who conducted and published their insightful model studies.

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