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Seasonal time series forewarning model for population dynamics of mango hopper (Hemiptera: Cicadellidae) in humid agro-climatic conditions

J. K. Bana[a,b], Jaipal Singh Choudhary[c], Sushil Kumar[a], P. D. Ghoghari[a], G. B. Kalaria[a], Himanshu Ramanlal Desai[a], S. J. Patil[a] and Prakash Patil[d]

[a]ICAR-AICRP on Fruits, Agriculture Experimental Station, Navsari Agricultural University, Navsari, India; [b]College of Agriculture, Sri Karan Narendra Agriculture University, Dausa, India; [c]Farming System Research Centre for Hill and Plateau Region, ICAR-RCER, Ranchi, India; [d]ICAR-AICRP on Fruits, Indian Institute of Horticultural Research, Bengaluru, India

ABSTRACT

Mango hopper (Hemiptera: Cicadellidae) is serious and widespread monophagous pests of mango, *Mangifera indica* L. in tropical and sub-tropical region of India. The present investigation was carried out for weekly data interval of 20 consecutive years (1998–2017) to understand the population dynamics of mango hoppers and developed good fit time series prediction model for better management of hoppers in humid agro-climatic conditions. The relationship between weather parameters and mango hopper population showed that maximum temperature and relative humidity had significant effect on mango hopper population dynamics. Time series seasonal autoregressive integrated moving average (SARIMA) model was fitted from several plausible SARIMA models for forecasting the mango hoppers population. A best-fit SARIMA $(1, 0, 2) \times (1, 1, 1)_{52}$ model within tolerable errors with fitted comparative performance parameters in terms of root mean square error (RMSE), MSE, mean absolute error (MAE) and MA percentage error (MAPE) parameters were observed. Forecasting model develop in this study will predict mango hopper well in advance which can be used for timely better management of hoppers in mango agro-ecosystem.

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KEYWORDS
Forewarning; climate; correlation; hoppers; seasonal; validation; weather parameters

1. Introduction

Mango (*Mangifera indica* L.) is an important fruit crop in tropical and sub-tropical regions known for its fabulous and delicious taste, sweet fragrance, and aroma. India is one of the major mango-producing countries in the world with nearly 40% of world total mango production (NHB 2017). The low production and productivity of mango are limited by various factors, such as incidence of insect pests, diseases and aberrations in weather. About 492 species of insects are reported on mango, of which 188 insect pests are reported from India (Tandon and Verghese 1985). Among them, very few are the major pests of mango (Pena et al. 1998). Mango hoppers (*Amritodus atkinsoni* (Lethierry); *Idioscopus nitidulus* (Walker 1870); and *Idioscopus nagpurensis* (Pruthi)) (Hemiptera: Cicadellidae) are considered as the most serious and wide-spread insect pests of mango causing up to 100% yield losses (Rahman and Kuldeep 2007). Mango hoppers damage to mango at each crop stages right from emergence of new flush to fruiting (Gundappa et al. 2014; Kumar et al. 2014; Gundappa and Shukla 2016; Rakshitha et al. 2017; Gundappa and Shukla 2018). Previous work has been focused on impact of environment on the population dynamics of mango hoppers (Varshneya and Rana 2008; Anitha et al. 2009; Lakshmi et al. 2010; Joshi and Sanjay 2012; Kumar et al. 2014). Temperature and precipitation have strong effect on insect development (Ali et al. 2020). This is also true for Southern part of Gujarat, which is one of major production hub of delicious Alphonso variety of mango in Western part of India where mango hoppers are considered as major pest of mango (Sushil et al. 2005; Kumar et al. 2014; Bana et al. 2015, 2016, Bana, Sushil, Hemant 2018; Bana, Sushil, Ghoghari, et al. 2018). Build up of hoppers population on mango depends on availability of new flush and flowers as well as on prevailing weather conditions (Gundappa et al. 2014; Gundappa and Shukla 2016; Kumar et al. 2014; Chaudhari et al. 2017). Correlation studies revealed that hopper population increased when temperature raised and

CONTACT J. K. Bana jugalbana@gmail.com College of Agriculture, Sri Karan Narendra Agriculture University, Lalsot, Dausa 303 511, India; Jaipal Singh Choudhary choudhary.jaipal@gmail.com ICAR-RCER, Farming System Research Centre for Hill and Plateau Region, Ranchi, Jharkhand 834 010, India

decreased in response to relative humidity (Varshneya and Rana 2008; Lakshmi et al. 2010; Joshi and Sanjay 2012). It is well evident that climatic conditions are continuously changing over the time period and are projected to increase 1.4–5.8 °C by 2100 in connection with occurrence of heat waves and increase precipitation (10–15%) (IPCC 2014). Timely and accurate prediction of hoppers in mango ecosystem would check hopper population outbreaks. Available information on factors affecting population buildup of hoppers in mango is meager and if available, it is based on simple correlation and regression of weather parameters and population dynamics of hopper (Pandey et al. 2003; Zagade and Chaudhari 2010; Kumar et al. 2014; Sahoo et al. 2016; Rakshitha et al. 2017). If data are collected in chronological order for long term than the time series models prefer compared to regression analysis where ordering in regression as per time does not matter (Knief and Forstmeier 2021). One of the most important assumptions of linear regression is that the residues should not be correlated. Linear regression will not be able to capture data trends in case of autocorrelated residues (Knief and Forstmeier 2021). Time series forecasting is an important area of prediction/forecasting where past long time observations are collected and analyzed to develop relationship model of variables. Recently most important and widely used time series model is the autoregressive integrated moving average (ARIMA) for insect pest forecasting (Boopathi et al. 2015; Prawin et al. 2015; Boopathi et al. 2017; Boopathi et al., 2017; Ali et al. 2020). Identification of suitable ARIMA model and incorporation of suitable seasonal factor makes it seasonal ARIMA modeling.

In view of shortcomings of previous studies and meager information's on time series seasonal modeling, this study was incepted for developing good forecasting model using time series techniques as well as possibilities of mathematical models to predict hoppers occurrence based on long time series data (20 consecutive years) of hopper incidence for formulating area-specific integrated pest management (IPM) strategies well in advance.

2. Materials and methods

2.1. Experimental field and data observation

The hopper population data of this study was recorded for 20 consecutive years (1998–2017) in the fixed mango orchard (cv. Alphonso) of ICAR-AICRP at fruits center, Agriculture Experimental Station (AES), Navsari Agricultural University (NAU), Paria, Gujarat, India (20°26'N, 72°58'E, 16 m at altitude) (Figure 1). The mango cv. Alphonso block was kept free from any pesticide application during the study periods. Hopper population was recorded at Standard Meteorological Week (SMW) interval on ten randomly selected trees by visual count method without disturbing the plant part (Kumar et al. 2014). Total number of hoppers (nymphs and adults) were counted and averaged to get hoppers per shoot/flower panicle for final analysis. The species of mango hoppers were identified as *Idioscopus nitidulus, Amritodus atkinsoni, I. clypealis and Amrasca splendens* Ghauri (Hemiptera: Cicadellidae) infesting on young leaves and flower panicles of mango during the study period. The data on weather parameters *viz.,* temperature (maximum and minimum), relative humidity (morning and evening), rainfall and wind speed were recorded for each SMW from meteorological observatory installed within the experimental site of AES, NAU, Paria (India).

2.2. Data analysis

Multiple linear regression (MLR) and seasonal ARIMA (SARIMA) were used for model building to get a reasonably accurate forecasting of hoppers population in humid agroclimatic conditions and presents with the relevant flowchart (Figure 2).

2.2.1. Regression

To determine the relationship between mango hoppers population dynamics and weather variables, correlation analysis of hopper weekly data as dependent factor and weather parameters (minimum and maximum temperature, rainfall and wind velocity) as independent variables was done. In multiple linear model, output of weekly mango hopper as dependent variable (Y) defined as:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots \beta_p x_p + \varepsilon \tag{1}$$

where Y is weekly mango hopper data as dependent variable; $\beta_{0 \ldots} \beta_p$ are regression coefficients; x_i' are weather variables and ε is random disturbance or error term where $i = 1,2,\ldots p$.

2.2.2. Seasonal autoregressive integrated moving average

We developed multiplicative SARIMA model from weekly time series data (1998–2017) of hopper incidence and weather data (Box et al. 2008). Time series models, like the ARIMA, effectively consider serial linear correlation among observations, whereas SARIMA models can satisfactorily describe time

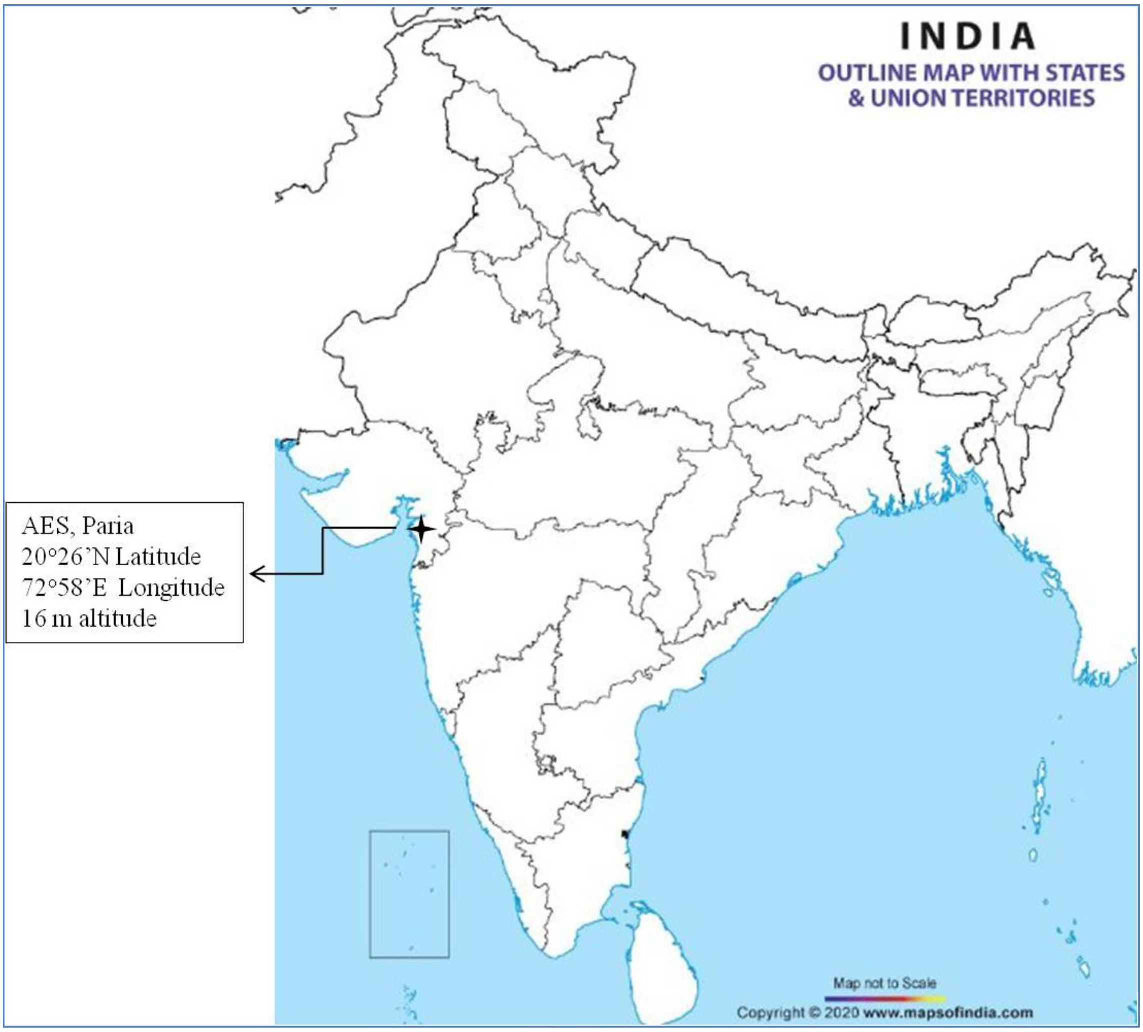

Figure 1. Map of experimental location.

series that exhibit non-stationary behaviors both within and across seasons. The model building was consisted of three stages based on Hipel et al. (1977) and Box et al. (2008) methodology, *viz.* Identification, estimation and diagnostic checking. Parameters of model were experimentally selected at the identification stage. A seasonal ARIMA model was expressed as SARIMA (p, d, q) (P, D, Q)$_s$, where p is order of autoregressive and P is the seasonal autoregressive parts; d and D are the order of integration and seasonal integration, respectively; q is the order of moving average and Q is seasonal moving average and finally s was the length of the seasonal period.

Generally, the original time series $\{Y_t\}$ utilizes a lag operator B to process SARIMA (p, d, q) (P, D, Q)$_s$. A seasonal ARIMA model may be written as (Box et al. 2008):

$$\varphi_p(B)\varphi_P(BS)d(1-B^S)DY_t = \theta_q(B)\Theta_Q(BS)\varepsilon t \quad (2)$$

In formula (1), B is lag operator (defined as $BkY_t = Y_t - k$);

$$\varphi_p(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi p B^P \quad (3)$$

$$\Phi_P(Bs) = 1 - \Phi sBs - \Phi_{2s} B^{2s} - \cdots - \Phi_{Ps} BP \quad (4)$$

$$\theta_q(B) = 1 - \theta_1 B - \theta_2 B2 - \cdots - \theta_q Bq \quad (5)$$

$$\Theta_Q(Bs) = 1 - \Theta sBs - \Theta 2sB2s - \cdots - \Theta QsBQs \quad (6)$$

where $\varphi(B)$and $\theta(B)$ are polynomials of order p and q, respectively; $\Phi(Bs)$and $\Theta(Bs)$ are polynomial in B of degrees P and Q, respectively; p is the order of non-seasonal auto regression; d is the number of regular differences; q is the order of non-seasonal moving average; P is the order of seasonal auto regression; D is the number of seasonal differences; Q is the order of seasonal moving average; and s is the length of season.

Stationarity is a necessary condition in building an ARIMA model and differencing is often used

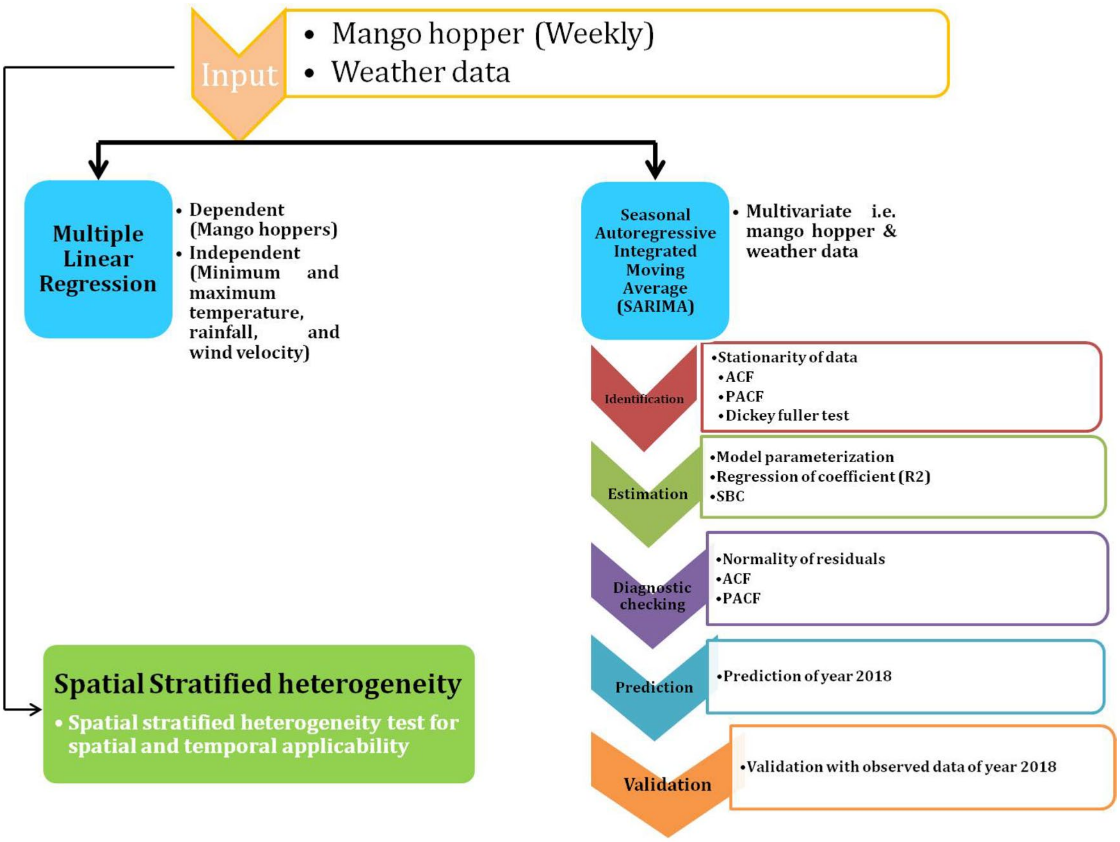

Figure 2. Flowchart of proposed modeling.

to stabilize the time series data. Autocorrelation function (ACF) and partial ACF (PACF) plots or augmented Dickey–Fuller unit root (ADF) test were used to identify whether or not the time series is stationary. The 5% critical values of the autocorrelation at any given lag d ($d \neq 0$) are given by $\pm 1.96/[T - d]^{1/2}$ (where T=number of observation = 1040 and d=lag). Different model combinations were tested and optimal model was chosen based on regression coefficient (R^2) and Schwarz Bayesian criterion (SBC) values that most closely fit the data.

The models fitting, prediction, and validation accuracy were evaluated by calculating coefficient of determination (R^2), mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE) and MA percentage error (MAPE) parameters using the formulae described by Vennila et al. (2017).

A test for heterogeneity examines measure of the degree of inconsistency in the studies' changes over the time or not and results applicability for global modeling was evaluated. Stratification of heterogeneity is a partition of a study area, in this study, the years, where observations are homogeneous within each stratum but not between strata. A stratified heterogeneity is mostly significant if the values within the strata are homogeneous or the variance within the strata is zero; a stratification of heterogeneity vanishes when there is no difference between the strata. To fit the common-sense concept that 0 represents absence and 1 presents definite presence, the value of the statistic is required to be within [0,1] (0 if there is no stratified heterogeneity, and 1 if the population is fully stratified). More formally, a study area is composed of N units (years) and is stratified into h= 1, 2… L stratum; stratum h is composed of N_h units; Y_i and Y_{hi} denote the value of unit i in the population and in stratum h, respectively.

The stratum mean is $\bar{Y}_h = \left(\frac{1}{N_h}\right)\sum_{i=1}^{N_h} Y_{hi}$

Stratum variance is $\sigma^2_{h=\left(\frac{1}{N_h}\right)=\sum_i^{N_h}\left(Y_{hi}-\bar{Y}_h\right)^2}$

Population mean is $\bar{Y} = \left(\frac{1}{N}\right)\sum_{i=1}^{N} Y_i$;

Population variance is $\sigma^2 = \left(\frac{1}{N}\right)\sum_i^N (Y_i - \bar{Y})\wedge 2$

The concept of spatial stratified heterogeneity is adopted by the PD-value in the geographical detector (Wang et al. 2016).

We rename it as the q-statistic as follows:

$$q = 1 - \sum_{h=1}^{L}\sum_{i=1}^{N_h}(Y_{hi} - \bar{Y}_h)^\wedge 2 / \sum_{i=1}^{N}\left(Y_i - \bar{Y}\right)^2$$
$$= 1 - \sum_{h=1}^{L} N_h \sigma_h^2 / N\sigma^2 = 1 - \frac{\text{SSW}}{\text{SST}}$$

where the total sum of squares

$$\text{SST} = \sum_{I}^{N}(Y_i - \bar{Y})^\wedge 2 = N\sigma_h^2$$

And the within sum of squares

$$\text{SSW} = \sum_{h=1}^{L}\sum_{i}^{N_h}(Y_h i - \bar{Y}_h)^\wedge 2 = \sum_{h=1}^{L} N_h \sigma_h{}^2$$

Statistical analysis and SARIMA modeling were performed using the SPSS version 16 (SPSS Inc., Chicago, IL). Graphs were drawn using Microsoft Excel program.

3. Results

3.1. Population dynamics of mango hoppers over the years

The population pattern of mango hoppers over the years revealed the wide variation in population dynamics during the studied period (Table 1). The weekly population abundance of hoppers showed the seasonality (Figure 3). Within year hopper population dynamics showed that hoppers were recorded throughout the year. The lowest population of hopper was recorded during rainy season (Figure 3). Maximum population was observed during flowering stages followed by vegetative stage (new flush) of the mango (Figure 4). During the study period, maximum mean population was recorded in the year 2006 (29.70 hoppers/panicle) followed by year 2011 (26.70 hoppers/panicle) and 2013 (25.50 hoppers/panicle). Whereas, minimum mean population was recorded (0.06 hopper/panicle) in the year 2000. The maximum and minimum temperatures ranges were varied from 23.8 to 40.8 °C and 5.5 to 28.6 °C, respectively, during the study periods. Evening and morning relative humidity was ranged between 18.8% and 99.3% and wind velocity varies from 0.1 to 15.6 km/h (Figure 5). An average rainfall (2294 mm/year) was recorded during studied periods (Figure 6).

3.2. Relationship between mango hoppers population and weather parameters

The results of relationship between hopper population and weather parameters showed that hopper population was found significant and positively correlated with maximum temperature (‘r’ =0.116, p<.01). Whereas, minimum temperature (‘r’=−0.416, p<.01), relative humidity (‘r’=−0.166 and ‘r’=−0.394, p<.01), rainfall (‘r’ =−0.192, p<.01) and wind velocity (‘r’ =−0.259, p<.01) indicated negatively significant relationship with hopper population (Table 2). The MLR analysis with all-weather parameters was elucidated only 18.90% variation of hopper population dynamics (p<.01). Further, stepwise regression models were developed using approach of systematically adding of most significant variable and removing of least significant variable at each step. The final model generated by stepwise regression indicated that minimum temperature and evening relative humidity were the most significant variables affecting mango hopper population dynamics which showed 18.50% of the variation of hopper population dynamics (p<.05). The most optimized stepwise regression model, $Y = 7.798^{a} + (-0.196)\ T_{\min} + (-0.038)\ \text{RH}_{\text{eve}}$ was developed in this study (Table 3).

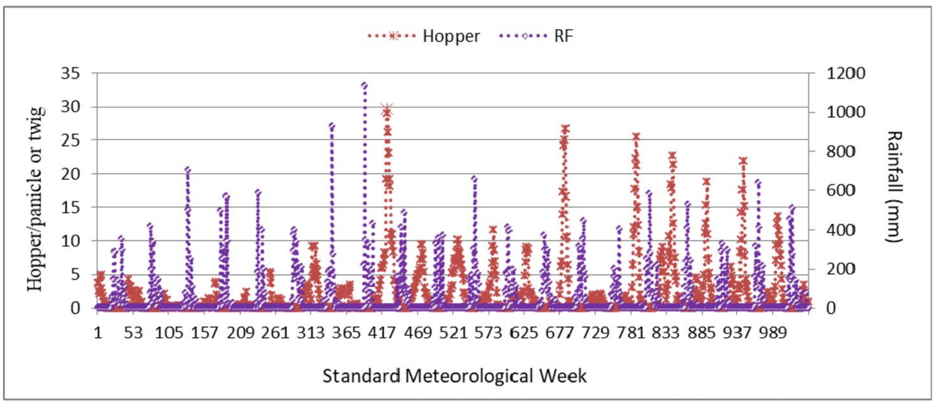

Figure 3. Mango hopper and rainfall periodogram during the study periods (1998–2017).

Table 1. Univariate descriptive statistics for population of mango hoppers during 1998–2017.

	Hopper/panicle or twig/tree			
Year (s)	Mean (SD)	Range	Skewness	Kurtosis
1998	1.00 (0.21)	4.90	1.24	0.19
1999	0.46 (0.11)	2.60	1.53	1.04
2000	0.06 (0.01)	0.40	1.82	3.61
2001	0.41 (0.11)	3.80	2.90	9.24
2002	0.48 (0.16)	5.40	3.18	9.85
2003	0.66 (0.14)	3.50	1.50	1.02
2004	1.64 (0.34)	9.20	1.62	2.06
2005	0.69 (0.18)	6.00	2.32	5.54
2006	5.89 (1.09)	29.70	1.77	2.40
2007	2.02 (0.37)	9.50	1.44	1.04
2008	2.50 (0.44)	10.20	1.07	−0.34
2009	1.88 (0.37)	11.60	1.98	3.69
2010	1.38 (0.37)	9.00	2.28	4.20
2011	3.44 (0.94)	26.70	2.37	4.78
2012	0.61 (0.08)	2.10	0.77	−0.35
2013	4.40 (0.89)	25.50	1.77	2.61
2014	3.54 (0.78)	22.70	2.16	4.10
2015	2.70 (0.58)	18.70	2.22	4.85
2016	2.57 (0.67)	21.90	2.57	6.26
2017	2.32 (0.52)	13.70	1.79	2.10

N, 52

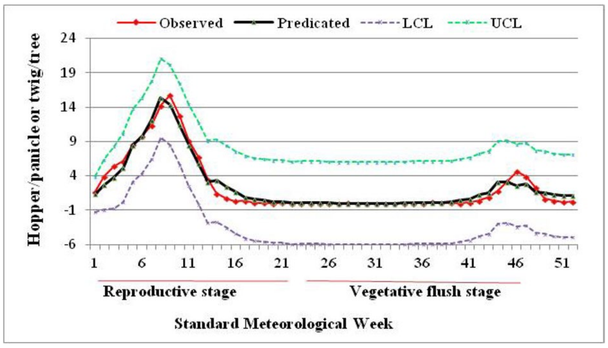

Figure 4. Validation of observed and predicted of hopper population on mango during the year 2018.

3.3. Time series SARIMA model

In construction of SARIMA model, several models were tested (Table 4). The ACF and PACF plots of best-identified SARIMA show that correlations fell around zero and within their 95% confidence intervals (CIs) after one order of differencing (Figure 6). Both plots of ACF and PACF also suggest that stationarity in data series was achieved before searching best fitted SARIMA model. Further, using Dickey–Fuller test for checking stationarity of time series, p value were smaller than .01. (Dickey–fuller= −7.6401, Lag order = 10, p value<.01). Thus, given series is stationary. The first-order autocorrelation limits at 5% critical values were determined as ±0.06 based on lag d and number of observations considered. Based on values of legs (24) maximum 2 legs can be accepted the exceeded the lines of given 95% CI (Figure 7). But ACF plot of residuals showed that all the values are within the acceptable leg limits. ACF plots of residual also suggest that model do not have autocorrelation and series achieved stationarity. The best optimal model combination was determined using high value of R^2 and lowest SBC. The best fitted SARIMA (1, 0, 2) × (1, 1, 1)$_{52}$ model had R^2 value as 0.89 and lowest SBC (0.62) (Table 4). The fitted parameters of seasonal ARIMA are shown in Table 5. The best-fitted model was SARIMA (1, 0, 2) × (1, 1, 1)$_{52}$ model for mango hopper population prediction in Southern region of Gujarat of India. As their correlation values are not outside 95% the CI limits, the residual error is considered to be white noise indicating that this model is appropriate for hopper population prediction. The fitted values of predicted model and the actual values of year 2018 were used for testing of prediction efficiency. The prediction error of model in fitting part and validation part was lower in the SARIMA model, as shown by MSE, RMSE, MAE and MAPE (Table 6). The model curve displays the point-to-point comparison of actual hopper population and predicted population in SARIMA model (Figure 4). The actual hopper population and model prediction did not show any particular pattern of occurrence throughout the year. In the year 2018, maximum hopper population predicted in SMW 8 by SARIMA model was matching with the actual data. Thus, from the peak curve we can conclude that hopper population fluctuates weekly but no specific seasonal pattern was observed for increasing or decreasing population. Q-statistics of heterogeneity test was 0.069 that denote no difference observed between temporal strata (F-stat = 19.18, and corresponding p< .00001). So, SARIMA model was developed for consecutive 20 years data performs better for this time horizon of mango hopper population prediction.

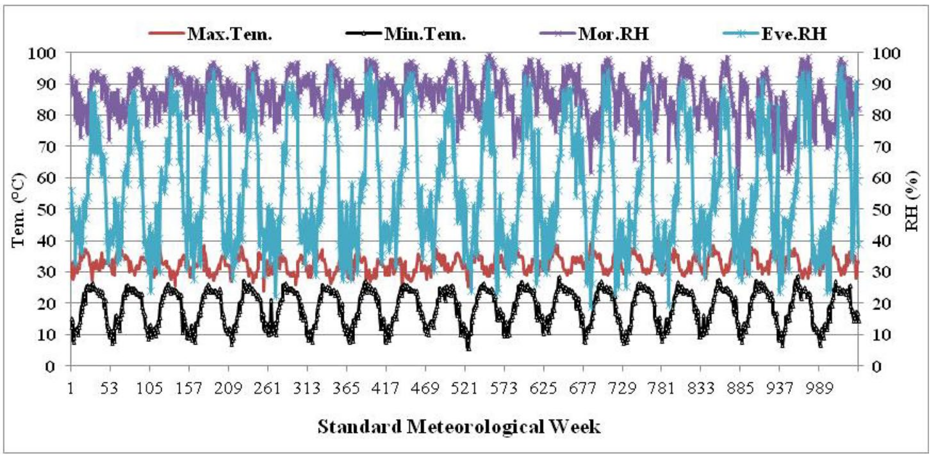

Figure 5. Weather conditions during the study periods (1998–2017).

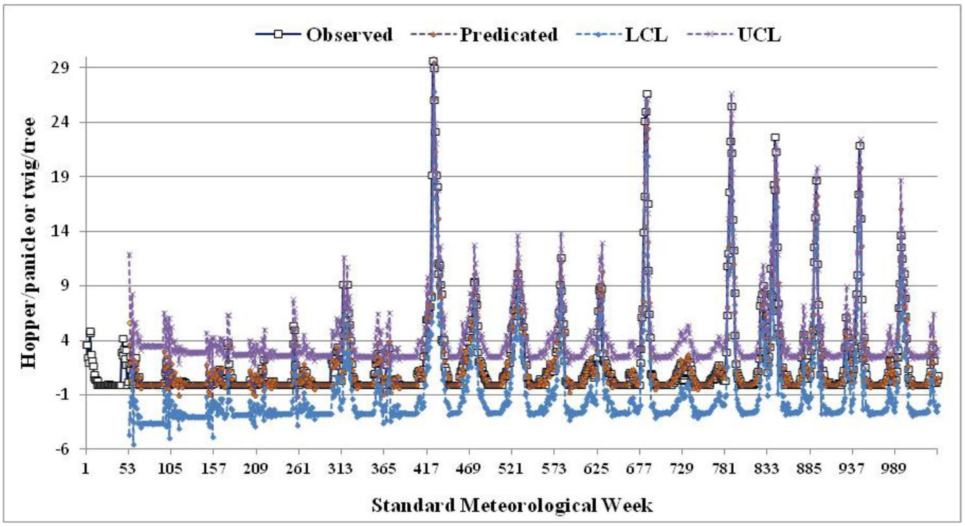

Figure 6. Model fitting and prediction values with actual hopper population on mango during the year 1998–2017.

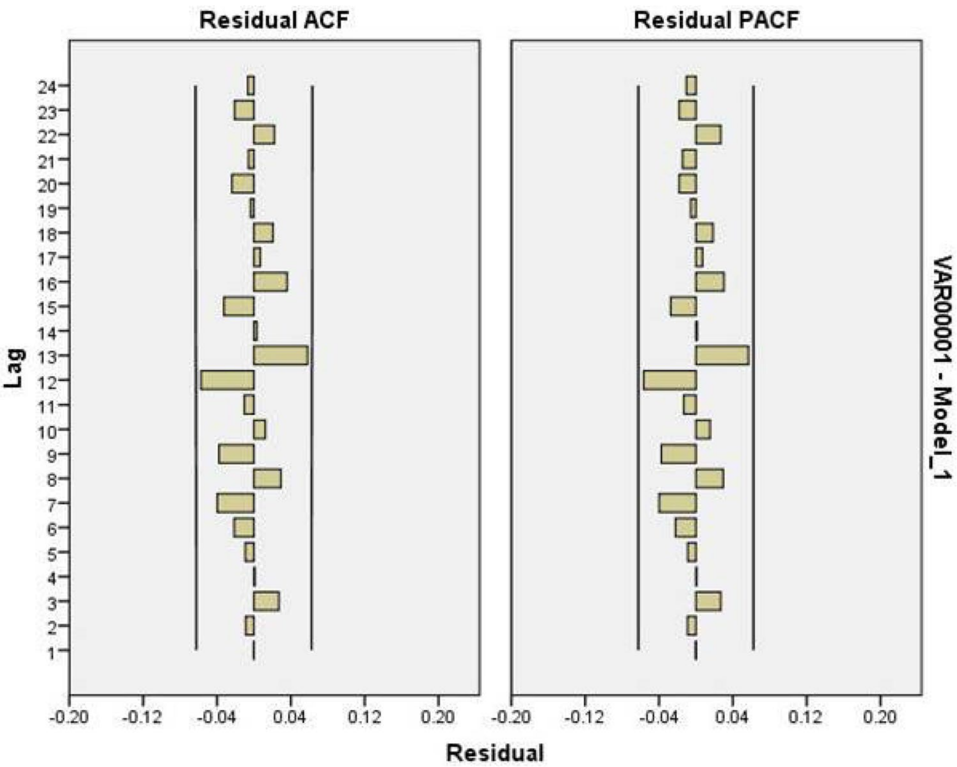

Figure 7. Fitted SARIMA (1, 0, 2) × (1, 1, 1)$_{52}$ model graphs of residuals autocorrelation function (ACF) and partial autocorrelation function (PACF).

Table 2. Correlation of mango hoppers population with weather variables during the study periods (1998–2017).

Weather variables	Correlation coefficient (r) Hoppers
T_{max}	0.116**
T_{min}	−0.416**
RH_{mor}	−0.166*
RH_{eve}	−0.394**
RF	−0.192**
WV	−0.259**

**Significant at 0.01 level; $N = 1040$.

Table 3. Regression model developed for mango hopper.

Regression equation	SE	R^2	F
	Multiple linear regression (MLR)		
$Y = 2.801^a + (0.102)\ T_{max} + (0.239) T_{min}\ (0.023)\ RH_{mor} + (-0.035)\ RH_{eve} + (0.001)\ RF + (0.076)\ WV$	3.61	0.189	40.11**
	Stepwise linear regression		
$Y = 7.471^a + (-0.294)\ T_{min}$	3.64	0.17	216.99**
$Y = 7.798^a + (-0.196)\ T_{min} + (-0.038)\ RH_{eve}$	3.61	0.185	118.72**

[a]Constant; **Significant at 0.01 level.

$N = 1040$.

Table 4. Comparison of different SARIMA Models.

Model combination	R^2	Schwarz Bayesian criterion (SBC)
SARIMA(1,0,2) (1,1,1)	0.89	0.62
SARIMA(1,0,1) (0,1,1)	0.88	0.68
SARIMA(1,0,0) (0,1,1)	0.88	0.70
SARIMA (1,0,0) (1,1,0)	0.86	0.89

Table 5. Parameter estimates and their testing results of the best fitted SARIMA model.

Model parameters		Coefficient	Standard error	T value
Non-seasonal legs (1,0,2)	AR1	0.838	0.022	38.613**
	MA1	−0.167	0.037	−4.470**
	MA1	−0.159	0.036	−4.427**
Seasonal legs $(1,1,1)_{52}$	Seasonal AR1	−0.148	0.041	−3.630**
	Seasonal MA1	0.783	0.031	25.312**

**Parameter estimations were considered statistically significant ($p < .05$).

Table 6. Models performance results in the fitting and validation (2018) part of hopper population prediction.

Prediction	Fitting error statistics	Validation error statistics
Statistical error	1998–2017	2018
R^2	0.893	0.963
MSE	1.788	0.622
RMSE	1.337	0.789
MAE	0.620	0.566
MAPE	1.203	2.111

4. Discussion

The successful implementation of IPM strategies against mango hopper requires accurate information on population dynamics of mango hopper well in advance. Therefore, this study is also conducted to gain the knowledge about mango hopper population dynamics in mango agro-ecosystem in humid climatic conditions of India. Earlier researchers have given the emphasis only to understand the relationships between weather variables and mango hoppers (Pandey et al. 2003; Zagade and Chaudhari 2010; Kumar et al. 2014; Sahoo et al. 2016; Rakshitha et al. 2017). Long data of time series-based analysis play an important role in prediction and forecasting from past observations (Boopathi et al. 2015). Lacking of long time series data-based analysis of mango hopper population in order to understand the pattern and develop the forecasting model was the prime basis of this study.

In this study, we used 20 years weekly data of mango hopper incidence in mango agro-ecosystem and analyzed the response of weather variables on population dynamics of mango hoppers. Results of this study indicated that weather has significant influence on mango hopper population build up. Individually and interactive weather parameters influences the mango hopper population which has been clearly observed through MLP and stepwise regression analysis. Even though the variation of hopper population dynamics was very less (18.90%), but it was significant due to use of long term time series in the analysis. The major weather factors, minimum temperature and evening relative humidity were responsible for hopper population fluctuations which were consistent with earlier studies. Slight increase of temperature and relative humidity accelerated the sharp rise in hopper population in mango ecosystem, which was also previously reported by various workers (Pandey et al. 2003; Anitha et al. 2009; Zagade and Chaudhari 2010; Kumar et al. 2014; Namni et al. 2017). Apart from weather depended growth of mango hoppers, hopper population coincides with emergence of inflorescence and floral development (Figure 3). Earlier, Zagade and Chaudhari (2010) also reported the maximum hopper activity in the month of December–January that coincides with emergence of inflorescence and floral development, later population decline gradually when fruits reached at marble stage in high rainfall zone of Konkan region, India. Ample availability of preferred food also favors hopper population's development (Pandey et al. 2003; Namni et al. 2017) consistently the maximum hopper population was observed during flowering phase of mango in this study. In similar line of this study, Kannan and Rao (2006) also reported that the host plants and weather parameters played significant role in the abundance and population dynamics of mango hopper, *A. atkinsoni*. In contrary to this, Chaudhari et al. (2017) reported that the incidence of hopper mainly depend on the flowering and new shoot initiation where weather did not played any significant role in the hopper population development on mango. Regression analysis results from previous studies and this study indicated good relationship with weather parameters but still have some limitations. When data collected for long term than ordering of data in regression as per time does not matter (Knief and Forstmeier 2021). And also linear regressions have not been able to capture data trends in case of autocorrelated residues (Knief and Forstmeier 2021).

Time series based analysis of mango hopper and weather components identified plausible SARIMA (1, 0, 2) × $(1, 1, 1)_{52}$ model with aim to capture different forms of the relationship in the time series data, to improve the forecasting performance in this study. Developed SARIMA model in this study had taken care of all assumptions of model, i.e. identification, estimation and diagnostic checking. Reasonably good values of fitting parameters i.e. MSE, MAE, MAPE and R^2 of time series model were observed. The peaks of observed hopper population were matched with trained and validated hopper population time series (Boopathi et al. 2015; Munj et al. 2021). The present SARIMA model developed according to the trends observed on mango hopper incidence over a 20 years period of time and presuming pattern stability of hoppers in all the fluctuated weather conditions. So, the developed time series SARIMA model was trained and validated and appeared to fit well with tolerable error levels in forecasting.

Spatial stratified heterogeneity may involve the existence of distinct mechanisms in strata (Davies et al. 2005), which may be buried or even lead to aggregation bias and ecological fallacy by global models (Schwanghart et al. 2008). This study data showed no difference between temporal strata which reduces misleading notions for implementation of wide modeling.

5. Conclusions

This study clearly indicates the two peaks of hoppers population, first at new flush stage and another at flowering cum fruit setting stage of the mango plants. The hopper population showed significantly positive relation with maximum temperature and negatively with minimum temperature. Good fit reliable time series SARIMA model predicted with in tolerable error level developed using dependable weather variables that directly influence the mango hoppers incidence. It is always very hard to draw exact predictions in continuous changing weather conditions and changes will affect specific herbivore-associations. In this study, we have used only single location (AES, Paria) data. It is always better that data from different geographic locations has to be collected to provide more reliable predictions in highly fluctuating temperature even for specific location. Even with some limitations, based on this study hopper population can be predicted using SARIMA models and can be used for forewarning to take suitable management measures.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

ORCID

J. K. Bana http://orcid.org/0000-0002-3234-0400
Jaipal Singh Choudhary http://orcid.org/0000-0002-4475-191X

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