Nature Environment and Pollution Technology
An International Quarterly Scientific Journal

p-ISSN: 0972-6268
e-ISSN: 2395-3454

Vol. 16 No. 3 pp. 737-744 2017

Original Research Paper Open Access

Study on Geographic Distribution of Fall Webworm Based on Maximum Entropy Model

Siyu Pan and Xiyou Su†
School of Information Science and Technology, Beijing Forestry University, Beijing, 100083, China
†Corresponding author: Xiyou Su

Nat. Env. & Poll. Tech.
Website: www.neptjournal.com

Received: 05-08-2016
Accepted: 24-08-2016

Key Words:
Fall webworm
Quarantine pest
Maximum entropy model
Geographical distribution

ABSTRACT

Fall webworm, is a quarantine pest, which has caused damage to agricultural and forestry production in China. In this paper, based on the use of maximum entropy method (MaxEnt), we constructed the geographic distribution prediction model of fall webworm. The results show that the accuracy of the prediction model is very high (AUC=0.921), and the distribution is mainly influenced by precipitation of warmest quarter (24.5%), altitude (24.4%), mean temperature of coldest quarter (20.5%), standard deviation of temperature seasonality (9.2%) and temperature annual range (3.7%). The current suitable areas of fall webworm in China are concentrated in the southern northeast China, Beijing-Tianjin-Hebei region and most parts of north China Plain. The common natural characteristics of these areas are: rain heat over the same period, higher relative humidity and no extreme low temperature. In the context of 3 representative concentration pathways (RCPs), the geographic distributions of fall webworm in 2050 share the same variation tendency, though the variation degree differs. There is a tendency of expansion towards the north, with distribution areas in parts of the northeast plain, parts of the Sichuan basin and the north China Plain. The results are conducive to a comprehensive understanding of the current and future distributions of fall webworm, and have theoretical significance for investigating and implementing scientific control tactics for the insect pest of fall webworm.

INTRODUCTION

The fall webworm, *Hyphantria cunea* (Lepidoptera: Arcidae), is native to North America, ranging from northern United States, southern Canada to Mexico. The ordinary insect pest in North America has been introduced into China, and as one of the biggest alien invasive species in China, the moth has become a quarantine pest that poses great dangers to trees. In China, the fall webworm was first found in Dandong, Liaoning province, in 1979, and later, it spread to Shandong province in 1984, to Hebei province in 1989, to the city of Tianjin in 1995 and to the city of Beijing in 2003; still, the expansion tendency is ongoing now (Zhang & Wang 2009). The larvae feed on a large quantity of food almost of any type, incessantly posing threats. The hosts of this pest cover almost all trees and crops, thus causing huge losses to the ecological environment as well as to the economy and society. Recent focus has been turned to the study of biological characteristics and occurrence regularity, of the fall webworm, as well as to that of biological control technology. Yang & Zhang (2007) developed an integrative biological control technique, which attained excellent control result without having influence on environment and biodiversity. Zhao et al. (2007) researched the evaluation of non-economic loss after fall webworm's invading China. Liu et al. (2012) used amplified fragment length polymorphism (AFLP) to analyse the genetic diversity and genetic differentiation in eight populations. Fall webworm mainly occurs in parts of eastern China, but because of the complexity of China's geographical conditions and the variety of its climate, there exists a potential of extensive invasion, which would in turn bring about a potential of spreading. Few studies on the distribution of fall webworm have been conducted in China, and the monitoring of and warning against this kind of insect pest is restricted. The prediction of the potential distribution of fall webworm and corresponding analysis of the environmental conditions influencing the distribution, laying a foundation for making measures to effectively and scientifically manage this kind of insect pest.

At present, ecological niche models are widely used in prediction of species distribution, such as environmental envelope, ecological niche factor analysis (ENFA), genetic algorithm for rule-set production (GARP) and maximum entropy (MaxEnt), etc. (Zhu 2013). There are researches that have suggested that an application of the MaxEnt model to the prediction of potential species distribution can bring about a result better than that achieved with an application of other prediction models of its kind, especially when there is a lack of sufficient data of species distribution (Yang et al. 2013).

With occurrence records of fall webworm in China, combined with environmental conditions of the occurrence sites, this paper applied the MaxEnt model to predict the potential geographic distribution of fall webworm in China, divides suitable areas into different grades, and analyses the dominant environmental factors that influence the distribution of this insect. Based on an analysis and judgement of the fitting effect of the MaxEnt model on fall webworm's geographic distribution, different climate change contexts in the future were closely examined, in an effort to predict the tendency of geographical distributions of fall webworm in China.

MATERIALS AND METHODS

Species Data

The species data of fall webworm derived from the Agriculture Pests Information System (http://pests.agridata.cn/), from the monitoring and investigation statistics by the Forest Disease and Pests Prevention Station (http://www.forest-pest.org/) affiliated to the State Forestry Administration, and from disclosed reports on the occurrence sites of fall webworm in China from the State Forestry Administration. Data of fall webworm disasters known to have occurred in the county and city levels are sifted, and the occurrence records between 2011 and 2016 were obtained. With the data on the county level as a minimum unit, the occurrence sites of fall webworm were defined. Google Earth was applied to gain the longitude and latitude coordinates of the geometrical center of fall webworm occurrence sites; repeated coordinates as well as occurrence sites with unspecific geographical coordinates were removed. Two hundred and sixteen copies of species data were finally sorted out, which consisted of such accurate information as pest names, longitudes and latitudes, and were saved in a .csv format.

Environmental Variables

Environmental variables in this paper involve climate variables and geographical ones. Data of climate variables, between the year of 1950 and 2000, came from the database of WorldClim(http://worldclim.org/) at the University of California, Berkeley, with a spatial resolution of 303 (about 1 km). Climate variables, including its 19 bioclimatic variables related to the life history of insects, are more applicable to the simulation and prediction of potential geographic distributions for insects. Geographical data originated from the data set of China's Digital Elevation Model with a resolution of 1 km, released by the National Earth System Science Data Infrastructure (http://westdc.westgis.ac.cn/). Altitude data of the investigated region were extracted with an application of Asia North Albers Equal Area Conic in ArcGIS 10.0. Slope and aspect algorithms in the module of the Surface of the Spatial Analyst Tools were used to extract corresponding data, with the aspect of due north set at 0° and due south at 180°. Twenty two environment variables were finally obtained (Table 1).

Table 1: 22 environmental variables used to predict the distribution of fall webworm.

Environmental variables	Code
Annual mean temperature	bio1
Mean diurnal temperature range	bio2
Isothermality (bio2/bio7)	bio3
Temperature seasonality (Standard Deviation)	bio4
Max temperature of the warmest month	bio5
Min temperature of the coldest month	bio6
Temperature annual range (bio5-bio6)	bio7
Mean temperature of the wettest quarter	bio8
Mean temperature of the driest quarter	bio9
Mean temperature of the warmest quarter	bio10
Mean temperature of the coldest quarter	bio11
Annual precipitation	bio12
Precipitation of the wettest month	bio13
Precipitation of the driest month	bio14
Precipitation seasonality	bio15
Precipitation of the wettest quarter	bio16
Precipitation of the driest quarter	bio17
Precipitation of the warmest quarter	bio18
Precipitation of the coldest quarter	bio19
Altitude	alt
Slope	slo
Aspect	asp

Apart from the current climate, future climate scenarios (in 2050) also applied the BCC-CSM (Beijing Climate Center Climate System Model), which is developed by China's National Climate Center and released by the database of WorldClim. This model is highly accurate in the simulation and prediction of such variables as temperature and precipitation, which has been widely applied (Lin & Zhou 2015). Future climate scenarios cover four representative concentration pathways (RCPs), among which RCP4.5 and RCP6 represent the scenario of the intermediate greenhouse gas concentration, the former with a priority higher than the latter (Moss et al. 2010). Three RCPs, including RCP2.6, RCP4.5 and RCP8.5, are finally selected, representing the scenario of the concentration of greenhouse gas with low, medium and high levels.

Research Methods

The principle: Entropy is a parameter describing the randomness of objective things, representing their degree of uncertainty. According to the principle of maximum entropy, everything, if not influenced by external forces, tends to develop toward the most random and uncertain direction. Under the condition that only part of the information about the unknown distribution is commanded, inference of unknown probability distribution is the most random and uncertain one made under the restriction of already-known information. When the entropy value reaches the maximum level, the probability distribution is closest to the real one, and any other choice would mean other added restrictions and assumptions, which cannot be drawn from the already-commanded information. Based on this principle of maximum entropy and the theory of ecology, MaxEnt can be applied to the study of ecology (Phillips et al. 2006). In this paper, the investigated regions are divided into finite pixel sets, named X. Each pixel $x \in X$ is allocated with one non-negative probability value p(x), representing the living suitability index in a pixel of fall webworm. The sum of the probability values of all pixels is 1. In this way, the probability distribution of the investigated regions, home to fall webworm, named π is established; π is unknown. According to the principle of maximum entropy, the probability distribution *p* is closest to the real one when the entropy value hits the maximum level. The solution of *p* necessitates the setting of conditions that restrict *p*. What information is commanded about the unknown π is that of the historical distribution of fall webworm as well as that of the environment around the distribution points. A characteristic function $f_x(...)$, therefore, is constructed to represent the environmental factor. Characteristic functions vary in forms, and the one adopted in this research is as follows:

$$f_x(\dots) = \gamma_1 f_1 + \gamma_2 f_2 + \gamma_3 f_3 + \dots + \gamma_i f_i \quad ...(1)$$

Where, γ is a group of parameters, and f_i refers to the value of the *i* environmental variable in the region of the pixel *x*. The already-known information can be expressed as the mean value of the characteristic function of fall webworm distribution:

$$e = \frac{1}{m}\sum_{1}^{m} f_{x_i}(\dots) \quad ...(2)$$

Where, *m* refers to the occurrence time of fall webworm, and $f_{xi,}$ is the characteristic function of the pixels experiencing the *i* fall webworm occurrence. The environmental factor expectation E = $E = \sum_{x \in X} p(x) f_x(\dots)$, of the distribution *p*, should be infinitely close to *e*. The constraint conditions of *p*, therefore, should be $|e - E| < \beta$, in which β is an arbitrarily small positive constant. Della et al. (1997) have proven that the maximum entropy distribution is commonly in such a form:

$$p(x) = \frac{e^{f_x(\dots)}}{Z} \quad ...(3)$$

Where, *p* is the probability value of the *x* pixel, and *z* is a constant ensuring that the sum of the probability values of all pixels is 1. With the canonical transformation, constraint conditions can produce a minimum value for the following expression:

$$\ln Z_\lambda - \frac{1}{m}\sum_{1}^{m} f_{x_i} + \sum_{j} \beta_j \lambda \quad ...(4)$$

Where, *m* refers to the historical occurrence times of fall webworm, λ is a group of parameters in the characteristic function, and β_j is an arbitrarily small positive constant. This expression is named log loss. When the parameter λ is defined to produce a minimum value of the log loss, the maximum entropy probability distribution *p* can then be determined. The MaxEnt model applies the continuous iterative algorithm, one of the classical algorithms in machine language acquisition, to define the coefficient λ. At the start of the iteration, the coefficient λ is endowed with an initial value λ =(0,0…0); that is, the function of each environment variable is the same. The value of λ should be adjusted continuously to decrease the value of the equation above; and the iteration should be stopped when the iteration times reach those designated by the user or when the value of the log loss does not become smaller in a significant way. The now λ value is the final one.

Initial model construction: The species data and the data of environmental variables between the year of 1950 and 2000 were imported into MaxEnt 3.3.3k (Phillips et al. 2006), to construct the maximum entropy model of geographic distribution for fall webworm. The algorithm should be repeated 10 times, and the mean simulation results should be exported. ROC curve should be applied to analyse the accuracy of the model.

Sifting of dominant environmental factors: Based on the contribution rate of each environmental variable on the geographic distribution of fall webworm, this paper proposed that dominant environmental factors are major contributors to the distribution. The species data and the data of dominant environmental factors (from the year 1950 to 2000) were used to reconstruct the MaxEnt model and to evaluate the accuracy of the reconstructed model. Afterwards, we compared the accuracies of initial model based on all environmental variables and reconstructed model based on dominant environmental factors, the model of higher accuracy were chosen to predict.

Grading of living suitability: The results of the MaxEnt Model should be loaded in ArcGIS 10.0, and the classification method of Natural Breaks should be adopted to reclassify the generated raster data. According to the values of *p*, which represents living suitability index of fall webworm in this paper, the study area should be divided into five grades in ascending order, including the unsuitable area (0

Table 2: AUC values of MaxEnt model of fall webworm distribution in China.

	AUC	
	Based on 22 environmental variables	Based on dominant environmental factors
Fall webworm	0.907	0.921

Table 3: Dominant environmental factors for fall webworm distribution.

Dominant environment factors	Contribution rate (%)	Cumulative contribution rate (%)
Precipitation of warmest quarter	24.5	24.5
Altitude	24.4	48.9
Mean temperature of coldest quarter	20.5	69.4
Temperature seasonality (standard deviation)	9.2	78.6
Temperature annual range	3.7	82.3

$\leq p \leq 0.08$), low suitable area ($0.08 \leq p \leq 0.24$), moderate suitable area ($0.24 \leq p \leq 0.40$), high suitable area ($0.40 \leq p \leq 0.55$) and extremely high suitable area ($0.55 \leq p \leq 0.81$).

Forecast of distributions under different climate scenarios: Climate change, especially the changes in temperature and precipitation, will transform the change law of species population on habitats. The changes in temperature and humidity are inextricably related to the life history of fall webworm, and therefore, climate change could exert influence on the disaster caused by this insect, triggering changes to the current disaster distribution. Based on the model we chose, the climate model of BCC-CSM was adopted, and the climate data associated with the life history of insects under the three scenarios of greenhouse gas concentration (RCP2.6, RCP4.5 and RCP8.5) were chosen to form future environmental variables, in an effort to predict the future geographic distributions for fall webworm.

RESULTS

Model accuracy evaluation: The receiver operating characteristic (ROC) curve analysis can reflect the prediction accuracy of the model, which relies on the accuracy of the model based on non-threshold value, using 1-specificity or false positive rate as abscissa and the sensitivity or true positive rate as ordinate to draw curves. The value of area under the ROC curve (AUC) can be a good illustration of the accuracy, which ranges [0, 1]. The larger the AUC value is, the better the model represents the prediction effect. Thus, the evaluation criteria of ROC curve can be divided into 5 levels based on the AUC values, failure (0.50 ~ 0.60), less (0.60 ~ 0.70), general (0.70 ~ 0.80), preferably (0.80 ~ 0.90), very good (0.90 ~ 1.0) (Wang et al. 2007). The results showed (Table 2), the AUC value of the model based on 22 environmental variables is 0.907, the AUC value of model based on dominant environmental factors is 0.921. Both two models have achieved very good prediction results, indicating that the MaxEnt model can be used for simulation and prediction of the geographic distribution. Moreover, it can be obtained that model based on dominant environmental variables has better performance in prediction, hence we choose this model to predict current and future geographic distributions of fall webworm.

Analysis of dominant environmental factors: Table 3 shows the single and cumulative contribution rate of the top 5 environmental variables which influence the distribution of the fall webworm. According to the contribution rate of the order of descending sort: precipitation of warmest quarter (24.5%), altitude (24.4%), mean temperature of coldest quarter (20.5%), standard deviation of temperature seasonality (9.2%) and temperature annual range (3.7%). Cumulative contribution rate of these variables reach 82.3%, more than 80%, which indicates that these variables are the dominant environmental factors affecting the distribution of the fall webworm.

The results reveal that the precipitation of the warmest quarter is related to the distribution of fall webworm. This may be a result of the fact that this insect favours a climate that is wet with a high temperature, and the most favourable climate environment is one that has a relative humidity of 70% to 80%, as well as a temperature lower than 22~25°C (Yaroshenko 1975). With the lowering of temperature, the death rate tends to grow gradually; and when the relative humidity hits 5%, the death rate remains at 10%, regardless of the temperature. A temperature of 24°C and a relative humidity of 75.5% are close to the natural environment, which are suitable for development (Zhang 1979). Furthermore, Kong (2010) found in her study that there is no significant difference in the hatching rate of eggs when the

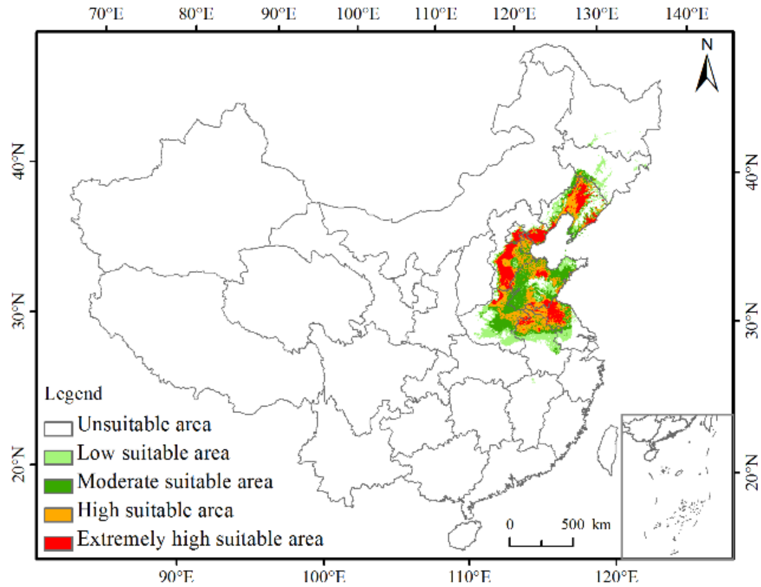

Fig. 1: Predicted current geographic distribution of fall webworm.

temperature ranges from 25°C to 32°C, and that when the relative humidity reaches 75% to 80%, the hatching rate can amount to 96% or above. Altitude, in addition, is another key factor that influences the distribution of fall webworm, possibly because it is inextricably related to the spatial distributions of water and vegetation. Altitudes with a small altitude difference can exert huge influence on the flow direction and flow amount of the regional ecological water supply every year; some regions could face the risk of failing to get any ecological water supply, because of nuance of altitudes, which would indirectly impact the growing and distribution of vegetation, so that parts of the habitats of fall webworm would be influenced, directly or indirectly (Liu & Shen 2011). Mean temperature of the coldest quarter is the third contributor to the distribution of fall webworm. Tian & Wang (2007) found that the lowest temperature of a region is the major obstacle to the survival of fall webworm. One study has also detected that the super-cooling points of female pupae of fall webworm before the overwintering period, during the overwintering period and after the overwintering period are -24.23 ± 0.31°C, -24.59 ± 0.34°C, and -10 ~ -25°C, respectively. The freezing points of female pupae before the overwintering period, during the overwintering period and after the overwintering period are -10.95 ± 0.69°C, -12.90 ± 0.44°C and -13.3 ± 3.29°C, respectively. The super-cooling points of the male pupae before the overwintering period, during the overwintering period and after the overwintering period are -24.28 ± 0.48°C, 24.26 ± 0.54°C and -18 ~ -25°C, respectively. The freezing points of male pupae before the overwintering period and after the overwintering period are -10.78 ± 0.69°C and -16.87 ± 1.43°C, respectively, with an average temperature between -10°C and -20°C (Ju et al. 2009). Moreover, a series of indoor measurements and outdoor investigations in the years of 2010 and 2011 suggested that the survival rate of fall webworm lowers with the prolonging of the processing time under different low temperatures (Kong 2010).

The predicted geographic distributions of fall webworm: The dominant environmental factors, combined with the maximum entropy model simulation as well as the grading standard of living suitability, the predicted current geographic distribution of fall webworm in China is presented in Fig. 1. It can be seen that the fall webworm is mainly distributed in Liaoning, the Beijing-Tianjin-Hebei region, most parts of the north China Plain as well as scattered in Inner Mongolia and Jiangxi in a few areas. Especially, the extremely high suitable area concentrated in the central and northern Hebei, central Liaoning, central and southern Shandong, northern Jiangsu and eastern Henan, the natural environmental conditions of which is very suitable for the growth and development of the fall webworm, and therefore can be concluded that these areas are more prone to the serious pests. According to the forest pest monitoring and pro-warning report yearly in China between 2011 and 2016, China's statistics in the fall webworm severe disaster frequency with city as unit showed the in areas mentioned above, have pests occurred every year, indicating that this model is relatively accurate.

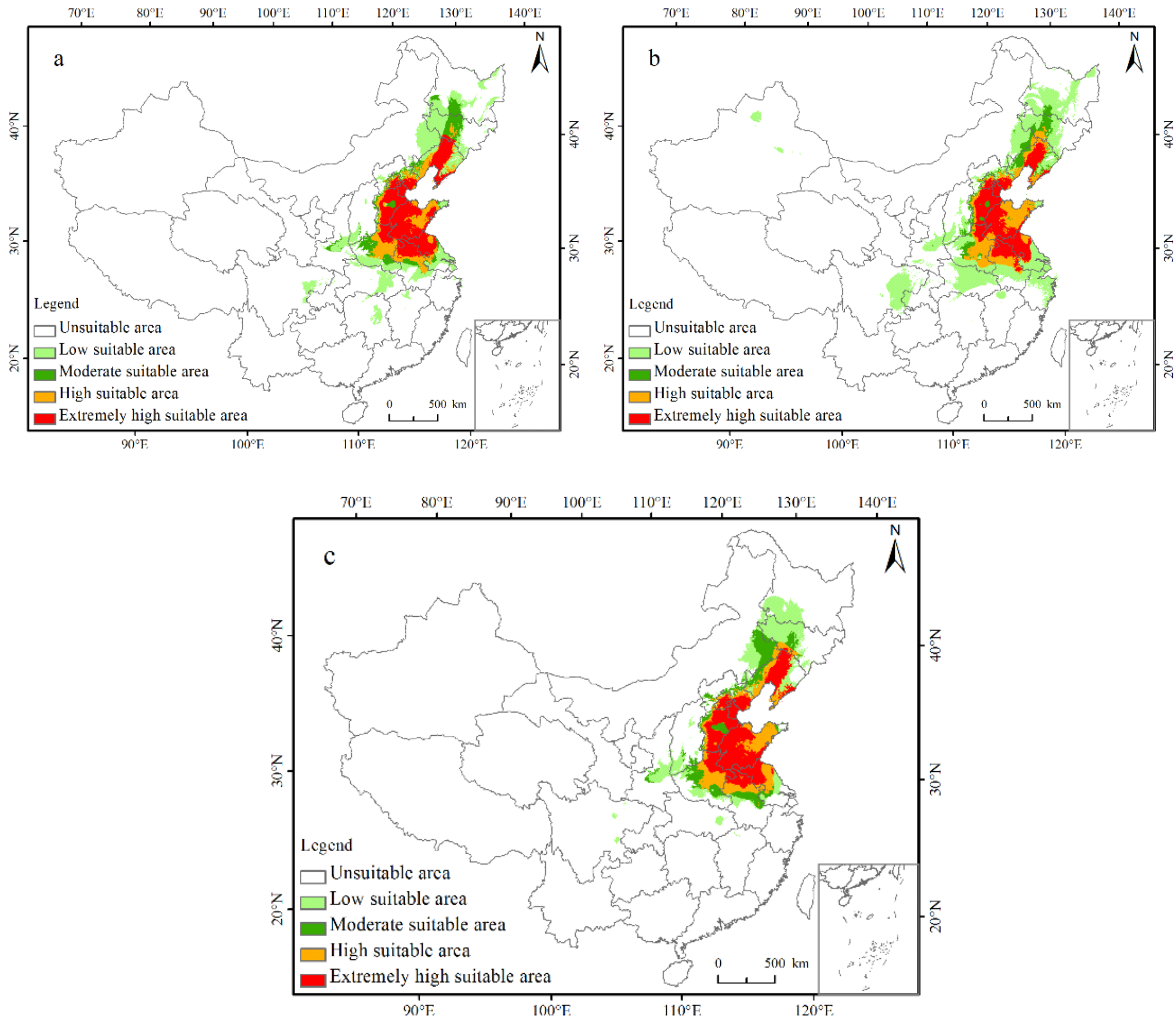

Fig. 2: Predicted future geographic distributions of fall webworm under climate change. a: Under RCP2.6 in 2050. b: Under RCP4.5 in 2050. c: Under RCP8.5 in 2050.

Fig. 2a, 2b and 2c represent, respectively, the three prediction results achieved in the contexts of the three RCPs (RCP2.6, RCP 4.5 and RCP 8.5) of the BCC-CSM climate model in 2050. In different contexts in the future, the area of fall webworm's geographic distribution in China would significantly expand towards the north. Such a result confirms that global warming would lead to an expansion of insects toward the two poles as well as regions with a high altitude. Global warming offers more opportunities to insects limited by low temperatures to expand toward the two poles and regions with a high altitude (Harrington et al. 2007). Fig. 2a indicates that in the context of RCP2.6 in 2050, the geographic distribution of fall webworm would spread towards the north, to the southern part of Heilongjiang province, and that new distribution areas could include Hubei, Hunan, Sichuan and Shaanxi. Fig. 2b reveals that in the context of RCP4.5, the geographic distribution of fall webworm would spread towards the north, to the central part of Heilongjiang province, and that the distribution areas in Hubei and Sichuan Basin have the potential to expand. It is also worth noticing that the Junggar Basin, the coldest of places in the same latitudes in China in the winter period, is also scattered with distribution areas. Fig. 2c shows that in the context of RCP8.5, the distribution pattern of fall webworm is more compact, compared with the former two, a small-scale expansion is taking place around the extremely high suitable area.

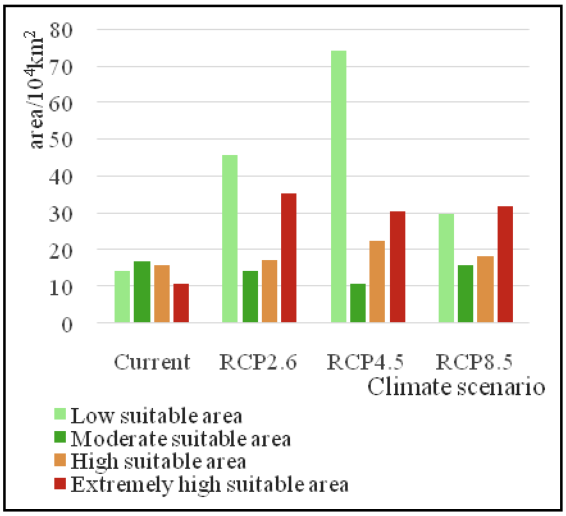

Fig. 3: Area of each suitable area under different climate scenarios.

Using the spatial analysis method of ArcGIS 10.0 to calculate the total area and the proportion of each area at different grade, total distribution area of the fall webworm is 580,100 km^2 within the current, under RCP2.6, RCP4.5 and RCP8.5 scenario, the total distribution area is respectively 1,126,600 km^2, 1,379,000 km^2 and 959,600 km^2 (Fig. 3).

DISCUSSION

MaxEnt model is widely used in simulating and predicting the species distributions with presence-only data in recent years. The paper based on the use of MaxEnt model, predicted the current and future potential geographic distributions under different climate scenarios of fall webworm, and visualized the outputs of MaxEnt and graded for the suitable area. Furthermore, the paper detected dominant environmental factors affecting the distribution. The results indicate that fall webworm is mainly distributed in the eastern coastal areas and scattered in Inner Mongolia and Jiangxi in a few areas in current. The natural environmental conditions of these areas are: rain heat over the same period, higher relative humidity as well as no extreme low temperature, which is in conformity with the requirements of the dominant environmental factors. Climate change, especially the temperature rise makes the distribution boundaries of fall webworm northward, and the distribution area will be expanded. These results have important theoretical and practical reference values for the control and prevention of China's fall webworm pests.

In the future, a smaller-scale prediction of the distribution of fall webworm can be carried out, and other distribution-related factors, such as interspecific relationship, adaptability, management measures, forest fires, natural enemies, and socio-economic development levels can be included into the model, so that the prediction result can be more precise and it can provide an important reference value for the monitoring and control of insect pests.

REFERENCES

Della, P.S., Della, P.V. and Lafferty, J. 1997. Including features of random fields. IEEE Transactions on Pattern Analysis and Machine Intelligence, (19): 380-393.

Harrington, R., Clark, S.J., Welham, S.J., Verrier, P.J., Denholm, C.H., Hullé, M., Maurice, D., Rounsevell, M.D. and Cocu, N. 2007. Environmental change and the phenology of European aphids. Global Change Biology, 13: 1550-1564.

Ju, Z., Li, M.G., Diao, Z. and Xu, Y.Y. 2009. Super-cooling ability and its relations to body's water and fat contents of overwintering *Hyphantrian cunea* (Lepidoptera: Arcidae) pupae. Chinese Jounal of Applied Ecology, 20(11): 2763-2767.

Kong, X.H. 2010. Effect of extreme temperatures on survival, development and growth of *Hyphantria cunea*. Shandong, China: Shandong Agriculture University.

Lin, R.P. and Zhou, T.J. 2015. Reproducibility and future projections of the precipitation structure in East Asia in four Chinese GCMs that participated in the CMIPS experiments. Chinese Journal of Atmospheric Sciences, 39: 338-356.

Liu, J., Li J., Chen, M., Luo, Y.Q. and Tao, J. 2012. Genetic diversity of *Hyphantria cunea* populations in China by AFLP analysis. Journal of Beijing Forestry University, 34(4): 107-113.

Liu, Y. and Shen, Z.H. 2011. The altitudinal pattern of insect species richness in the three Gorge reservoir region of the Yangtze River: effects of land cover, climate and sampling effort. Acta Ecologica Sinica, 19: 5663-5675.

Moss, R.H., Edmonds, J.A., Hibbard, K.A., Manning, M.R., Rose, S.K., van Vuuren, D.P., Carter, T.R., Emori, S., Kainuma, M., Kram, T., Meehl, G.A., Mitchell, J.F.B., Nakicenovic, N., Riahi, K., Smith, S.J., Stouffer, R.J., Thomson, A.M., Weyant, J.P. and Wilbanks, T.J. 2010. The next generation of scenarios for climate change research and assessment. Nature, 463: 747-756.

Phillips, S.J., Anderson, R.P. and Schapire, R.E. 2006, Maximum entropy modeling of species geographic distributions. Ecological Modelling, 190: 231-259.

Tian, X.W. and Wang, X.L. 2007. Occurring regularity and integrated control of *Hyphantria cunea*. Northern Horticulture, 12: 230-231.

Wang, Y.S., Xie, B.Y., Wan, F..H., Xiao, Q.M. and Dai L.Y. 2007. Application of ROC curve analysis in evaluating the performance of alien species' potential distribution models. Biodiversity Science, 43(10): 71-76.

Yang, X.Q., Kushwaha, S.P.S., Saran, S., Xu J.C. and Roy, P.S. MaxEnt modeling for predicting the potential distribution of medicinal plant, *Justicia adhatoda* L. in Lesser Himalayan foothills. Ecological Engineering, 51: 83-87.

Yaroshenko, V.A. 1975. Particulars of the flight of the American white butterfly. Zashchita Rastenii, 11: 53.

Yang, Z.Q. and Zhang, Y.A. 2007. Researches on techniques for biocontrol of the fall webworm, *Hyphantria cunea*, a severe invasive insect pest to China. Chinese Bulletin of Entomology, 44(4): 465-471.

Zhang, S.F. 1979. Fall webworm- one kind of plant quarantine insects should be vigilant. Plant Quarantine, 02: 18-27.

Zhang, X.X. and Wang, Z.J. 2009. Research progress on the *Hyphantria cunea* (Drury) of alien invasive species. Journal of ANHUI Agricultural Sciences, 37(1): 215-219.

Zhao, T.Z., Gao, L., Ke, S.F. and Wen, Y.L. 2007. Establishment on the loss evaluation index system of *Hyphantria cunea* Drury's invading China. Journal of Beijing Forestry University, 29(2): 156-160.

Zhu, G.P., Liu, G.Q. and Bu, W.J. 2013. Ecological niche modeling and its applications in biodiversity conservation. Biodiversity Science, 21(1): 90-98.