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Predicting the potential geographic distribution of cotton mealybug *Phenacoccus solenopsis* in India based on MAXENT ecological niche Model

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Abstract

Mealybug, *Phenacoccus solenopsis* Tinsley has recently emerged as a serious insect pest of cotton in India. This study demonstrates the use of Maxent algorithm for modeling the potential geographic distribution of *P. solenopsis* in India with presence-only data. Predictions were made based on the analysis of the relationship between 111 occurrence records for *P. solenopsis* and the corresponding current and future climate data defined on the study area. The climate data from worldclim database for current (1950-2000) and future (SRES A2 emission scenario for 2050) conditions were used. DIVA-GIS, an open source software for conducting spatial analysis was used for mapping the predictions from Maxent. The algorithm provided reasonable estimates of the species range indicating better discrimination of suitable and unsuitable areas for its occurrence in India under both present and future climatic conditions. The fit for the model as measured by AUC was high, with value of 0.930 for the training data and 0.895 for the test data, indicating the high level of discriminatory power for the Maxent. A Jackknife test for variable importance indicated that mean temperature of coldest quarter with highest gain value was the most important environmental variable determining the potential geographic distribution of *P. solenopsis*. The approaches used for delineating the ecological niche and prediction of potential geographic distribution are described briefly. Possible applications and limitations of the present modeling approach in future research and as a decision making tool in integrated pest management are discussed.

Key words

DIVA-GIS, Entropy, *Phenacoccus solenopsis*, Potential distribution

Introduction

Recently, the emergence of new or invasive insect-pests is quite frequent due to certain anthropogenic changes to agro-ecosystems such as agricultural intensification, international trade, habitat fragmentation and climate change. The temperature alterations due to global climate warming have been predicted to affect significantly the geographic distribution and abundance of insect pests of agriculturally important crops (Bale *et al*., 2002, IPCC, 2007). Consequently, the pests of minor importance earlier, are now assuming the status of economically important pests in many parts of the world. India, during the last decade, has witnessed an increased build-up of various mealybug species in crop plants and in wild. The so called cotton mealybug *Phenacoccus solenopsis* Tinsley (Hemiptera: Pseudococcidae) is one such recent example known to cause large scale epidemics in the Indian cotton growing belt during 2005-09. *P. solenopsis* is an exotic species native to USA which was hitherto not reported to occur in India. It has accidentally entered and spread throughout the country causing devastation, both in Bt and non-Bt cotton crops, where crop losses ranged between 30 to 40% (Dhawan *et al*., 2007). After its first documentation in 2005 in North-Western parts of Gujarat State (Jhala *et al*., 2008), now appears to be widespread in almost all cotton growing states of India (Nagrare *et al*., 2009). Meanwhile, *P. solenopsis* was also reported to infest several other crops of economic importance such as okra, chilli, brinjal, tomato, ornamentals like *Hibiscus rosa-sinensis* L., and weeds as well

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(Vennila *et al*., 2010). *P. solenopsis* has been the major focus of researchers because of its invasiveness and rapid spread across India within a short period of time.

Early predictions on the pest distribution and abundance through forecasting models could facilitate better preparedness to combat outbreaks of serious insect pests by developing effective pest management strategies well in advance. Ecological niche modeling is one such suitable approach to predict potential geographic distribution and spread of agricultural pests. Availability of computer-aided modelling tools and algorithms integrated or coupled with Geographic Information System (GIS), such as MAXENT (Phillips *et al*., 2006), and DIVA-GIS (Hijmans *et al*., 2005a) have facilitated better understanding of spatial patterns of species spread in relation to climatic conditions. Geostatistical functions integrated in GIS allow predicting and mapping the trends of potential changes in geographical distribution of invasive insect pests (Liebhold *et al.,* 1993). DIVA-GIS and MAXENT have been successfully employed in a wide range of situations for ecological modeling and predictions. MAXENT is an open source computer-aided tool (downloadable at *http://www.cs.princeton.edu/~schapire/Maxent*) which is extensively used in predicting species geographic distribution. It estimates probability values which represent the suitability or unsuitability of a location for presence of the species, based on the relationship between presence points and climatic conditions. Maxent is used in present study because it is one of the best among many different modeling programmes, and estimates probability distribution for species occurrence even with small sample sizes (Phillips *et al*., 2006; Elith *et al*., 2011). DIVA-GIS is also an open source computer programme (downloadable at *http://www.diva-gis.org*) used for mapping and analysing spatial data.

Climatic variables, especially temperature and rainfall patterns are known to play key role in population dynamics and local abundance of *P. solenopsis* (Jeyakumar *et al*., 2009; Saroja *et al.,* 2009). With present modeling approach, the gradients of habitat suitability identified for the occurrence of *P. solenopsis* were further related to the spatial distribution of its main host crop *i.e* cotton by masking the prediction maps using a shape file of the cotton growing areas. An attempt was made to predict the potential geographical spread of the pest in the context of changing climate so that the crop growers can be informed well in advance for undertaking timely prophylactic measures.

Materials and Methods

Pest occurrence data : The data on current distribution of *P. solenopsis* in India were compiled from published literature (Table 1). The data comprised of total of 111 occurrence records for *P. solenopsis*, 100 of which were from only nine major cotton growing states of India *viz*., Punjab (09), Haryana (06), Rajasthan (08), Gujarat (11), Madhya Pradesh (04), Maharashtra (31), Andhra Pradesh (09), Karnataka (09) and Tamil Nadu (12). Only 11 records for *P. solenopsis* occurrence were held from other states like West Bengal (08), Uttar Pradesh (01), Bihar (01) and Jharkhand (01), where cotton is grown on a very small scale. The administrative boundaries of study area (India) were digitized from a georeferenced image in DIVA-GIS and the places of occurrence of the pest were marked as presence-only points on a digitized map.

Environmental data : The climate data required for carrying out multiple analyses such as delineation of ecological niche, prediction of potential geographic distribution and impact of climate change on future distribution and spread were obtained from DIVA-GIS website (*http://www.diva-gis.org/climate*). The climate data at 2.5 arc-minutes resolution (~5 km at the equator) were used for making predictions on *P. solenopsis* habitat distribution. The current climate data comprised of derived values of monthly temperature and precipitation using long term time series from 1950 to 2000, from a global network. The future climate data were based on climate projections for the year 2050 under the SRES A_2 emission scenario downscaled from three different global circulation models (GCM): CCCMA, HADCM3 and CSIRO (Hijmans *et al.,* 2005b).

19 bioclimatic variables (BIOCLIM) were considered as potential predictors of *P. solenopsis* habitat distribution, based on their biological relevance to species distributions, habitat modeling and ability to define eco-physiological tolerance of species (Table 2). These climatic variables along with 111 presence records were used to establish the relationship between *P. solenopsis* habitat distribution and present climate conditions. The predictions were made based on the analysis of relationships between the presence-only data on current distribution of *P. solenopsis* and environmental variables defined on the study area.

Modeling software : Maxent (Maximum Entropy Species Modeling), a freely available software for predicting species geographic distribution (version 3.3.3e) was used in this study. Maxent estimates probability values which represent the suitability or unsuitability of a location for presence of the species based on the relationship between presence points and climatic conditions. The programme has different output formats like cumulative and logistic. In cumulative format, the output ranges from 0 (unsuitable) to 100 (highly suitable), and logistic format has values ranging from 0 to 1 which indicates habitat suitability ranging from low to high. Predictions from Maxent were mapped in DIVA-GIS (version 7.4), an open source computer programme for mapping and analysing spatial data.

Model fitting and interpretation : The algorithm was run with selected environmental variables, 111 presence-only points and a set of background values (pseudoabsences) drawn from the entire study region to determine the potential distribution. The

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Table 1 : Occurrence points for *Phenacoccus solenopsis* in India

State	Location	Longitude	Latitude	Reference
Punjab	Abohar	74°10' E	30°10' N	Dhawan *et al.* (2007); Nagrare *et al.* (2009); Tanwar *et al.* (2011); Sharma and Pati (2013)
	Mansa	75°23' E	29°59' N	
	Bathinda	75°00' E	30°11' N	
	Muktsar,	74°43' E	30°30' N	
	Faridkot	74°45' E	30°44' N	
	Firozpur	75°54' E	30°12' N	
	Sangrur	74°40' E	30°55' N	
	Ludhiana	75°54' E	30°55' N	
	Amritsar	74°52'E	31°38'N	
Haryana	Fatehabad	75°30' E	29°31' N	Nagrare *et al.* (2009); Pala and Saini (2010); Tanwar *et al.* (2011)
	Sirsa	75°1.12'E	29°31'N	
	Hisar	76° 23'E	29°19'N	
	Bhiwani	76°18'E	28°46'N	
	Jind	76° 26'E	29°48'N	
	Rohtak	75° 17'E	30° 01'N	
Delhi	New Delhi	77°12'E	28°38'N	Nagrare *et al.* (2009); Vennila *et al.* (2010); Tanwar *et al.* (2011)
Rajasthan	Kota	75°52'E	25°10'N	Nagrare *et al.* (2009); Vennila *et al.* (2010); Tanwar *et al.* (2011);Verma *et al.* 2011
	Hanumangarh	74°21'E	29°35'N	
	Sriganganagar	73°53'E	29°55'N	
	Ajmer	74°38'E	26°27'N	
	Jodhpur	73°01'E	26°14'N	
	Nagour	73°44'E	27°11'N	
	Pali	73°19'E	25°46'N	
	Alwar	76°37E	27°33'N	
Gujarat	Surendranagar	71°43'E	22°43'N	Jhala *et al.* (2008); Nagrare *et al.* (2009);Vennila *et al.* (2010);Tanwar *et al.* (2011)
	Rajkot	70°56'E	22°18'N	
	Porbandar	69°49'E	21°37'N	
	Junagarh	70°36'E	21°31'N	
	Amreli	71°15'E	21°36'N	
	Bhavnagar	72° 00'E	21°46'N	
	Ahmedabad	72°40'E	23°3'N	
	Anand	73° 00'E	22°32'N	
	Vadodara	73°16'E	22°00'N	
	Bharuch	73°01'E	21°41'N	
	Surat	72°49'E	21°11'N	
Madhya Pradesh	Indore	76°22'E	21°49'N	Nagrare *et al.* (2009); Vennila *et al.* (2010)
	Khandwa	75°50'E	22°44'N	
	Jabalpur	79°57'E	23°10'N	
	Devas	76°3'E	22°57'N	
Maharashtra	Akola	77° 02' E	20° 42'N	Nagrare *et al.* (2009); Vennila *et al.* (2010)
	Amravati	77° 48' E	20° 56' N	
	Aurangabad	75° 23' E	19° 53' N	
	Buldana	76° 14' E	20° 32' N	
	Dhule	74° 47' E	20° 58' N	
	Hingoli	77° 11' E	19° 43' N	
	Jalgaon	75° 40' E	21° 05' N	
	Jalna	75° 56' E	19° 51' N	
	Latur	76° 36' E	18° 24' N	
	Nagpur	79° 09' E	21° 09' N	
	Nanded	77° 27' E	19° 09' N	
	Beed	75° 50'E	19° 00'N	
	Gangakhed	76° 43' E	18° 52' N	
	Parbhani	76° 5' E	19° 08' N	
	Wardha	78° 39' E	20°45' N	

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	Washim	77° 10'E	20° 05' N	
	Yeotmal	78° 11' E	20° 23' N	
	Moregaon	77°44'E	19°20'N	
	Temburda	79°1'E	20°20'N	
	Warora	79°00'E	20°13'N	
	Sakoli	80°00'E	21°5'N	
	Jintur	76°41'E	19°36'N	
	Majalgaon	76°13'E	19°9'N	
	Georai	75°45'E	19°16'N	
	Parali	76°31'E	18°51'N	
	Bhokar	77°40'E	19°13'N	
	Deglur	77°34'E	18°32'N	
	Kandhar	77°11'E	18°52'N	
	Vasmat	77°9'E	19°19'N	
	Aundha Nagnath	77°2'E	19°32'N	
	Solapur	75°54'E	17°39'N	
Andhra Pradesh	Kurnool,	78° 05' E	15° 50' N	Nagrare *et al.* (2009); Vennila *et al.* (2010)
	Anantpur	77° 39'E	14° 41' N	
	Adilabad	78°30'E	19° 37' N	
	Karimnagar	79° 6'E	18° 28' N	
	Warangal	79° 40'E	17° 58' N	
	Amravati	80° 15'E	16° 50' N	
	Hyderabad	78° 30'E	17° 20' N	
	Guntur	80° 29'E	16° 18' N	
	Shayampet	79°34'E	17°58'N	
Karnataka	Raichur	77°22'E	16°12' N	Hanchinal *et al.* (2011)
	Belgaon	74°34'E	15°52' N	
	Dharwad	75°05'E	15°27' N	
	Bijapur	75°47'E	16°50' N	
	Gulbarga	76°54'E	17°19' N	
	Bellary	76°55'E	15°9'N	
	Haveri	75°24' E	14°48'N	
	Hubly	75°7'E	15°21'N	
	Bengaluru	77°59'E	12°58'E	
Tamil Nadu	Coimbatore	77° 00'E	11°00'N	Nagrare *et al.* (2009); Suresh *et al.* (2010)
	Madurai	78° 10'E	9°58'N	
	Tirunelvelli	77°44'E	8°44'N	
	Ramnathpuram	78° 50'E	9° 22' N	
	Cuddalore	79°44'E	11°24"N	
	Virudhanagar	78°1'E	9°52"N	
	Kanyakumari	77°55'E	8°08'N	
	Dindugal	77°3'E	10°05'N	
	Chettikulam	77°07'E	10°09'N	
	Trichy	77°45'E	11°3'N	
	Salem	77°62'E	11°6'N	
	Pudukottai	77°82'E	10°38'N	
West Bengal	Mohanpur	87°25'E	21°50'N	Satpathy *et al.* (2009)
	South 24 Parganas	88°22'E	21°51'N	
	Noth 24 Parganas	88°42'E	22°42'N	
	Murshidabad	88°16'E	24°10'N	
	Nadia	88°33'E	23°28'N	
	Burdman	87°37'E	23°27'N	
	Hoogley	88°24'E	22°53'N	
	Barrackpore	88°23'E	22°46'N	
Jharkhand	Namkum	85o22'E	23°19'N	Anonymous (2013)
Bihar	Pusa	85°40'E	25°59'N	Tanwar *et al.* (2008)
Uttar Pradesh	Varanasi	82°58'E	25°19'N	Anonymous (2012)

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available occurrence data of *P. solenopsis* was divided randomly into two parts to create quasi-independent data for model testing and validations (Fielding and Bell, 1997). The 75% of the data were used for model training and the remaining (25%) were used for model testing. Additionally, we also fitted model on full data set with 5-fold cross validation to estimate the errors around the fitted functions and to compare the model consistency. Maxent model was run with the following settings: auto features (feature types selected automatically based on the training sample size), output format = logistic (default output in Maxent), random test percentage = 25, regularisation multiplier = 1, maximum iterations = 1000, convergence threshold = 0.0001 and maximum number of background points = 10,000. The model was fitted to the current climate using default regularization parameters for estimation of the unknown probability distribution (species' potential distribution in present case) over a geographic region of interest (X). Individual elements of X *i.e.* $x_1, x_2, ..., x_m$ were taken as presence points for species occurrence and the environmental variables (f) defined on the X were $f_1, f_2, ..., f_n$. The maximum entropy of approximate probability distribution (ρ) was estimated in accordance with Phillips *et al.* (2006)

The model produced a set of probabilities presented as logistic transformations of cumulative thresholds with values ranging from 0 to 1(low to high suitability range) across the entire study area. A Jackknife test was used to measure the variable importance in model development and Receiver Operating Characteristic curve analysis (ROC) was used to assess the discriminative power of the model (Fielding and Bell, 1997; Phillips *et al.,* 2006; Elith *et al*., 2011). A ROC plot was built by plotting sensitivity (1- omission rate) against 1- specificity (fractional predicted area) for all available probability thresholds (Manel et al., 2001). The area under ROC curve (AUC), ranging from 0.5 to 1.0 was taken as a measure of model performance (Araujo *et al*., 2005). For discrimination of suitable and unsuitable areas, the threshold was applied by selecting the point on the ROC curve that was closest to the upper-left corner (0, 1), as it represents a perfect test with 100% sensitivity and specificity (Cantor *et al.*, 1999). The areas with probability values below the threshold were excluded from predictions. Predictions were mapped in DIVA-GIS. Further, the prediction map was masked using vegetation or land cover data. For this, the shape file of cotton growing areas was used as filter to obtain map which displays pest risk for cotton growing regions only, *i.e.* where *P. solenopsis* populations could establish according to the presence of its main host plant.

Analysis of climate change impact : The downscaled data of SRES A_2 emission scenario for the year 2050 (Hijmans et al., 2005b) was used to project future climatic conditions. The model was run for second time with same setting as above, except for the addition of future climate data in 'projection layer' directory option. The future changes in geographic distribution of *P. solenopsis* were predicted based on relationship established between its habitat distribution and present climatic conditions. While projecting, a Multidimensional Environment Similarity Surface (MESS) analysis was applied to find out 'Novel Climate Conditions' for the predicted range of *P. solenopsis.* The analysis finds out future climate values outside the range in current climate and also shows how similar each point is in future climate layers to conditions seen during model training at current climate, *i.e.* the degree of novelness (Phillips *et al*., 2006; Elith *et al*., 2010).

The binary rasters for the presence and absence of species potential distribution areas were generated in Maxent by applying same threshold as above, which limits the potential distribution area. Each binary raster has two values: presence (1) and absence (0) of the species. The rasters for current and future potential distribution areas were reclassified in DIVA-GIS by changing their cell values to 0, 1 and 0, 2 respectively. Using option grid overlay in DIVA-GIS, the cell values of two rasters were substracted by superimposing them to visualize the impact of climate change on *P. solenopsis* distribution (Scheldeman and van Zonneveld, 2010). The grid overlay generated four categories of impact situations, *viz*., high impact zone, areas outside of the

Table 2 : Environmental variables used in Maxent ecological niche model

Variable	Variable type
Bio 1	Annual mean temperature
Bio 2	Mean diurnal range: mean of monthly (max temp – min temp)
Bio 3	Isothermality: (Bio 1/ Bio 7) x 100
Bio 4	Temperature seasonality (coefficient of variation)
Bio 5	Maximum temperature of warmest month
Bio 6	Minimum temperature of coldest month
Bio 7	Temperature annual range (Bio 5 – Bio 6)
Bio 8	Mean temperature of wettest quarter
Bio 9	Mean temperature of driest quarter
Bio 10	Mean temperature of warmest quarter
Bio 11	Mean temperature of coldest quarter
Bio 12	Annual precipitation
Bio 13	Precipitation of wettest month
Bio 14	Precipitation of driest month
Bio 15	Precipitation seasonality (coefficient of variation)
Bio 16	Precipitation of wettest quarter
Bio 17	Precipitation of driest quarter
Bio 18	Precipitation of warmest quarter
Bio 19	Precipitation of coldest quarter

Table 3 : Evaluation statistics *i.e.* values for area under ROC curve for training and test data for model run with 5-fold cross validation and random data partitioning

Data partition	Training AUC	Test AUC
P. solenopsis 1	0.933	0.920
P. solenopsis 2	0.940	0.884
P. solenopsis 3	0.943	0.838
P. solenopsis 4	0.929	0.884
P. solenopsis 5	0.938	0.874
***P. solenopsis* (75% : 25 %)**	**0.930**	**0.895**

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realized niche, low impact zone and potential new suitable zone.

Results and Discussion

For the present model, the fit as measured by area under ROC curve (AUC) was high with value of 0.930 for the training data and 0.895 for the test data, indicating better ability of the Maxent for discrimination between suitable and unsuitable areas for *P. solenopsis* occurrence (Fig. 1). The ROC analysis has been recognised as the best measure of model performance with wider applicability in species distribution modeling (Fielding and Bell, 1997; Phillips *et al*., 2006, Elith *et al*., 2011). The model run with random data partitioning with 75 % training data and 25 % test data has the highest AUC values for both training and test data (Table 3), and hence the results of this model only are discussed in this paper. The test of random partition applied to the occurrence data of *P. solenopsis* helped to minimise the substantial errors in predictions by creating two independent data sets (training and test data) for model validation (Fielding and Bell, 1997). The logistic threshold value of 0.256 represented a perfect test with 100 % sensitivity and specificity based on the point closest to the upper-left corner (0, 1) of the ROC curve, with fractional predicted area 0.216, trainingomission rate 0.084, and test omission rate 0.074 (Table 4). The algorithm developed for *P. solenopsis* distribution modeling in Maxent consistently performed significantly better than random; showing low omission of test localities with significant predictions for the potential geographic distribution of *P. solenopsis*. Low omission rates are crucial for precise discrimination of climatically suitable and unsuitable areas and to avoid under and over predictions about the species occurrence (Guisan and Thuliier, 2005), especially for invasive species like *P. solenopsis*. In order to avoid under and over fitting of the model which may give misleading predictions about the species distribution, the value of the regularization multiplier was kept as default of 1.0. Application of MESS analysis suggested no novel climate conditions exist for the predicted range of *P. solenopsis* (Phillips *et al*., 2006).

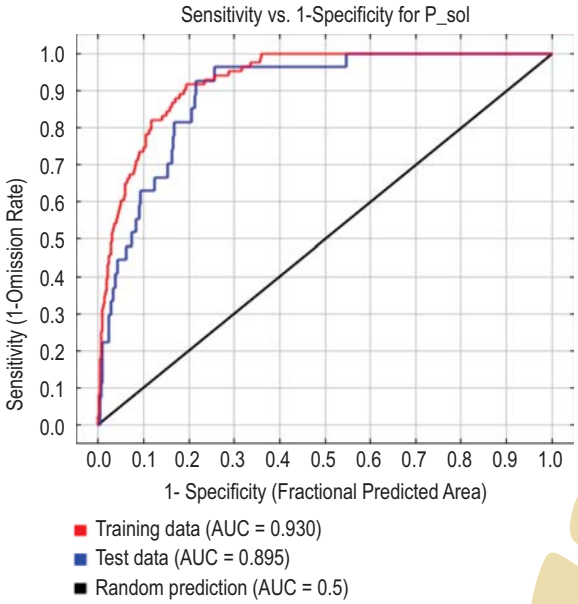

Fig. 1 : The receiver operating characteristics curve (ROC) for training and test data with the area under the ROC curve (AUC)

According to Jackknife test, the most important abiotic factor influencing the geographic distribution of *P. solenopsis* was Bio11 (mean temperature of coldest quarter); it had highest gain when used in isolation. The omission of Bio19 (precipitation of coldest quarter) as main explanatory variable decreased the gain of the model significantly, indicating its relative importance to other 18 bioclim variables in determining pest's potential distribution. Additionally, Bio 1(mean annual temperature), Bio 5 (maximum temperature of warmest month), Bio9 (mean temperature of driest quarter) and Bio 10 (mean temperature of warmest quarter) were also found influencing *P. solenopsis* distribution as well (Fig. 2). Climatic variables, especially the temperature and rainfall patterns are known to play a key role in population dynamics and local abundance of *P. solenopsis* (Jeyakumar *et al.*, 2009; Saroja *et al.*, 2009).

Table 4 : Test of omission with fractional predicted areas for *P. solenopsis* as modeled by Maxent

Logistic threshold	Description	Fractional predicted area	Training omission rate	Test omission rate	P-value
0.044	Fixed cumulative value 1	0.501	0.000	0.037	7.998E-7
0.119	Fixed cumulative value 5	0.370	0.000	0.037	8.779E-11
0.178	Fixed cumulative value 10	0.288	0.048	0.037	4.931E-15
0.127	Minimum training presence	0.359	0.000	0.037	2.893E-11
0.290	10 percentile training presence	0.189	0.096	0.185	4.514E-17
0.338	Equal training sensitivity and specificity	0.157	0.157	0.296	2.592E-15
0.285	Maximum training sensitivity plus specificity	0.193	0.084	0.185	1.371E-16
0.295	Equal test sensitivity and specificity	0.185	0.108	0.185	1.834E-17
0.256	**Maximum test sensitivity plus specificity**	**0.216**	**0.084**	**0.074**	**1.382E-19**
0.102	Balance training omission, predicted area and threshold value	0.396	0.000	0.037	8.322E-10
0.181	Equate entropy of thresholded and original distributions	0.286	0.060	0.037	3.26E-15

Maxent model predicted extensive areas for the occurrence of *P. solenopsis* almost throughout the Northern, Central and Southern regions which constitutes major cotton growing belts of India (Fig. 3). The most suitable areas were distributed in Punjab and Haryana states from North Zone; Gujarat and Maharashtra states from Central Zone; and Andhra Pradesh and Tamil Nadu states from South Zone. Severe losses in cotton crop (30-40 %) due to *P. solenopsis* infestation has been reported in states of Punjab (Dhawan *et al*., 2007), Haryana (Pala and Saini, 2010), Gujarat (Jhala *et al*., 2008), Maharashtra (Nagrare *et al.,* 2009), Andhra Pradesh (Nagrare *et al.,* 2009) and Tamil Nadu (Suresh *et al*., 2010), indicating high suitability of these areas for natural occurrence and abundance of *P. solenopsis*. Northern cotton growing area in Rajasthan, Madhya Pradesh, and South-Central Karnataka states were predicted as moderately suitable areas for occurrence of *P. solenopsis*. A moderate to high infestation of *P. solenopsis* in cotton was reported in Karnataka state (Hanchinal *et al*., 2010). Uttar Pradesh, Odisha and West Bengal, where cotton is grown on small scale were predicted as marginally suitable for *P. solenopsis* occurrence, whereas rest of the areas are predicted unsuitable.

The results of the Maxent model, when projected to the future climate scenario for the year 2050 suggested that, the current geographic distribution of the *P. solenopsis* in India will be significantly affected by the climate change (Fig. 4). The areas less or marginally suitable for natural occurrence of *P. solenopsis* at present climatic conditions will become more conducive with changing climate for rapid spread and multiplication of *P. solenopsis*. The areas predicted by model with high risk of future *P. solenopsis* invasion are far Western part of Gujarat, South Eastern Rajasthan, Northern Madhya Pradesh and extensive new areas from Gangetic Plains in Uttar Pradesh.

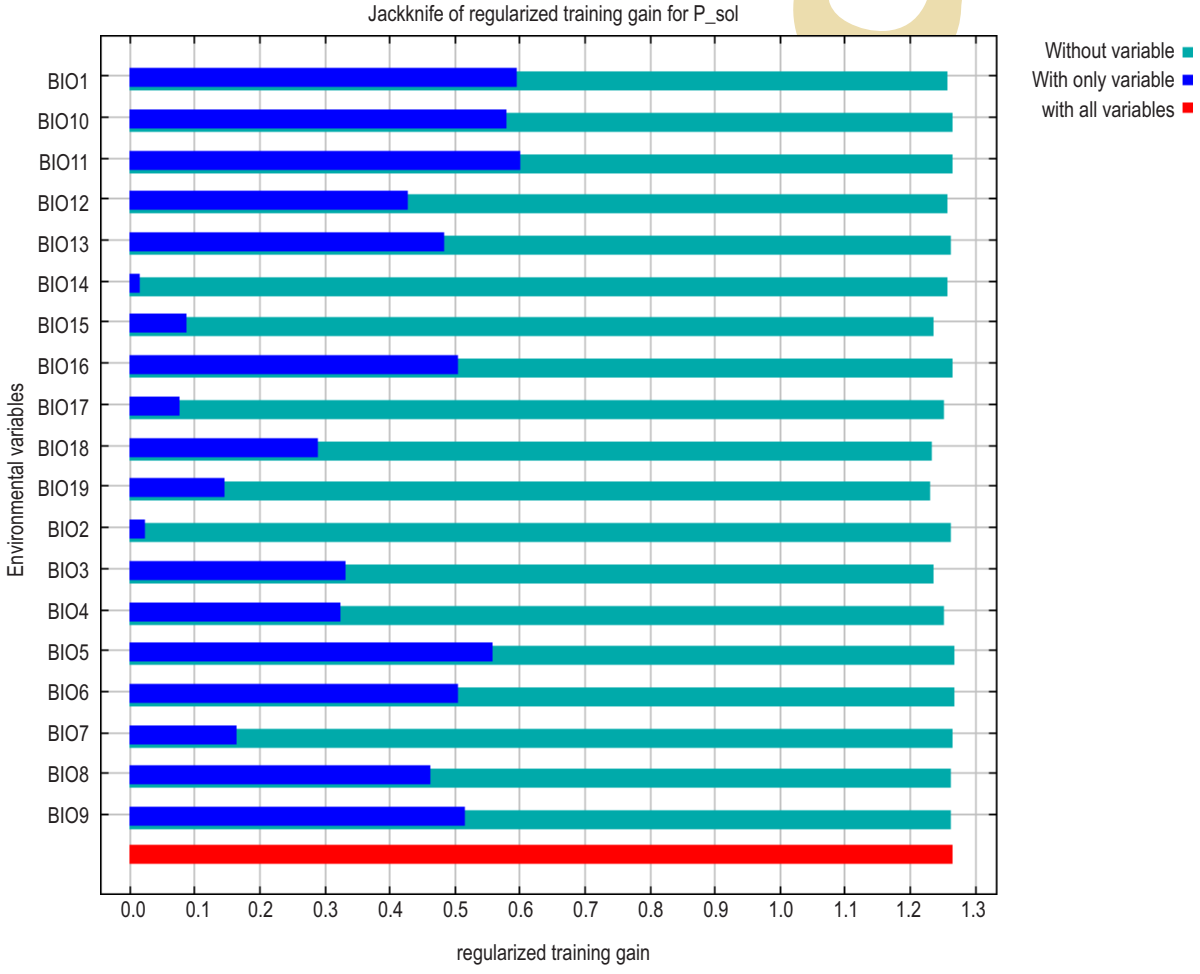

Fig. 2 : Jackknife test for relative importance of environmental variables in the development of the Maxent model

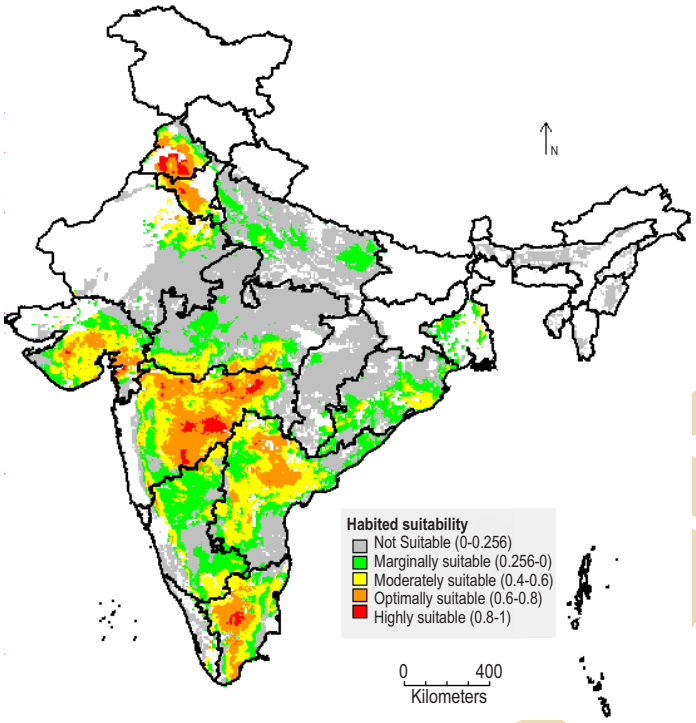

Fig. 3 : Habitat suitability for potential geographic distribution of *P. solenopsis* in cotton cropping areas of the country (Values ranging from low (0) to high (1)

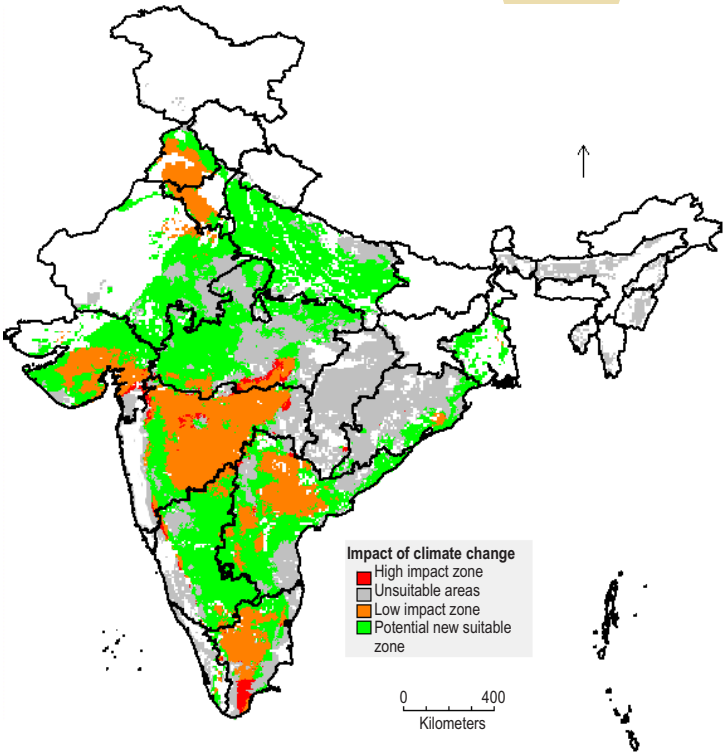

Fig. 4 : Impact of climate change on the future geographic distribution of *P. solenopsis*

The Maxent modeling approach was employed in present study because of certain merits it has over the others. It is one of the best among many different computer packages and estimates probability distribution for species occurrence with presence-only data and works well even with sample sizes as small as 10 (Phillips *et al*., 2006; Elith *et al*., 2011). Presence-only modeling represents the fundamental niche of the species that determines potential habitat suitability (Guisan and Thuliier, 2005). Considering the invasiveness of *P. solenopsis,* it was assumed to model the fundamental niche rather than realized niche in order to estimate maximum potential distribution of the pest. This will greatly help pest management authorities in making pest management decisions such as strict quarantine inspections of plants and planting materials to slow down the spread of injurious pests and timely provision of pest management information to the farmers from areas having high risk of future pest invasion.

The entire range of natural distribution of *P. solenopsis* was estimated by modeling in Maxent, which indicated extensive areas for its occurrence in India. The absence of *P. solenopsis* from geographical areas with environmental conditions favourable for its occurrence may be due to lack of sampling from those areas, certain dispersal limitations such as reproductive and or geographical barriers and human interferences preventing the species from occupying an area (Scheldeman and van Zonneveld, 2010). The present predictions are in agreement with Wang *et al*. (2010), who based on CLIMEX modeling, reported that *P. solenopsis* represents significant threat to agriculture and horticulture in most of the tropical and subtropical countries in the world.

The species distribution model developed with Maxent can be used to forecast the potential changes in the distribution and activity of *P. solenopsis* in response to global climate warming. The predictions made in this study will be of great help in developing effective management strategies for this destructive and polyphagous pest of cotton, vegetables and ornamentals of economic importance under Indian conditions. More specifically, such predictions will facilitate better preparedness to combat outbreaks of serious insect pests well in advance.

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