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Spatio and temporal variations in population abundance and distribution of peach fruit fly, *Bactrocera zonata* (Saunders) during future climate change scenarios based on temperature driven phenology model

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ABSTRACT

The peach fruit fly, *Bactrocera zonata* (Saunders) (Diptera: Tephritidae) is a poylphagous and serious insect pest of horticultural crops. The purpose of study was to understand the spatial and temporal variations in population abundance and distribution of *B. zonata* in response to climate change-based variations in temperature across the India. To examine the likely possibilities of changes in abundance and distribution of *B. zonata,* temperature driven process based phenology models were linked with climatic data of multiple General Circulation Model (eight models) and climate change scenarios (RCP 2.6, 4.5, 6.0 and 8.5) using the Insect Life Cycle Modeling (ILCYM) software. The risk indices (establishment, generation, and activity index) were mapped and quantified the changes in respect to locations, scenarios, models and times (2050 & 2070). The risk indices results revealed that, 1.73 (0.8–1.0 establishment risk), 14.15 (>16 high abundance) and 59.69% (>8.0 generation per year) area is projected to be highly suitable for *B. zonata* regarding establishment, abundance and generation indices, respectively in India under current climatic conditions. In spite of decreased permanent establishment (Establishment Risk Index > 0.6) in future climatic conditions, it is predicted that abundance and generation indices would increase in all the locations of the country. The variation in the results due to use of multiple GCM-scenario combinations suggested that choice of GCM and scenario combinations have impact on future prediction of the species. Overall, results indicate that *B. zonata* would be significant threat to horticultural crops in India. Therefore, present findings are of immensely useful to provide important information to design integrated pest management strategies and phyto-sanitary measurements for local, regional and national level to restrain the insect pest activity across different layers.

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1. Introduction

Significant changes and variability is projected in future climate by Intergovernmental Panel on Climate Change (IPCC) in the Coupled Model Intercomparison Project Phase 5 (CMIP5) which will lead to harsh impacts on various agro-ecological systems (Field et al., 2007). Major changes in global climate are expected to occur with increase in temperature (1.5–5.8 °C) and shift in seasonality of rainfall by the end of the century (IPCC, 2014). Climate change will be more evident in tropical region of developing countries like India, which are already facing staid challenges for food security and economic development (Mwalusepo et al., 2015). Future changes of temperature are expected to vary spatially and temporally within geographical region. These variations in temperature will affect many natural systems that are sensitive to temperature including insect establishment, abundance and development (Wing et al., 2005; Kroschel et al., 2013; Fand et al., 2014; Choudhary et al., 2019d).

Being insect as poikilothermic with relatively short life cycle and multivoltine, their growth, development, survival, distribution, behavior and reproduction are temperature dependent. Therefore, insects are appropriate model candidate for climate change related studies (Briere et al., 1999; Bale et al., 2002). Although, temperature is the key determinant, many other biotic and abiotic factors can also influence insect establishment, abundance and development. Impact of predicted climate variability's has been projected on insect pests of many agricultural crops in respect to changes in their developmental rate, number of generations in a year, geographic range suitability, risk of invasive alien species and changes in overwinter survivals (Porter et al., 1991; Ward & Masters, 2007; Bale & Hayward, 2010; Fand et al., 2014; Srinivasa Rao et al., 2016; Tonnang et al., 2017).

Pests' simulation models are principal methodological tools used to determine pest associated risk in agricultural production system under different environmental conditions. These simulation models with climate change scenarios were used for future prediction of insect distribution and abundance in many agricultural systems (Kroschel et al., 2013; Fand et al., 2014; Estay et al., 2009; Choudhary et al., 2019c). Outputs of crop simulation models are supportive to farmers for developing effective pest management strategies well in advance which ultimately reduce crop losses (Fand et al., 2014; Estay et al., 2009). Frequently, two types of insect pest simulation models, i.e. climatic pattern matching functions and process-based pest simulation models have been used for future prediction of insect distribution and abundance in agricultural systems (Fand et al., 2014; Tonnang et al., 2017; Choudhary et al., 2019b). Climate pattern matching function also referred as inductive method based simulation models which estimates potential establishment of new invasive pests (Hill et al., 2016; Choudhary et al., 2019c), demographic risk analysis of possible invades (Rafoss & Saethre, 2003; Ni et al., 2012) and possible climate change effects on already established pests (Ni et al., 2012; Berzitis et al., 2014; Choudhary et al., 2019a) based on the relationship between occurrence of the species and long-term meteorological data of each location. These simulation models use the limited data sets and easy validation with good fit linear relationship to understand species response in relation to climate change. In contrast to climate pattern matching function, the process based (phenology) models use non-linear equations of higher biological significance for stochastic simulation of developmental time variability within populations, based on comprehensive laboratory evaluation of life table parameters. So, phenology models based on deductive method are detailed mathematical simulation models that consider primary physiological parameters of insect development, survival and reproduction and thus, these models can predict a high quality results on future pest dynamics (Wagner et al., 1984). The outputs of phenology models can be presented through algorithms in geographic information system (GIS) to understand the spatial and temporal variation of pest activity in various agro-ecological areas in response to climate change (Kroschel et al., 2013).

Better understanding and accurate prediction of future pest status requires the selection of appropriate simulation model, one or more General Circulation Model (GCM), Representative Concentration Pathway (RCP)/emission scenarios (i.e. RCP 2.6, RCP 4.5, RCP 6.0, RCP 8.5), different time periods, environmental variables and method of climatic data downscaling (Vuuren et al., 2011; Gouache et al., 2013). Ensemble output with different GCM or with RCPs have advantages over single model based predictions. The ensemble with large number of GCM/RCPs may eliminate the mismatch of spatial scales and uncertainties associated with climate change projections and could also reduce the importance of outlier model results (Moss et al., 2010). So, prediction results from linking of large number of GCM/RCPs in combination with good phenology models can lead to better decisions and formulating climate change adaptation techniques.

The peach fruit fly, *Bactrocera zonata* (Saunders) (Diptera:Tephritidae) is a serious insect pest infesting peach (*Prunus persica* (L.), mango (*Mangifera indica* L.), guava (*Psidium guajava* L.) and many other economical horticultural crops in India (Kapoor & Agarwal, 1983; Choudhary et al., 2020). Being multivoltine, large host range and capacity to overcome extreme environmental conditions, this species has high adaptability in to a broad range of climatic conditions in various agro-ecological zones (Duyck et al., 2004; Ni et al., 2012). In India, *B. zonata* is reported from foothills of the Himalaya to southern part of country where it causes 25 to 100% yield loss (Gupta et al., 1990; Sanjeev et al., 2008; Choudhary et al., 2012). Infestations associated with fruit fly species, *B. zonata* directly and indirectly limit the social and economic benefits of country. Temperature based phenology models were fitted for development, mortality and reproduction parameters of *B. zonata* and were validated under fluctuating temperatures (Choudhary et al., 2020). Current study hypothesized that the expected spatial and temporal variations of temperature due to global climate change may alter population abundance and distribution of *B. zonata* in different agro-ecologies of India. Considering the economic importance of the *B. zonata* in India, we employed *B. zonata* phenology model (Choudhary et al., 2020) with WorldClim temperature data (Hijmans et al., 2005) to predict the spatio-temporal variation in abundance and distribution of *B. zonata* using the ILCYM (Insect Life Cycle Modeling) software (Sporleder et al., 2009) in respect to climate change under different future scenarios in India. Simulation data generated from ILCYM software were further examined for spatial and temporal variations and pest risk maps were generated.

2. Materials and methods

2.1. B. zonata temperature based phenology model

The temperature based phenology model of *B. zonata* used in the present study was developed based on life cycle data generated in the laboratory condition at five different constant temperatures, and it was validated with life cycle data generated under fluctuating temperatures (Choudhary et al., 2020). The phenology model of the present study was developed using open source ILCYM (version 3.0) tool from International Potato Centre, Lima, Peru (Tonnang et al., 2013). This software facilitates tool “model builder”, for the insect phenology models development based on experimental temperature data of a specific pest. Module also provides tools for analyzing the insect life-table and validating the developed models. Furthermore, in the second module, the developed phenology model is implemented in a GIS environment and allows for spatial simulation of pest activities (“pest risk mapping”).

The validated phenology model of *B. zonata* can be applied in large scale predictions of population abundance and demographic distribution of *B. zonata* in various agro-ecological areas of India and world. The phenology model comprised of a set of functions that have details about temperature based development, mortality and adult senescence rate variability from one stage to next. Normalized development time for cumulative frequency of development times of egg and pupae were fitted with Complementary log–log (Cloglog) function whereas, larvae, male and female were fitted with Weibull distribution curves. The non-linearity in the rate of development of immature stages (egg, larvae and pupae) were fitted with Janish-1 function. The adult senescence rates were fitted with simple exponential model whereas, the mortality rates in immature life stages (egg, larvae and pupae) were fitted with Wang model. A Wang model was chosen to describe the effects of various constant temperatures on reproduction (for details about the functions, parameters and validation refer Choudhary et al., 2020). The model predicts 20–35 °C as suitable temperature ranges for *B. zonata* population increase with 25–28 °C as the most suitable for reproduction and development. At extreme low temperature (15 °C), rate of mortality was highest in all the immature life stages of *B. zonata* and was considered as highly unfavorable for survivability. Whereas at high temperature (35 °C), mortality of different stages was lower as compared to low tested temperature. A Sharp decline in longevity of both the adult sexes was observed from lower to higher tested temperatures. Egg laying of *B. zonata* was not observed at 15 °C temperature constant while observed at 35 °C temperature constant. Significant near values of simulated development times (1.52, 4.60 and 11.99 days for eggs, larvae and pupae, respectively) were experiential with fluctuating temperature treatment observed development times (1.62, 5.89 and 10.42 days for eggs, larvae and pupae, respectively) of *B. zonata*. Phenology models fitted for *B. zonata* development, mortality and reproduction indicated higher preference of this species towards the warm climatic conditions (Choudhary et al., 2020).

2.2. Climate data (temperature data)

The temperature data used in the current study for historical (near to current) and future scenarios were downloaded from WorldClim database (ver. 1.4; http://www.worldclim.org/) (Hijmans et al., 2005). The high level spatial resolution data, approx. ~ 4.6 km (2.5 arc min) at the equator, were used in the study. Use of high resolution spatial data will facilitate clear cut delineation of boundaries of zones with different ranges of pest risk indices. These data contain monthly mean of minimum and maximum temperatures interpolated from historical temperature records from 1960 to 2000 periods. Future temperature data (years 2050 and 2070) from eight GCMs under four greenhouse gas concentration trajectories scenarios RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5 as proposed in the Fifth Assessment of the Intergovernmental Panel for Climate Change (CMIP5) (Taylor et al., 2012; Moss et al., 2010), at the same resolution of current data, were downloaded from WorldClim (ver. 1.4). The future climate change periods were the average of years 2041–2060 and 2061–2080 for the time period 2050 and 2070, respectively (Hijmans et al., 2005). Keeping in view that large uncertainties induced by GCMs in climate change impact assessments (Chen et al., 2011; Sharma et al., 2018) a simple arithmetic average of the ensemble with an equal weight is more reliable over a single model approach (Kim et al., 2016; Ahmed et al., 2019) thus in the current study, we used an arithmetic ensemble average of eight GCMs. Ensemble averaging of spatio-temporal data pertaining to eight GCMs under different RCPs was done in ArcGIS™ (ver. 10.4) environment. The details of eight GCMs and their ensemble used in the current study were given in the Table 1. The world region data files were extracted for Indian region by masking the India boundary in

Table 1
Details and abbreviation used about General Circulation Models (GCMs).

S. No.	General Circulation Model	Abbreviation code
1	**BCC-CSM1-1**- the Chinese Beijing Climate Center, China Meteorological Administration and Analysis model	BCC
2	**GISS-ER-R**- the NASA’s Goddard Institute for Space Studies model	GISS
3	**HADGEM2-AO**- the UK’s Met Office Hadley Global Environment Model 2-Atmosphere Ocean	HadA
4	**HadGEM2-ES**- the UK’s Met Office Hadley Centre’s model	HadE
5	**IPSL-CM5A-MR**- the French Institut Pierre-Simon Laplace model	IPS
6	**MIROC-ESM-CHEM-** the Japan’s Atmosphere and Ocean Research Institute, National Institute for Environmental Studies and Agency for Marine-Earth Science and Technology model	MI
7	**MRI-CGCM3**- the Japan’s The Meteorological Research Institute climate model	MRIC
8	**Nor-ESM1-M1**- the Norwegian Climate Centre model	NES
9	Ensemble averaging	Ensemble

ArcGIS. The file format of temperatures data file were converted into required format using the ArcGIS raster data converting package. Thus, future data of minimum and maximum temperatures were downloaded for 2 climate change periods (2050 and 2070) and 4 RCP scenarios across 9 models (including ensemble average) for spatio-temporal analysis of *B. zonata* in different zones of India.

2.3. Spatial and temporal analysis and mapping

The simulations of life table parameters *viz.,* generation time, net reproduction rate, intrinsic rate of increase, finite rate of increase, and doubling time in ILCYM were based on daily minimum and maximum temperature and use of 15 min time step for within day temperature variability (Kroschel et al., 2013; Tonnang et al., 2013; Fand et al., 2014). A cosine function was used for temperature-dependent pest population parameters calculation of each 15 min time step. For the prediction of first half-day the following equation was used (Kroschel et al., 2013; Tonnang et al., 2013):

$T_i = \frac{(Max-Min)}{2} \times cos\left(\frac{\pi\ X\ (i-05)}{48}\right) + \frac{(Min+\ Max)}{2}$ n which T_i is the temperature (°C) of time step i ($i = 1, 2, 3, \ldots, 48$), and Max and Min are the daily maximum and minimum temperatures, respectively.

The same procedure was then repeated to obtain T*i* for the second half-day while using minimum temperature (Min) of the next day in the equation. The database used in present study was from WorldClim which only include monthly temperature data. ILCYM replaces monthly averages of minimum and maximum temperatures in to the daily minimum and maximum temperatures in above given equation for half-day temperature predictions in each 15 min time step. By this way, except last day of month value of T*i* remains constant for all days of the month. A value of T*i* for last day of month was calculated while employing minimum temperature of the second half-day of first day of the next month.

For the developing of Indian region maps, monthly minimum and maximum temperature data for one year (WorldClim datasets for 12 months starting from January to December) along with their corresponding geographical coordinates were further processed for a selected region in the ILCYM. The life table parameters were calculated for each Julian day based on the simulated temperatures and outputs of the phenology model using the methods suggested by Curry et al. (1978), Kroschel et al. (2013) and Tonnang et al. (2013).

Further, for the assessment of the potential distribution and abundance of *B. zonata* in the region, the life table parameters values were used to calculate the three pest risk indices (Establishment risk index (ERI); Generation index (GI) and Activity index (AI)) at each data point in the ILCYM programme (Kroschel et al., 2013). The ERI (value ranges from 0 to 1) used for identification of the region where *B. zonata* having the risk of survival and establishment in particular region. When all the immature stages of *B. zonata* are able to survive every day of year then maximum ERI value of particular area is denoted as 1. Generation Index denotes the mean number of generations produced by *B. zonata* in a particular year. This index is based on the average of generation length of each day of year, which depends on average temperature. It means higher mean temperature more number of generations in a year. But practically it is not possible in case of temperature extremities where higher number of generation's leads to low population build-up due to increased mortality of immature stages. So it is always better to correlate GI with AI for true representation of pest's damage potential. The AI explains the temperature driven population increase based on finite rate of population taking an account into entire life history of pest within a year. Increase in one for AI value indicates a 10-fold increase in pest population in an area with assuming no restrictions of

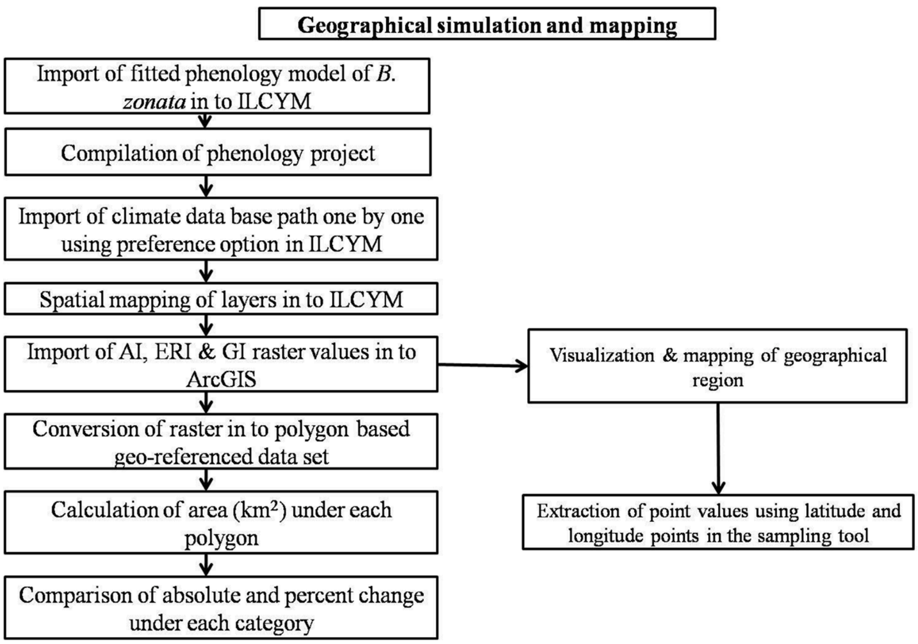

Fig. 1. Scheme implemented in the ILCYM and ArcGIS environment for geographical simulation and mapping of *Bactrocera zonata* in the India.

biotic and abiotic factors. The geographical simulation, mapping and area calculations were done in the ILCYM 3.0 and ArcGIS (Fig. 1).

In present study, phenology model generated number of generations in a year of historical data (1960–2000) of WorldClim was compared through number of generations calculated in a year using daily gridded (1×1^0 resolution) temperature data of India Meteorological Department (IMD). The corresponding value of number of generations of 10 representing locations (Table 2) of agro-ecology regions were extracted from generation index file using latitude and longitude point in the sampling tool. The gridded data of IMD available from 1969 to 2005 of each locations were used for calculating the number of generations using Growing Degree Day (GDD) approach. The freely available software '*ingen*' (Insect Generations) was used to calculate yearly *B. zonata* generations using 13.7 °C lower developmental threshold and a total of 497° days required for completing the life cycle calculated from phenology model (Srinivasa Rao et al., 2014; Choudhary et al., 2020).

The locations data on activity, establishments risk and generation numbers were subjected to one way analysis of variance (ANOVA) and further Tukey's honestly significant difference (HSD) tests were used to compare the means at probability level of 5%. These statistical analyses were performed using SPSS 16.0.

3. Results

3.1. Agro-ecological regions of India and point data comparison

Ten representative locations of different zones were selected for better representation of agro-ecological zones for assessing and understanding the spatio-temporal variations in risk indices of *B. zonata* in agro-ecologies of India (Table 2). Fair variation in minimum and maximum temperature was noted and depicted among the selected locations. The annual minimum temperature vary from 7.69 °C (Leh) to 23.87 °C (Port Blair) in cold arid ecosystem to hot humid eco-region, respectively in India. Similar trend was also observed in maximum temperature (Table 2). Number of generations evaluated based on degree days approach using gridded daily historical data (IMD) and monthly temperature data of locations from WorldClim database in ILCYM, showed similar prediction for average number of yearly generations of *B. zonata* across the 10 locations except Madurai where slight deviation as 0.5 generation per year was observed (Table 2).

3.2. B. zonata establishment risk across locations, models and scenarios

The suitable area for establishment and survival of *B. zonata* in India were visualized using ArcGIS for current (baseline WorldClim climate data for the year 2000) and future projections based on ensemble of eight GCMs of each scenario (2050 & 2070) (Fig. 2). Southern states of India including Kerala, part of Tamil Nadu and Karnataka and some coastal parts of Maharashtra and Odisha were predicted to have high ERI (0.8–1.0) indicating that certain proportion of *B. zonata* population would establish and survive throughout the year in these areas (Fig. 2 & Table 3) and is only 1.73% of total area (3,287,263 square kilometers) (Table 4). The ERI values below 1.0 indicate the low probability of permanent establishment of *B. zonata*. The highly suitable areas are projected to reduce from −23.6

Table 2
Representative location information and generations of *B. zonata* in a year through phenology model simulations and degree day's model.

Location (State)	Location agro-ecological features	Longitude	Latitude	Annual mean Temperature (°C) (IMD)		Average number of generations	
				MaxT (°C)	MinT (°C)	Weather data (IMD) (1969–2005)	WorldClim database (1950–2000)
Leh (Ladakh)	Cold Arid Eco-region with Shallow Skeletal Soils	77.58° E	34.16° N	20.43	7.69	2.76 ± 0.29	2.57
Sri Ganganagar (Rajasthan)	Hot Arid Eco-region with Desert and Saline Soils	73.8° E	29.91° N	32.09	17.04	8.45 ± 0.44	8.34
Bhavnagar (Gujarat)	Hot semi-arid eco-region with medium and deep black soils	72.15° E	21.76° N	33.69	21.21	8.11 ± 0.27	8.81
Dharwad (Karnataka)	Hot semi-arid eco-region with shallow and medium (dominant) black soils	75.01° E	15.46° N	31.68	20.33	8.05 ± 0.23	7.45
Madurai (Tamil Nadu)	Hot semi-arid eco-region with red loamy soils	78.12° E	09.92° N	32.03	23.06	10.01 ± 0.21	9.41
Chhindwara (Madhya Pradesh)	Hot sub-humid eco-region with red and black soils	78.94° E	22.06° N	31.45	18.15	8.16 ± 0.28	7.62
Ranchi (Jharkhand)	Hot sub-humid eco-region with red and lateritic soils	85.31° E	23.34° N	31.03	19.04	7.37 ± 0.24	7.33
Darbhanga (Bihar)	Hot sub-humid (moist) eco-region with alluvium-derived soils	85.89° E	26.15° N	31.09	19.43	7.90 ± 0.60	7.98
Daporijo (Arunachal Pradesh)	Warm sub-humid eco-region with brown and red hill soils	94.22° E	27.98° N	29.03	22.90	6.24 ± 0.45	6.64
Port Blair (Andaman & Nicobar Islands)	Hot humid per-humid Island eco-region with red loamy and sandy soils	92.73° E	11.62° N	32.14	23.87	8.63 ± 0.24	8.03

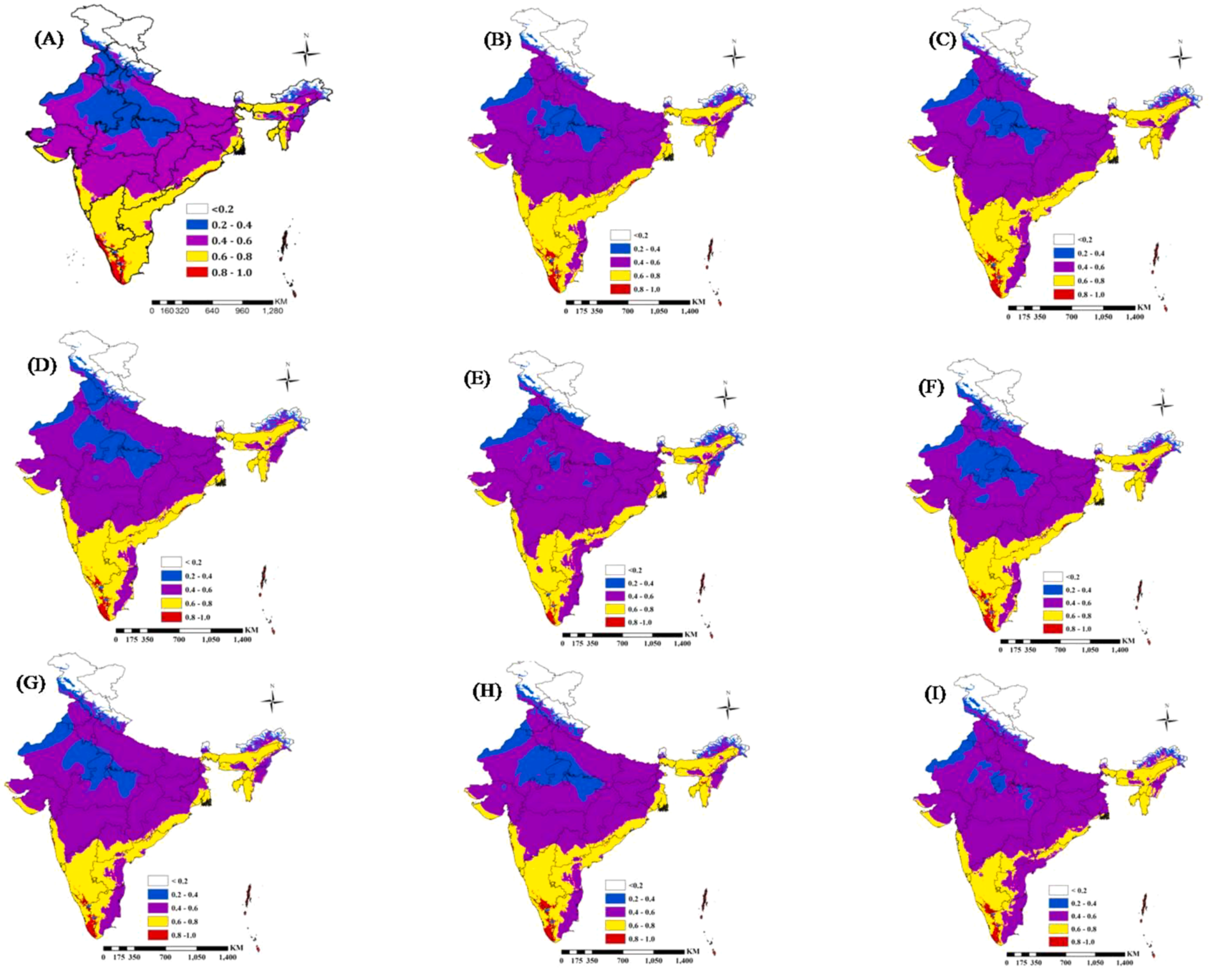

Fig. 2. Current (1950–2000) (A) and ensemble average of eight GCMs of each future scenarios (B = 2.6/2050; C = 4.5/2050; D = 6.0/2050; E = 8.5/2050; F = 2.6/2070; G = 4.5/2070; H = 6.0/2.070; I = 8.5/2070) establishment of *Bactrocera zonata* in India based on phenology based model prediction of establishment risk index (ERI). The index values > 0.6 indicated permanent establishment of pest.

to −63.5 percent over current in year 2050 under different RCPs. Highly suitable areas of coastal Maharashtra and Odisha for establishment of *B. zonata* are projected to reduce as moderately suitable (0.6–0.8 ERI) in the year 2050 and 2070 (Fig. 2). The area under permanent establishment (>0.6 ERI) in north-eastern regions is projected to increase during future climate change scenarios (2050 & 2070). The ensemble ERI maps show that the major changes in the establishment risk is going to happen in central and north part of India where major part is projected to reduce the risk of establishments from less suitable (0.4–0.6 ERI) to very less suitable (0.2–0.4 ERI) during 2050 over current periods. But the overall area under less suitable (0.4–0.6 ERI) is projected to increase due to reduction in ERI area from moderately suitable to less suitable during 2050 to 2070 (Fig. 2, Table 4). Results showed that area under permanent establishment (>0.6 ERI) is projected to narrow down and area would increase from very less suitable to less suitable during future climate change.

Projected establishment risk under climate change scenarios (RCPs) across all representative locations of agro-ecological regions of India showed significant differences except Bhavnagar and Chhindwara in the future climate periods (2050 & 2070) over the current periods (Table 3). The lowest establishment risk is projected at Leh and highest at Port Blair where *B. zonata* population can sustain itself alive nearly throughout the year (Table 3). The significant gradual and consistent increase in ERI among four scenarios has been projected at Leh, Daporijo, and Ranchi locations where there is an increasing potential for *B. zonata* establishment whereas in other locations, decrease in establishment risk is predicted during future time periods. The reduction in projected risk areas under 'permanent risk establishment' may be due to deviation of temperature from lower and higher temperature thresholds conditions required for *B. zonata* in the future time periods. The high temperature extremities have balancing effect on finite rate of natural increase due to increase in mortality and reduction in reproduction rates which ultimately decreases the rate of establishment in the year.

Substantial variations were observed in the establishment risk indices generated using eight GCMs and scenarios in present study. Establishment risk indices variations over representative locations and time periods predicted through different GCM models is illustrated in spider web network (Fig. 3A) where index values depicted along with axis from centre to outer ring. The highest and

Table 3
Agro-ecological zone representative locations and scenario based variation in establishment risk index of *Bactrocera zonata* in India under future climate change periods. Values are means ± standard deviation; ^{a,b,c,d}means in a row followed by different letters are significantly different using Tukey's HSD test (P > 0.05).

Location/s Scenario/time period	Current	RCP 2.6/ 2050	RCP 4.5/ 2050	RCP 6.0/ 2050	RCP 8.5/ 2050	RCP 2.6/ 2070	RCP 4.5/ 2070	RCP 6.0/ 2070	RCP 8.5/ 2070	F cal (*df* = 64)	*LSD* (*P* = *0.05*)
Leh	0.11^{a}	0.11 ± 0.04^{a}	0.11 ± 0.04^{a}	0.11 ± 0.04^{a}	0.11 ± 0.05^{a}	0.15 ± 0.01^{b}	0.16 ± 0.00^{b}	0.16 ± 0.01^{b}	0.16 ± 0.07^{b}	7.69	0.03
Sri Ganganagar	0.40^{c}	0.35 ± 0.03^{b}	0.30 ± 0.02^{a}	0.34 ± 0.04^{b}	0.30 ± 0.03^{a}	0.34 ± 0.02^{b}	0.29 ± 0.03^{a}	0.30 ± 0.02^{a}	0.28 ± 0.04^{a}	14.44	0.03
Daporijo	0.54^{a}	0.59 ± 0.04^{b}	0.60 ± 0.04^{b}	0.60 ± 0.04^{b}	0.62 ± 0.04^{b}	0.59 ± 0.03^{b}	0.62 ± 0.03^{b}	0.61 ± 0.04^{b}	0.63 ± 0.03^{c}	5.68	0.04
Darbhanga	0.55^{b}	0.52 ± 0.03^{ab}	0.52 ± 0.04^{ab}	0.52 ± 0.03^{ab}	0.51 ± 0.04^{a}	0.52 ± 0.01^{ab}	0.53 ± 0.03^{ab}	0.52 ± 0.03^{ab}	0.53 ± 0.05^{ab}	4.61	0.04
Ranchi	0.46^{a}	0.47 ± 0.02^{ab}	0.47 ± 0.01^{ab}	0.48 ± 0.02^{ab}	0.49 ± 0.02^{b}	0.47 ± 0.01^{ab}	0.48 ± 0.02^{ab}	0.49 ± 0.02^{b}	0.52 ± 0.04^{c}	4.58	0.02
Bhavnagar	0.53^{a}	0.54 ± 0.03^{a}	0.55 ± 0.04^{a}	0.55 ± 0.01^{a}	0.55 ± 0.03^{a}	0.55 ± 0.03^{a}	0.56 ± 0.05^{a}	0.56 ± 0.04^{a}	0.53 ± 0.07^{a}	ns	ns
Chhindwara	0.44^{a}	0.44 ± 0.01^{a}	0.44 ± 0.04^{a}	0.44 ± 0.02^{a}	0.45 ± 0.01^{a}	0.45 ± 0.01^{a}	0.45 ± 0.03^{a}	0.45 ± 0.02^{a}	0.45 ± 0.04^{a}	ns	ns
Dharwad	0.67^{b}	0.68 ± 0.02^{b}	0.68 ± 0.04^{b}	0.68 ± 0.02^{b}	0.67 ± 0.02^{b}	0.68 ± 0.02^{b}	0.68 ± 0.03^{b}	0.68 ± 0.02^{b}	0.62 ± 0.04^{a}	7.74	0.02
Port Blair	0.90^{b}	0.90 ± 0.00^{b}	0.89 ± 0.02^{b}	0.90 ± 0.01^{b}	0.89 ± 0.01^{b}	0.90 ± 0.01^{b}	0.89 ± 0.03^{b}	0.89 ± 0.01^{b}	0.85 ± 0.03^{a}	9.68	0.02
Madurai	0.65^{d}	0.55 ± 0.03^{c}	0.53 ± 0.04^{bc}	0.53 ± 0.04^{bc}	0.51 ± 0.04^{bc}	0.56 ± 0.04^{c}	0.52 ± 0.06^{bc}	0.50 ± 0.04^{b}	0.42 ± 0.06^{a}	20.58	0.04

lowest values of establishment risk index values with respect to GCMs vary with locations of different agro-ecological regions for prediction. However, IPS model predicted a higher range of values compared to other models for maximum locations during the period of 2050 but this pattern was not consistent for the period of 2070. The inconsistencies may be due to distinctive trend in temperatures during 2070s on account of which the model results for 2070s did not show similar trends as during 2050s.

3.3. B. zonata population abundance across locations, models and scenarios

The potential activity of *B. zonata* in India under the current and future climatic conditions is depicted in Fig. 4. Under the current climatic conditions, hot semi-arid and hot sub-humid regions of Southern states and East and Western coastal areas including some very lower part of North-Eastern region of India are predicted to be optimal for population abundance. Major parts of India including Northern plains, Western semi-arid region, Deccan plateau and Eastern region are predicted highly suitable for *B. zonata* abundance. A total of 2136331 km^2 area is predicted to fall under the highly suitable index for abundance which is approximately 65% of total geographical area of India (Table 4 & Fig. 4). The maximum area from high to optimal suitability of *B. zonata* abundance is projected in the Southern, coastal and North-Eastern part of India under future climate change scenarios (2050 & 2070) (Fig. 4).

Abundance of *B. zonata* across all representative locations of agro-ecological regions of India showed significant changes under climate change scenarios (RCPs) during the future climate periods (Table 5). During 2070, extreme climate change projection i.e. RCP 8.5 is projected to significantly decrease in abundance of *B. zonata* across many locations. However, overall area under optimal abundance (>16), as predicted from ensemble of GCMs, is going to increase from 21 to 54.7% compared to current area under different RCPs during 2050 to 2070 periods (Table 5). In spite of decreasing AI values in some locations, *B. zonata* abundance and damage activities will increase significantly in larger areas of India during future climatic conditions (2050 & 2070 scenarios) (Table 4, Fig. 4). The GCMs model-based prediction variation for different locations and periods shows that the GCM model IPS predicted higher abundance followed by HadE during future time periods with minor differences (Fig. 3C). GCM model MRIC predicted the lowest activity across all locations and time periods. With respect to locations, the lowest activity has been projected for Leh location while maximum activity of *B. zonata* will occur in the islands of Port Blair in the future (Fig. 3C).

3.4. B. zonata generation variations across locations, models and scenarios

The total number of generations that can be completed by *B. zonata* in a year as indicated by generation index (GI) in the current and future (2050 & 2070) climate change scenarios are visualized in Fig. 5. The generation indices are directly correlated with abundance and potential infestation of *B. zonata* in the field conditions. According to ensemble of GCM models predictions, maximum area of India (≃60%) is predicted with more than 8 generations of *B. zonata* per year. The Himalayan region area and its ranges from north to north-eastern regions, central plateau regions and South-western regions are predicted to have less than 8 generations per year under current climatic conditions. Under future climate change scenarios (2050 & 2070), maximum regions of India, except Northern Himalayan and top of north-eastern states, are predicted with more than 8 generations (8–10 generations) per year of *B. zonata*. Therefore, on the basis of the generation index value ≃80.0% area of the India will be highly suitable for *B. zonata* abundance and

Table 4
Projected area (km^2) and percent changes over current time index values of respective category with suitability of pest risk indices of *Bactrocera zonata* under different climate scenarios from ensemble of eight GCMs.

Pest risk indices and their ranges	Current (% area of total)	RCP 2.6/2050*	RCP 4.5/2050	RCP 6.0/2050	RCP 8.5/2050	RCP 2.6/2070	RCP 4.5/2070	RCP 6.0/2070	RCP 8.5/2070
Establishment risk index									
0.0–0.2	330071.7 (10.04)	310246.9 (−6.0)	305738.6 (−7.4)	310325.7 (−6.0)	304459.0 (−7.8)	313219.7 (−5.1)	304557.4 (−7.7)	300462.5 (−9.0)	289949.7 (−12.2)
0.2–0.4	617737.7 (18.79)	348951.5 (−43.5)	365941.4 (−40.8)	453351.5 (−26.6)	289437.8 (−53.1)	468864.9 (−24.1)	399291.1 (−35.4)	443271.8 (−28.2)	215237.6 (−65.2)
0.4–0.6	1574051.9 (47.88)	1852701.3 (17.7)	1884535.1 (19.7)	1802578.3 (14.5)	2062210.0 (31.0)	1735071.6 (10.2)	1881404.9 (19.5)	1793167.9 (13.9)	2174425.7 (38.1)
0.6–0.8	708652.1 (21.56)	732000.9 (3.3)	690481.1 (−2.6)	684378.1 (−3.4)	610394.5 (−13.9)	723299.2 (2.1)	669278.2 (−5.6)	708612.8 (0.0)	575036.7 (−18.9)
0.8–1.0	56718.2 (1.73)	43331.0 (−23.6)	40535.5 (−28.5)	36598.1 (−35.5)	20730.4 (−63.5)	46776.2 (−17.5)	32700.1 (−42.3)	41716.7 (−26.4)	32581.9 (−42.6)
Activity index									
Marginal abundance (<4)	348144.4 (10.59)	322433.2 (−7.4)	317688.6 (−8.7)	321153.5 (−7.8)	310109.1 (−10.9)	324244.4 (−6.9)	312806.3 (−10.2)	311762.8 (−10.5)	299616.0 (−13.9)
Moderate abundance (4–8)	72270.9 (2.20)	68806.0 (−4.8)	63352.7 (−12.3)	66955.4 (−7.4)	61758.0 (−14.5)	66167.9 (−8.4)	66128.5 (−8.5)	64770.1 (−10.4)	54907.0 (−24.0)
Optimal abundance (8–12)	265498.5 (8.08)	209469.4 (−21.1)	177241.8 (−33.2)	191790.5 (−27.8)	208248.8 (−21.6)	165193.4 (−37.8)	206319.4 (−22.3)	165606.8 (−37.6)	254021.0 (−4.3)
High abundance (12–16)	2136331.4 (64.99)	2105285.1 (−1.5)	2079948.0 (−2.6)	2144757.5 (0.4)	1954955.4 (−8.5)	2124972.1 (−0.5)	2087448.7 (−2.3)	2025986.0 (−5.2)	1979268.8 (−7.4)
Very high abundance (>16)	464986.5 (14.15)	581238.1 (25.0)	649000.6 (39.6)	562574.8 (21.0)	752160.3 (61.8)	606653.9 (30.5)	614528.7 (32.2)	719105.9 (54.7)	699418.9 (50.4)
Generation Index									
< 2	233920.6 (7.12)	189211.5 (−19.1)	178108.0 (−23.9)	186356.8 (−20.3)	167733.0 (−28.3)	189683.9 (−18.9)	171493.2 (−26.7)	174505.3 (−25.4)	146254.5 (−37.5)
2–4	88748.9 (2.70)	107431.8 (21.1)	111802.3 (26.0)	108258.6 (22.0)	117747.8 (32.7)	106801.8 (20.3)	116113.7 (30.8)	114401.0 (28.9)	130071.8 (46.6)
4–6	127138.4 (3.87)	121409.5 (−4.5)	115129.4 (−9.4)	119283.3 (−6.2)	109715.5 (−13.7)	119696.8 (−5.9)	113436.3 (−10.8)	113534.8 (−10.7)	99281.4 (−21.9)
6–8	875263.0 (26.63)	448941.6 (−48.7)	319598.3 (−63.5)	402322.9 (−54.0)	251402.6 (−71.3)	412973.5 (−52.8)	331882.9 (−62.1)	287055.7 (−67.2)	174367.5 (−80.1)
>8	1962160.8 (59.69)	2420237.2 (23.3)	2562593.7 (30.6)	2471009.9 (25.9)	2640632.8 (34.6)	2458075.6 (25.3)	2554305.5 (30.2)	2597734.9 (32.4)	2737256.5 (39.5)

*Values in bracket are % area changes over current time area

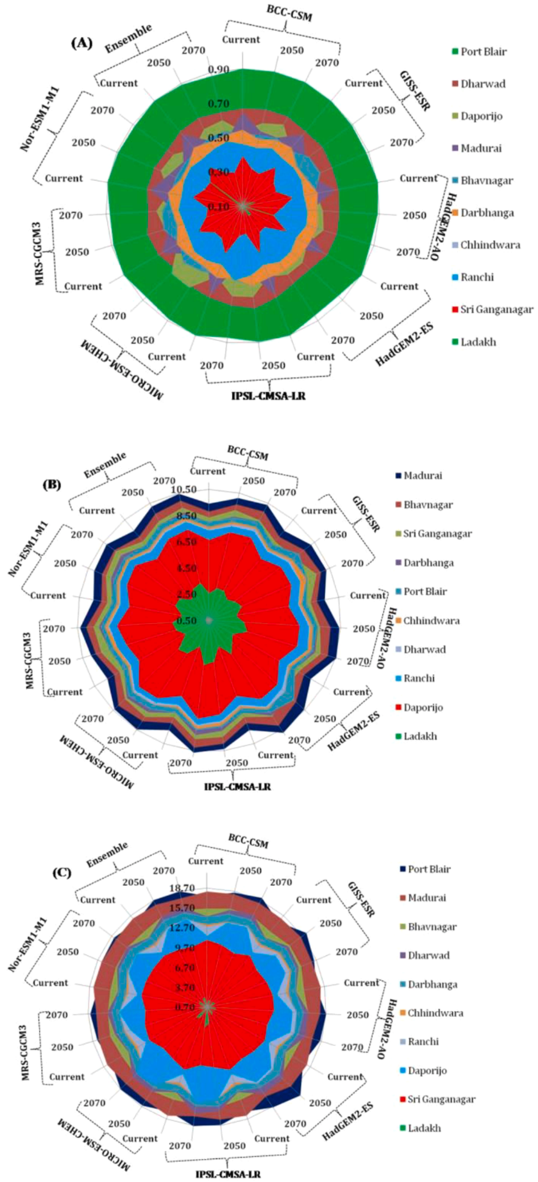

Fig. 3. Inter model and temporal variations in pest risk indices of *Bactrocera zonata* (A = ERI; B = GI; C = AI) during future climate change periods across agro-ecological zones of India.

potential infestation under future climate change scenarios (Table 4 & Fig. 5).

In contrast to ERI and AI, significant increase in the GI values is projected over the current period under each climate change scenarios in future climate periods (Table 4). In current periods, the total numbers of generations were estimated to be 2.57 (Leh, cold arid region) to 9.41 (Madurai, hot semi-arid region), which will be expected to increase to 3.89 (Leh, cold arid region) to 11.03 (Madurai, hot semi-arid region) during 2070 time periods under RCP 8.5 scenario (Table 6). The number of generations change across the location indicates that most of the representative location will be expected to increase with an average of 1.0–1.5 generation per year over present generations. A gradual increase in the number of generations among climate change scenarios (RCPs) and time periods (2050 & 2070) was consistently observed. Inter model and temporal variations showed that the maximum numbers of generations were predicted by IPS and HadE models during each time periods and at all the locations (Fig. 3B).

4. Discussion

The linking of simulated future climate change with phenology models derived on the basis of insect development and population dynamics for future projections to a regional level can be useful for quantitative estimates of the possible impacts of climate change on

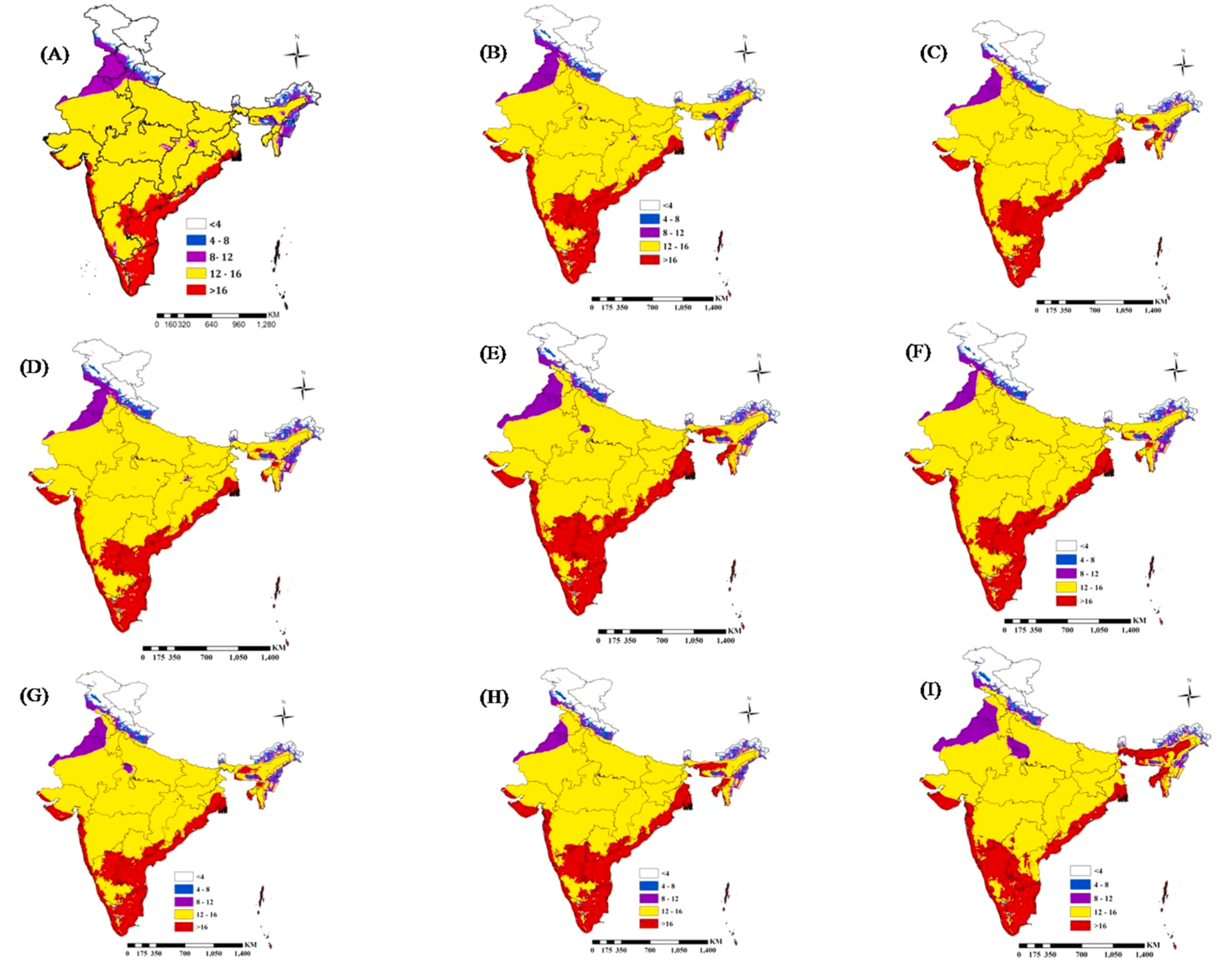

Fig. 4. Current (1950–2000) (A) and ensemble average of eight GCMs of each future scenarios (B = 2.6/2050; C = 4.5/2050; D = 6.0/2050; E = 8.5/2050; F = 2.6/2070; G = 4.5/2070; H = 6.0/2.070; I = 8.5/2070) change in activity of *Bactrocera zonata* in India based on phenology based model prediction of activity index (AI). The index values 1 indicated 10-fold increases of possible population of a pest in a year. It means an index value of 3 indicate that potential population would increase by a factor of 10^3 (1000) in a year excluding biotic and abiotic limiting factors.

insect pest species (Choudhary et al., 2020). Reliability of future projections always involves some level of uncertainty, but these predictions can be made more dependable with the use of multiple GCMs and their ensemble averaging as used by the various researchers (Ahmed et al., 2019; Kim et al., 2016). It was incepted in line that how change in air temperature will impact the abundance, range distribution and damage potential of *B. zonata* at different zones of India and spatio-temporal changes in the abundance and distribution of *B. zonata* under future climate scenarios were also predicted and quantified. The changes in air temperature not only affects the life cycle parameters of insects but also the feeding rate of insects, growth and chemical composition of host plant, activities of bio-control agents of insect pests etc. (Dillon et al., 2010; Kumar et al., 2020).

4.1. Spatial and temporal changes in abundance and distribution of B. zonata

The climate of India ranges from tropical in the southern region to temperate and alpine in the Himalayan region in northern part. Being highly polyphagous and multivoltine species, risk of establishment and survivability of *B. zonata* in India is expected to be high due to the availability of large number of host plants throughout year and capacity to overcome extreme environmental conditions (Kapoor & Agarwal, 1983; Duyck et al., 2004). Wide spread presence of *B. zonata* in different ecologies of Indian states from South (Kerala, Tamil Nadu, Karnataka and Andhra Pradesh) to North (Himachal Pradesh, Jammu and Kashmir) and East (West Bengal, Bihar, Jharkhand) to West (Gujarat, Maharashtra) with wide host ranges confirms the capacity to overcome extreme environmental conditions and host availability limitations for its establishments (Kapoor, 1993; CABI, 2020). The present study is in line of above confirmations of the incidence of *B. zonata* in different ecologies of India using the predicted risk indices under current climatic conditions. Recent report of this species from Kashmir valley, an area of severe climate including the cryic/frigid temperature regime during winter indicating tolerance towards low temperature stress conditions (Mir et al., 2014). No reports of *B. zonata* occurrence

Table 5
Agro−ecological zone representative locations and scenario based variation in activity index of *Bactrocera zonata* in India under future climate change periods. Values are means ± standard deviation; ^{a,b,c,d}means in a row followed by different letters are significantly different using Tukey's HSD test (P > 0.05).

Location/s Scenario/time period	Current	RCP 2.6/ 2050	RCP 4.5/ 2050	RCP 6.0/ 2050	RCP 8.5/ 2050	RCP 2.6/ 2070	RCP 4.5/ 2070	RCP 6.0/ 2070	RCP 8.5/ 2070	F cal (*df* = 64)	*LSD* (*P = 0.05*)
Leh	0.78^{a}	1.69 ± 0.47^{b}	2.07 ± 0.51^{bc}	1.80 ± 0.48^{bc}	2.41 ± 0.73^{c}	1.68 ± 0.40^{b}	2.29 ± 0.64^{bc}	2.27 ± 0.70^{bc}	3.48 ± 0.92^{d}	13.07	0.65
Sri Ganganagar	10.82^{c}	10.67 ± 0.39^{c}	10.14 ± 0.50^{bc}	10.47 ± 0.43^{c}	10.17 ± 0.53^{bc}	10.69 ± 0.39^{c}	9.94 ± 0.55^{b}	10.44 ± 0.38^{c}	9.28 ± 0.60^{a}	10.26	0.48
Daporijo	11.42^{a}	13.51 ± 0.70^{bc}	14.01 ± 0.59^{bc}	13.75 ± 0.61^{bc}	14.32 ± 0.91^{c}	13.29 ± 0.62^{b}	14.17 ± 0.66^{c}	14.18 ± 0.79^{c}	15.68 ± 0.95^{d}	22.95	0.75
Darbhanga	14.31^{a}	15.24 ± 0.35^{b}	15.46 ± 0.34^{bc}	15.38 ± 0.35^{bc}	15.56 ± 0.30^{c}	15.16 ± 0.31^{b}	15.45 ± 0.26^{bc}	15.39 ± 0.23^{bc}	15.55 ± 0.26^{c}	16.93	0.30
Ranchi	12.79^{a}	13.82 ± 0.38^{b}	14.20 ± 0.39^{c}	14.00 ± 0.45^{bc}	14.44 ± 0.34^{c}	13.84 ± 0.15^{b}	14.34 ± 0.36^{c}	14.38 ± 0.36^{c}	15.0 ± 0.36^{d}	29.80	0.36
Bhavnagar	15.60^{a}	16.02 ± 0.14^{b}	16.07 ± 0.17^{b}	15.97 ± 0.20^{b}	15.97 ± 0.24^{b}	15.99 ± 0.26^{b}	15.97 ± 0.26^{b}	16.01 ± 0.18^{b}	15.36 ± 0.68^{a}	6.34	0.30
Chhindwara	13.15^{a}	13.90 ± 0.33^{b}	14.19 ± 0.33^{bc}	14.04 ± 0.39^{bc}	14.28 ± 0.32^{c}	14.04 ± 0.54^{bc}	14.29 ± 0.36^{c}	14.33 ± 0.32^{c}	14.24 ± 0.49^{bc}	11.31	0.35
Dharwad	14.37^{a}	15.69 ± 0.34^{bc}	16.03 ± 0.62^{b}	15.96 ± 0.52^{bc}	16.24 ± 0.45^{c}	15.62 ± 0.42^{b}	16.20 ± 0.50^{c}	16.12 ± 0.42^{c}	16.84 ± 0.55^{d}	21.52	0.46
Port Blair	17.46^{a}	18.60 ± 0.68^{bc}	18.87 ± 0.86^{c}	18.73 ± 0.82^{bc}	18.81 ± 0.66^{bc}	18.25 ± 0.61^{b}	18.72 ± 0.49^{bc}	18.48 ± 0.23^{bc}	19.04 ± 0.24^{c}	5.95	0.60
Madurai	18.16^{b}	18.18 ± 0.28^{b}	18.00 ± 0.24^{b}	18.00 ± 0.30^{b}	17.80 ± 0.39^{b}	18.09 ± 0.29^{b}	17.92 ± 0.56^{b}	17.76 ± 0.34^{b}	16.62 ± 0.84^{a}	11.84	0.44

were available in the areas which are projected to have < 0.2 ERI, <4.0 AI and < 2.0 generations per year in present study.

The projected risk maps of *B. zonata* showed that area under permanent establishment (>0.6 ERI) is projected to be reduced but with increase in the area under highly suitable index for abundance and number of generations under the future climate change period. These results show that activities of species may be ceased down to number of days in a year with high number of flies in a year. The reduction of establishment index values in Rajasthan, Haryana, Uttar Pradesh, parts of Madhya Pradesh (particularly, northern and western regions) and part of Gujarat may be due to increase in temperature stresses particularly during 2050. Only increase in number of generations does not give decisive information about increase in the damage potential because high temperature extremities have balancing effect on finite rate of natural increase due to increase in mortality and reduction in reproduction rates (Kroschel et al., 2013; Fand et al., 2014). A multi-model climate change study projected very high increase of temperature (4.0–6.5 °C) for cold arid ecoregion (Leh) in the future time periods (Chaturvedi et al., 2012). This increase of temperature in cold arid may have positive impact on *B. zonata* establishment in the future time periods. Similarly hot and warm sub-humid ecoregions (Daprijo and Ranchi) have been projected very low increase of temperature (1–1.5 °C) in the future scenarios. The low increase of temperature may not have increase in temperature threshold required for *B. zonata* establishment in these locations. So, we adopted to link GI with AI and found that the projected areas with high generation index (>8.0 generations per year) also predicted with high activity index (AI > 12.0). The results of all three indices also indicate that the North-Eastern region of India is predicted to have higher risk for *B. zonata* fruit fly infestation in the future compared to present scenario. In another study conducted by Sridhar et al. (2014) on co-existing fruit fly species, North-Eastern region was found to have more suitability for *Bactrocera dorsalis* and our results also proved to be in agreement. Moreover, the results suggested that as climate change, abundance and number of generations of *B. zonata* will increase in Southern states of India include Kerala, part of Tamil Nadu and Karnataka and some coastal parts of Maharashtra and Odisha. Projected increase in suitability indices of abundance and number of generations of *B. zonata* in these areas also predicted optimal by CLIMEX based study (Ni et al., 2012). Our present results indicate that tarai regions of northern India would be highly suitable for *B. zonata* and in contrary to Ni et al. (2012) who predicted these areas as optimal.

4.2. Phenology model and sources of variations

For a detailed study of spatio-temporal changes in abundance, establishment and distribution of *B. zonata* in the present study, we linked climatic data generated from present and future eight GCMs using process based phenology model constructed in the ILCYM software (Sporleder et al., 2004). Phenology model was constructed using detailed life table parameters studied at different temperature regimes ranging from 15 °C to 35 °C (Choudhary et al., 2020). As we all know that linear estimates in degree models often either over or under estimate the developments at both high and low temperature (Bergant et al., 2005) and thus adoption of non linear relationships in phenology models will have more precision (Kroschel et al., 2013; Fand et al., 2014; Choudhary et al., 2020). In contrast to bioclimatic envelope created by niche based modelling for a region that is restricted to describe the pest range expansion (Ni et al., 2012), present modelling results can determine risk indices for actual zone of interest (Kroschel et al., 2013).

Results of present study showed that risk indices (establishment, abundance and generations) significantly vary among locations, scenarios, GCMs and time periods. Variation in number of generations is due to geographical locations, time periods and GCMs was

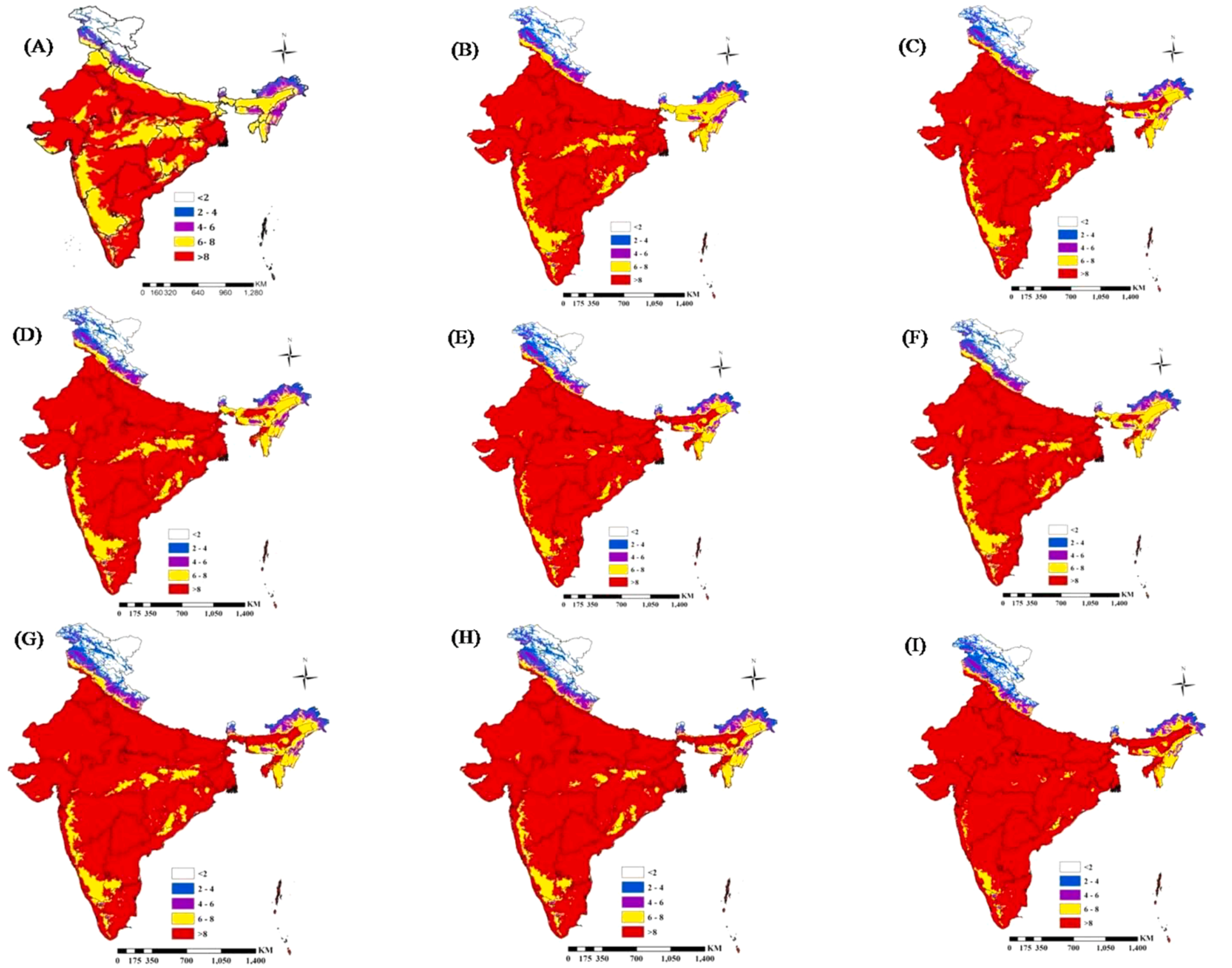

Fig. 5. Current (1950–2000) (A) and ensemble average of eight GCMs of each future scenarios (B = 2.6/2050; C = 4.5/2050; D = 6.0/2050; E = 8.5/2050; F = 2.6/2070; G = 4.5/2070; H = 6.0/2.070; I = 8.5/2070) abundance and damage potential of *Bactrocera zonata* in India based on phenology based model prediction of generation index (GI). The index values > 8.0 indicated economic damage is most likely to be occur in the particular area.

well understood earlier by Choudhary et al. (2019d), Srinivasa Rao et al. (2016) for Indian region on different crops. Since, it is well known that insects being a poikilothermic organism, temperature act as a major factor to govern the insect phenology. The distant geographical locations have variations in temperature which will lead to variation in risk indices as indicated in the present study (Choudhary et al., 2019d). Uncertainty and variation of risk indices based on climate scenarios (RCPs) are plausible in the present study for the future due to factors innately difficult to predict i.e. anthropogenic factors and socio-economic assumptions (Nakicenovic et al., 2000). Variation in risk indices of *B. zonata* on account of use of different GCMs was noticeable among GCMs, ranging high values from IPS model to low due to MRIC model projections. It is known that no single GCM model performs best for all regions but each GCM has its own strengths and weaknesses (Bader et al., 2008; Berzitis et al., 2014). It is impossible to select most appropriate single GCM which provide highly accurate future climate change projections for a region due to undetermined 20th century monsoon rainfall pattern or factors affecting earth climate or socio-economic assumptions etc. (Kripalani et al., 2007; Berzitis et al., 2014). The findings indicate the merits and precision of ensemble model which surmount the variations arises from selection of GCM and scenario and thus we feel that adoption of ensemble model is apt in the present study.

In present study, average numbers of generations of *B. zonata* predicted by ILCYM model were compared with generation calculated based on degree days approach using gridded daily historical data (IMD). The generation indices simulated for locations were reasonably predicted with minor discrepancies when compared to gridded daily temperature historical data. The number of generation simulation for several locations from gridded daily historical data and ILCYM WorldClim interpolated records allowed us to apply two different sets of temperature data for comparison. The minor discrepancies of generation indices may be due to variability in climate data used from different sources. IMD gridded datasets is derived from real time daily data of network of weather stations while WorldClim data is generated through interpolations over several decades of historical data (Hijmans et al., 2005; Kroschel et al., 2013).

Table 6
Agro-ecological zone representative locations and scenario based variation in generation index of *Bactrocera zonata* in India under future climate change periods. Values are means ± standard deviation; ^{a,b,c,d,e}means in a row followed by different letters are significantly different using Tukey's HSD test (P > 0.05).

Location/s Scenario/time period	Current	RCP 2.6/ 2050	RCP 4.5/ 2050	RCP 6.0/ 2050	RCP 8.5/ 2050	RCP 2.6/ 2070	RCP 4.5/ 2070	RCP 6.0/ 2070	RCP 8.5/ 2070	F cal (*df* = 64)	*LSD* (*P* = *0.05*)
Leh	2.57^{a}	3.04 ± 0.26^{b}	3.22 ± 0.28^{bc}	3.13 ± 0.28^{bc}	3.42 ± 0.32^{c}	3.13 ± 0.25^{bc}	3.37 ± 0.35^{c}	3.41 ± 0.30^{c}	3.89 ± 0.35^{d}	14.32	0.30
Sri Ganganagar	8.34^{a}	8.75 ± 0.39^{b}	9.00 ± 0.42^{bc}	8.84 ± 0.39^{b}	9.28 ± 0.36^{c}	8.90 ± 0.28^{b}	9.29 ± 0.40^{c}	9.38 ± 0.14 ^{cd}	9.70 ± 0.25^{d}	14.28	0.34
Daporijo	6.64^{a}	7.28 ± 0.22^{bc}	7.46 ± 0.21^{bc}	7.36 ± 0.21^{bc}	7.63 ± 0.34^{c}	7.20 ± 0.19^{b}	7.55 ± 0.25^{c}	7.51 ± 0.26^{c}	8.23 ± 0.44^{d}	23.77	0.28
Darbhanga	7.98^{a}	8.55 ± 0.19^{b}	8.76 ± 0.22^{bc}	8.63 ± 0.22^{b}	8.90 ± 0.20^{c}	8.55 ± 0.17^{b}	8.93 ± 0.28^{c}	8.88 ± 0.22^{c}	9.53 ± 0.30^{d}	33.62	0.23
Ranchi	7.33^{a}	7.79 ± 0.11^{b}	8.03 ± 0.16^{c}	7.87 ± 0.17^{bc}	8.16 ± 0.15^{c}	7.78 ± 0.12^{b}	8.19 ± 0.29^{c}	8.14 ± 0.16^{c}	8.70 ± 0.21^{d}	43.15	0.18
Bhavnagar	8.81^{a}	9.43 ± 0.17^{b}	9.63 ± 0.16^{bc}	9.58 ± 0.21^{bc}	9.80 ± 0.23^{c}	9.46 ± 0.19^{b}	9.80 ± 0.27^{c}	9.86 ± 0.17^{c}	10.41 ± 0.46^{d}	36.82	0.22
Chhindwara	7.62^{a}	8.09 ± 0.14^{b}	8.29 ± 0.16^{c}	8.23 ± 0.22^{bc}	8.45 ± 0.19 ^{cd}	8.12 ± 0.13^{bc}	8.47 ± 0.26 ^{cd}	8.49 ± 0.17^{d}	9.04 ± 0.34^{e}	41.07	0.19
Dharwad	7.45^{a}	7.98 ± 0.16^{b}	8.13 ± 0.28^{bc}	8.13 ± 0.26^{bc}	8.27 ± 0.23^{c}	7.96 ± 0.20^{b}	8.25 ± 0.34^{c}	8.19 ± 0.22^{bc}	8.86 ± 0.27^{d}	31.30	0.25
Port Blair	8.03^{a}	8.62 ± 0.31^{bc}	8.78 ± 0.39^{c}	8.72 ± 0.40^{bc}	8.83 ± 0.32^{c}	8.46 ± 0.29^{b}	8.80 ± 0.24^{c}	8.67 ± 0.17^{bc}	9.23 ± 0.29^{d}	11.19	0.30
Madurai	9.41^{a}	10.05 ± 0.20^{b}	10.20 ± 0.24^{bc}	10.19 ± 0.24^{bc}	10.43 ± 0.26^{c}	9.97 ± 0.19^{b}	10.37 ± 0.31^{c}	10.35 ± 0.24^{c}	11.03 ± 0.34^{d}	28.21	0.26

5. Conclusion

The present study highlights the importance of linking the climate change scenarios and temperature driven process based phenology model using ILCYM software for future impacts on distribution and damage potential of *B. zonata* on different scales in India. The changes in future predicted temperature due to climate change will lead to increase in the activity of *B. zonata with* higher generations and thus lead to increased suitable area under this pest in India. Present findings also provide impetus to formulate integrated pest management measures and also to plan the possible quarantine measures across various regions/states to restrain the abundance and population activity in the country. Although the present study takes account into variations based on GCM and scenarios, some additional life cycle affecting factors of *B. zonata* such as soil moisture, irrigation, land use pattern, host range, suitability of host species etc. should also be taken into consideration in the future risk assessment studies.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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