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Prediction of early blight severity in tomato (*Solanum lycopersicum*) by machine learning technique

RANJIT KUMAR PAUL[1], SENGOTTAIYAN VENNILA[2], MITHUR NARAYANA BHAT[3], SATISH KUMAR YADAV[4], VIPIN KUMAR SHARMA[5], SHABISTANA NISAR[6] and SANJEEV PANWAR[7]

ICAR-Indian Agricultural Statistics Research Institute, New Delhi 110 012, India

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ABSTRACT

Study of scenario and weather based prediction of severity of early blight (*Alternaria solani* Ell. & Mart) on tomato (*Solanum lycopersicum* L.) for five Indian states, viz. Rajendranagar (Telangana), Bengaluru (Karnataka), Rahuri (Maharashtra), Raipur (Chhattisgarh) and Ludhiana (Punjab) was made using advanced statistical method of support vector regression (SVR) with its accuracy compared with conventional multiple linear regression (MLR) model. Comparisons of early blight severity for mean and maximum severity levels across seasons for each location was carried out using Duncan's Multiple Range Test (DMRT). Early blight mean and maximum severity levels were in order: Bengaluru (KA) > Rajendranagar (TS) > Rahuri (MH) > Raipur (CG) > Ludhiana (PB). Ludhiana (PB) had nil incidence during 2015 and not greater than 5% of either mean or maximum severity in any season. Both minimum temperature and morning relative humidity of one and two lagged weeks had negative and positive influence respectively, on mean and maximum severity of early blight at Rajendranagar (TS), Bengaluru (KA) and Rahuri (MH), which had higher blight severity over Raipur (CG) and Ludhiana (PB). MLR indicated 22–56% and 21–61% of variability with respect to mean and maximum severity of early blight due to weather factors that varied with locations. SVR predicted early blight severity nearer to actual values over MLR in terms of goodness of fit as well as Root Mean Square Error (RMSE).

Key words: Early blight, MLR, SVR, Tomato, Weather

India is one of the largest global producers of tomato (*Solanum lycopersicum* L.) and second only to China with a market contribution of 11%. Madhya Pradesh, Karnataka and Andhra Pradesh occupy first three positions of tomato production. Indian productivity of tomatoes has grown substantially from 16.3 t/ha in 2001–02 to 24.4 t/ha in 2016–17 with area under crop increasing from 458.1 thousand ha in 2001–02 to 808.5 thousand ha in 2016–17 (Anonymous 2017). Productivity recorded was highest in Himachal Pradesh followed by Uttar Pradesh, Karnataka and Madhya Pradesh.

The productivity of tomato is still quite low because of its vulnerability to insect pests, diseases and abiotic factors. Among diseases, leaf curl, bacterial wilt, late blight and early blight cause severe crop loss at times of unseasonal climatic conditions (Bhat *et al.* 2018). Tomato early blight (*Alternaria solani* Ell. & Mart.) is a disease of worldwide economic importance with moderate to high severity levels recorded across India from time to time (Prasad and Naik 2004). Saha and Das (2012) reported a yield loss of 0.75 to 0.77 t/ha for a unit per cent increase in disease severity. Bhat *et al.* (2017) has investigated the influence of weather on the occurrence of early blight in Bengaluru region of Karnataka highlighting the paramount importance of weather variables and their relationship with disease progression and its forecast. Generally, the relationship between population size/pest severity and climatic variables is analysed based on simple correlations or using the weather variables as an additive covariate in statistical models (Stenseth *et al.* 2002). The main problem in using the regression model is the violation of assumptions of normality particularly due to high kurtosis in the data. Moreover, the influence of temperature (Huey and Berrigan 2001) and humidity on population dynamics may not necessarily be additive, and more complex interactions could be involved. Kaundal *et al.* (2006) introduced a new prediction approach based on support vector machines for developing weather-based prediction models of plant diseases. Vennila *et al.* (2018a, 2018b) applied MLR for studying pigeonpea leaf webber damage dynamics in relation to weather and also investigated the abundance, infestation and disease transmission by thrips on groundnut influenced by climatic variability at

Present address: [1]Scientist (ranjitstat@gmail.com), ICAR-IASRI; [2,3]Principal Scientist (svennila96@gmail.com, mnbhat.ncipm@icar.org.in), [4]Research Associate (satishkumaryadav.akash@gmail.com) [5,6]Senior Research Fellow (mr.vipinsharma007@gmail.com, shabistanisar08@gmail.com) ICAR-NCIPM; [7]Principal Scientist (scientist1775@gmail.com) ICAR, New Delhi.

Kadiri, Andhra Pradesh. Paul *et al.* (2018) carried out comparative performance of advanced statistical models such as autoregressive integrated moving average model with exogenous variable (ARIMAX), support vector regression (SVR) model and artificial neural network (ANN) for predicting the severity of sterility mosaic disease (SMD) in pigeonpea and reported that SVR model outperformed the other models. In the present study, powerful nonparametric machine learning technique of SVR has been used for prediction of early blight in tomato for different locations belonging to varied agroclimatic zones of India.

MATERIALS AND METHODS

Study locations involved in assessing severity of early blight on tomato were from different agroclimatic zones and agroeco regions of India and constituted a network of implementing partners of electronic pest and weather surveillance of National Innovations in Climate Resilient Agriculture (NICRA) project operated between 2011–16. Raw data on pests and weather entered and uploaded at weekly intervals to centralised server by the study locations were accessed through associated reporting system hosted on web. Data on early blight severity and of weather factors were extracted on standard meteorological week (SMW) basis for all individual seasons (2011–16) in respect of locations. Differences in mean severity across seasons were compared using one-way analysis of variance (ANOVA). Pearson correlation coefficients were worked out between early blight (% severity) and weather variables lagged by one and two weeks over all seasons accounted together. Weather factors considered were maximum and minimum temperature (MaxT & MinT) (°C), morning and evening humidity (RHM & RHE) (%), sunshine h (SS) (h/d), wind velocity (Wind) (km/h), total rainfall (RF) (mm) and rainy days (RD).

Stepwise multiple linear regression (Montgomery *et al.* 2012) models have been applied using weather variables lagged up to two weeks as regressors for predicting the severity of early blight. Besides MLR, SVR model was also used to investigate the possible increase in accuracy of prediction for severity of early blight. SVR model is given for a data set as:

$$D = \{(x_i, y_i)\}_{i=1}^{N}$$

where $xi \in R^n$ input vector, $yi \in R$ is scalar output and N corresponds to size of data set.

General form of Nonlinear SVR estimating function is:

$$f(x) = w^T \varphi(x) + b,$$

where $\varphi(.): R^n \rightarrow R^{n_h}$ is a nonlinear mapping function from original input space into a higher dimensional feature space, which can be infinitely dimensional, $w \in R^{nh}$ is weight vector, b is bias term and superscript T indicates transpose. The coefficients w and b are estimated from data by minimizing the following regularized risk function:

$$R(\theta) = \frac{1}{2}\|w\|^2 + C\left[\frac{1}{N}\sum_{i=1}^{N} L_\varepsilon\left(y_i, f(x_i)\right)\right]. \quad (2)$$

This regularized risk function minimizes both empirical error and regularized term simultaneously and implements structural risk minimization (SRM) principle to avoid under and over fitting of training data. In Equation (2), $\frac{1}{2}||w||^2$ first term iscalled ‘ regularised term’, which measures flatness of the function. Minimizing $\frac{1}{2}||w||^2$ will make a function as flat as possible. Second term $\frac{1}{N}\sum_{i=1}^{N} L_\varepsilon(y_i, f(x_i))$ called ‘empirical error’ is estimated by Vapnik ε -insensitive loss function representing radius of tube of accuracy located around the regression function given by:

$$L_\varepsilon\left(y_i, f(x_i)\right) = \begin{cases} \left|y_i - f(x_i)\right| - \varepsilon \; ; & \left|y_i - f(x_i)\right| \geq \varepsilon, \\ 0 & \left|y_i - f(x_i)\right| < \varepsilon, \end{cases}$$

where y_i is actual value and $f(x_i)$ is estimated value. C in equation (2) referred to as regularized constant determines trade-off between empirical error and regularised term. The value ε is called as tube size equivalent to approximation accuracy in training data. Both C and ε are user-determined hyper-parameters. The SVR model was applied using R software package (e1071). Data on mean and maximum severity of early blight for available seasons under each location along with the weather variables (lagged by one and two weeks) considered under MLR were used for SVR.

RESULTS AND DISCUSSION

Seasonality of early blight severity: Epidemics of diseases have increased in recent years due to climate change and there is a need to understand the impact of climate change on host pathogen interaction to outline appropriate management strategies (Chowdappa 2010). Early blight is becoming more severe partly due to warmer temperatures experienced worldwide (Keinath *et al.* 1996). Present study explored the dynamics of early blight severity over seasons during *kharif* on tomato across five locations from different states, viz. Raipur in Chattisgarh, Ludhiana in Punjab, Rahuri in Maharastra, Hyderabad in Telengana and Bengaluru in Karanataka.

Comparisons of early blight severity for mean and maximum severity levels across seasons for each location was carried out using Duncan’s Multiple Range Test (DMRT). Non-significant variations at Bengaluru (KA) and Rahuri (MH) and significant variations at Rajendranagar (TS) and Ludhiana (PB) were noted for both mean and maximum severity of early blight amongst seasons. At Raipur (CG), mean severity was significantly lower in 2014 as compared to 2012 with on par severity during other seasons similar to Rajendranagar (TS). Maximum severity variations were non-significant at Raipur (CG). Maximum severity at Rajendranagar (TS) was significantly higher in 2012 and lower during three consecutive seasons 2013–15 with 2011 and 2016 having on par severity with both severity groups. In Ludhiana (PB), the mean and maximum severity higher in 2014 and traces of disease in 2015 were noted although other seasons too had relatively lower severity over other locations.

Early blight mean and maximum severity pooled over seasons describes the overall status of the disease in relation to geographical locations. Mean severity at Rajendranagar (TS) and Rahuri (MH) were on par significantly different from Ludhiana (PB) and Raipur (CG) that had lower severity and of Bengaluru (KA) with highest severity. Significant differences for maximum severity were observed across locations with severity levels in order of Bengaluru (KA) >Rajendranagar (TS) >Rahuri (MH) >Raipur (CG) >Ludhiana (PB). Although mean severity was par between Rajendranagar (TS) and Rahuri (MH), the former had significantly higher maximum severity over the later possibly due to the longer *versus* shorter crop growing seasons in respective locations. Variations in early blight severity are well known across the country although delineating factors have not been mentioned. While Prasad and Naik (2004) reported 30–65 and 17–37 % severity respectively in northern Karnataka, current investigation at southern Karnataka indicated a mean severity of 42.5%. Available literature from Maharashtra recorded severity levels of 26-50, 20-42 and 35-55 %in respect of Konkan, Raigad and Thane districts (Munde *et al.* 2013, Kamble *et al.* 2009) as against a maximum 17.8% at Rahuri of Ahmednagar. Similar to the lowest severity levels at Ludhiana (PB), Abhinandan *et al.* (2004) reported a disease intensity of 8% at Babakala district of Punjab.

Association of early blight severity with weather: Preliminary correlative analysis of early blight with weather variables (Table 1) indicated significant and positive influence of morning RH lagged by one week and both morning and evening RH of both one and two lagged weeks on mean as well as maximum severity at Rajendranagr (TS). Also, impact of maximum and minimum temperature and wind of both first and of second lagged weeks on mean and maximum severity were significantly negative. Similar positive and negative influence of lagged week weather variables were noted at Bengaluru (KA) but for non-significance of maximum temperature (lagged by one week) and evening relative humidity (lagged by two weeks) on mean severity and of the later on maximum severity. Present finding of negative correlation of early blight with minimum temperature alone was in line with studies of Roopa *et al.* (2016) from northern Karnataka. Negative influence of MinT and positive effect of RHM during one and two lagged weeks on mean and maximum severity of early blight was similar at Rajendranagar (TS), Bengaluru (KA) and Rahuri (MH) that had higher values of severity over Raipur (CG) and Ludhiana (PB). In Rahuri (MH), significant positive correlations with morning RH (lagged by both one and two weeks) and negative associations with minimum temperature cum wind with mean and maximum severity of disease were found. All weather variables except sunshine lagged by both one and two weeks of disease severity had significant negative associations at Raipur (CG). Low severity and slow disease progression of early blight at Raipur due to unfavourable weather conditions reflected in the significant negative association of all weather variables but for sunshine. All significant associations at Ludhiana (PB) were negative for both mean and maximum severity conveying the limiting factors for disease progression to be

Table 1 Correlation coefficients of early blight with weather factors lagged by one and two weeks#

Weather variable	Location				
	Rajendranagar (TS)	Raipur (CG)	Bengaluru (KA)	Rahuri (MH)	Ludhiana (PB)
Mean severity					
MaxT-1	-0.1*	-0.1	0.1	-0.2**	0.0
MinT-1	-0.3**	-0.2**	-0.5**	-0.5**	-0.1
RHM-1	0.3**	0.2*	0.2*	-0.4**	0.0
RHE-1	-0.0	0.1	-0.2*	-0.5**	-0.4**
RF-1	-0.0	0.1	0.1	-0.3**	-0.1
RD-1	-0.2	-0.0	0.2	-0.3**	-0.2
SS-1	-0.0	-0.1	0.0	0.2**	0.0
Wind-1	-0.4**	-0.1	-0.4**	-0.2**	-0.2**
MaxT-2	-0.2**	-0.2	0.0	-0.2**	0.1
MinT-2	-0.2**	-0.1	-0.6**	-0.5**	-0.0
RHM-2	0.3**	0.2*	0.3**	-0.4**	0.0
RHE-2	0.2*	0.1	-0.1	-0.5**	-0.4**
RF-2	0.0	0.1	0.1	-0.3**	-0.1
RD-2	-0.1	-0.0	0.0	-0.3**	-0.2*
SS-2	-0.1	-0.1	0.0	0.3**	0.0
Wind-2	-0.3**	-0.1	-0.3**	-0.3**	-0.2**
Maximum severity					
MaxT-1	-0.2*	-0.2*	0.0	-0.2**	0.0
MinT-1	-0.3**	-0.3**	-0.6**	-0.6**	-0.0
RHM-1	0.3**	0.2*	0.2*	-0.3**	0.0
RHE-1	0.0	0.2*	-0.2*	-0.5**	-0.3**
RF-1	-0.0	0.1	0.1	-0.3**	-0.1
RD-1	-0.2	-0.1	0.1	-0.3**	-0.2
SS-1	-0.0	-0.1	0.1	0.3**	0.0
Wind-1	-0.4**	-0.1	-0.4**	-0.3**	-0.1*
MaxT-2	-0.3**	-0.3**	-0.0	-0.2**	0.1
MinT-2	-0.3**	-0.1	-0.6**	-0.6**	-0.0
RHM-2	0.4**	0.2*	0.3**	-0.3**	-0.0
RHE-2	0.2*	0.2*	-0.0	-0.5**	-0.3**
RF-2	0.0	0.1	0.2	-0.4**	-0.1
RD-2	-0.2*	-0.0	0.0	-0.4**	-0.2*
SS-2	-0.1	-0.1	0.0	0.3**	0.0
Wind-2	-0.3**	-0.1	-0.3**	-0.3**	-0.3**

The suffix 1 and 2 denote the lag in weeks of weather relating to disease severity considered for correlations. ** significant at $P < 0.01$; * significant at $P < 0.05$

evening as well as morning RH and wind of both lagged weeks. Negatively significant associations of RH with disease severity at Ludhiana (PB) and Raipur (CG) confirms the importance of RH and the reason for low severity of disease compared to the positive significance of RH in other three locations. Influences of weather variables on early blight severity were similar at some locations although differences were also obvious.

Prediction of early blight severity through conventional approach of multiple regressions: The MLR models with stepwise selection procedure adopted for prediction of mean and maximum severity of the disease based on weather variables are furnished in Table 2 along with corresponding coefficient of determination (R^2). All the parameters of the equations were found to be statistically significant at 5% level of significance. Weather parameters accounted for 22-56 and 21-61 % of variability in respect of mean and maximum severity of early blight. Weather factors differed across locations for their influence on disease incidence largely confirmed the results of correlative analysis (Table 2).The factors of influence reflected in models for both mean and maximum severity were similar at Bengaluru (KA) and Rahuri (MH). In other three locations [Rajendranagar (TS), Raipur (CG) and Ludhiana (PB)] the mean and maximum and severity predictions had essentially common factors of influence in addition to some factors (one to two) determining maximum severity. All locations had weather variables lagged by one and two weeks in the models but for Bengaluru (KA) that had weather variables lagged by two weeks.

Prediction of early blight severity through support vector regression: As an improvement to the usual regression model, powerful machine learning technique namely SVR has been used for prediction considering the weather factors. Out of total 105, 129,101,72 and 137 data points on mean

Table 2 Multiple regression models for prediction of early blight severity

Location	Model equation	R^2
Mean severity		
Rajendranagar (TS)	50.987-3.204 Wind-1-2.089 RD-2-2.728 SS-2	0.33
Bengaluru (KA)	71.382-0.915 MinT-2-0.525 RHM-2	0.38
Rahuri (MH)	87.487+2.295 RHM-1+0.129 RF-1-0.794 Wind-1-7.287 MaxT-2+0.119 RF-2-1.228 Wind-2	0.29
Raipur (CG)	13.265-3.854 MinT-1+3.179 MaxT-2-4.007 MinT-2+0.983 RHM-2	0.56
Ludhiana (PB)	6.061-0.057 RHE-1+0.016 RF-1-0.040 RHE-2	0.22
Maximum severity		
Rajendranagar (TS)	-34.491-4.522 RD-1-2.717 SS-1-4.107 Wind-1+1.243 RHM-2	0.42
Bengaluru (KA)	79.626-1.427 MinT-2-0.467 RHM-2	0.44
Rahuri (MH)	144.560+3.105 RHM-1+0.132 RF-1-0.834 Wind-1-10.806MaxT-2+0.122 RF-2-1.394 Wind-2	0.37
Raipur (CG)	75.037-5.192 MinT-1+3.323 MaxT-2-4.855 MinT-2+0.837 RHM-2+ 0.048 RF-2-1.045 RD-2	0.61
Ludhiana (PB)	11.56-0.061 RHE-1-0.080 RHE-2+0.030 RF-2-0.794 Wind-2	0.21

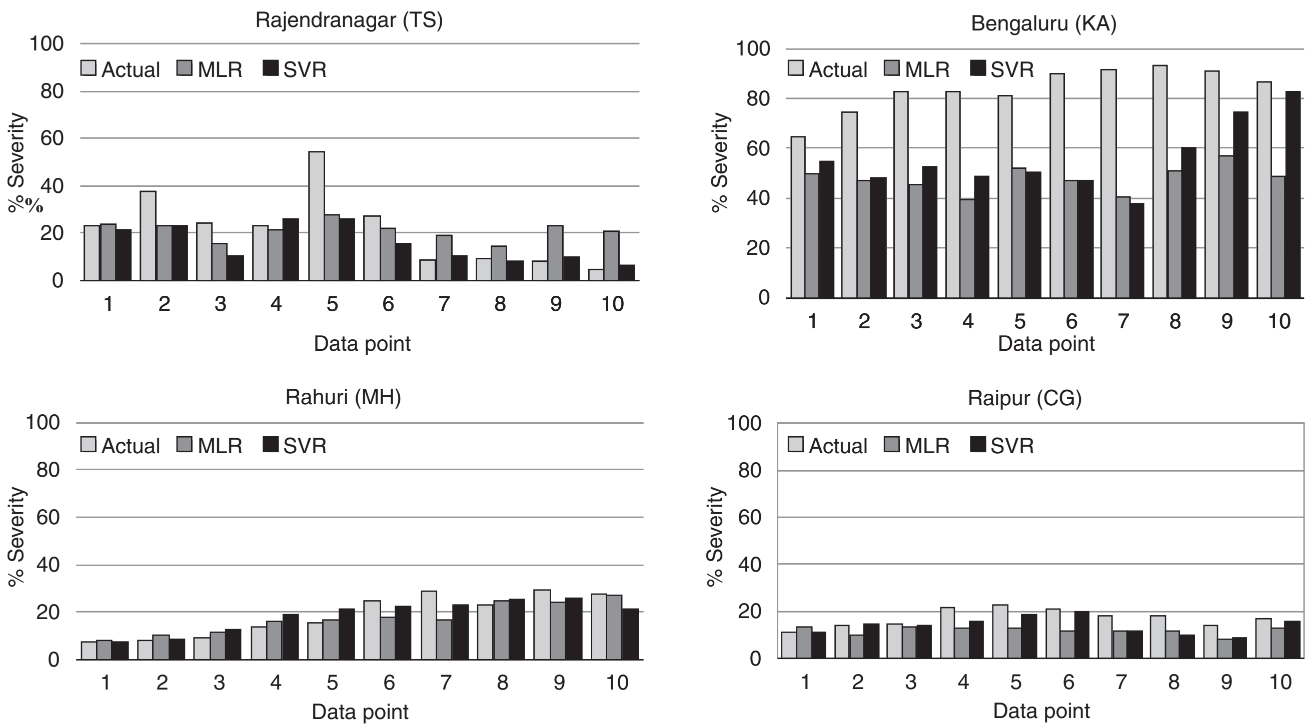

Fig 1 Prediction performance of early blight mean severity using MLR and SVR.

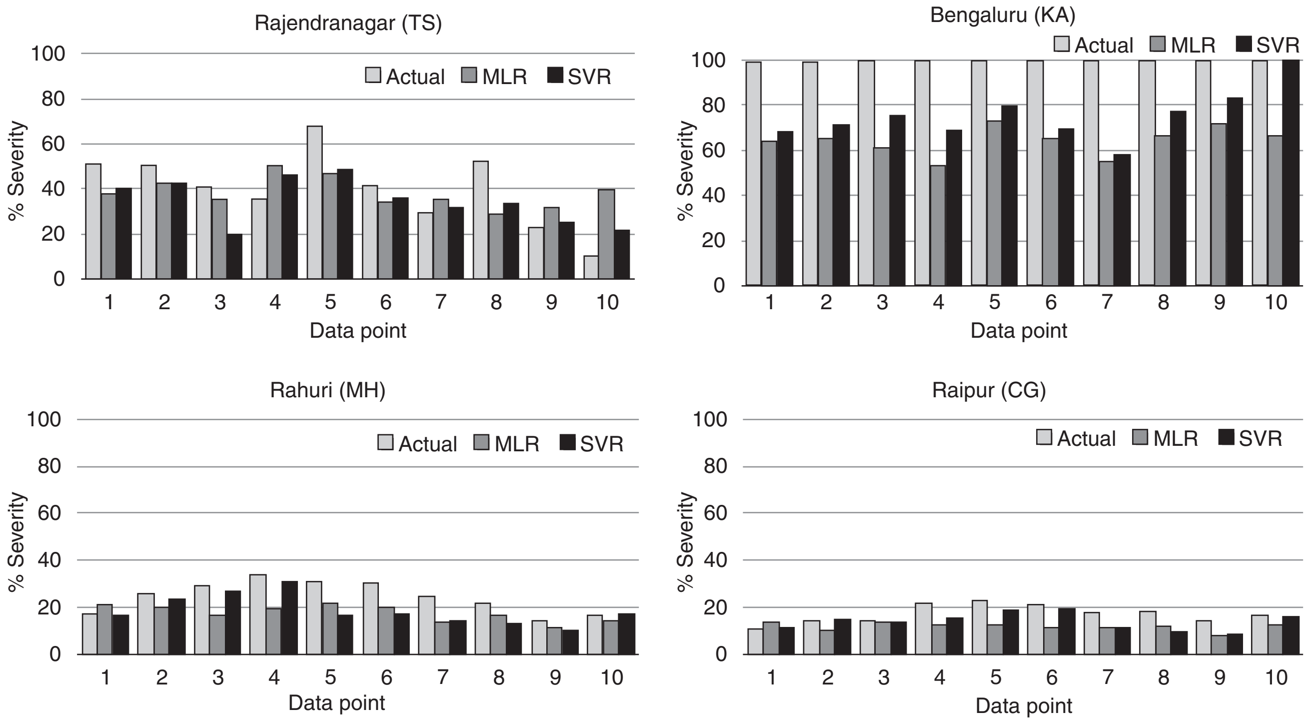

Fig 2 Prediction performance of early blight maximum severity using MLR and SVR.

and maximum severity along with the weather factors over seasons, 95, 119, 91, 62 and 127 observations were used for SVR model building with 10 data points reserved for model validations for locations of Rajendranagar (TS), Raipur (CG), Bengaluru (KA), Rahuri (MH) and Ludhiana (PB), respectively. The actual, MLR and SVR predicted severity mean and maximum values validated are depicted in Fig 1 and Fig 2 respectively.

It is evident from figures that SVR model predictions of mean and maximum severity of early blight are nearer to actual values over the MLR for all four locations. Considering the very low severity values at Ludhiana (PB), validation figure is not given. The characteristic feature of SVR model is that the residuals have been found out to be white noise as against MLR model where they are not thus confirming the adequacy of SVR over MLR model. Plots of actual *versus* SVR model fitted values of mean and maximum severity of the disease relating the location of higher mean and maximum severity, i.e. Bengaluru (KA) are displayed in Fig 3. The plots clearly indicated the closeness of fitted values to actual severity particularly in predicting maximum severity of the disease.

Table 3 furnishes the prediction performance of both MLR and SVR models for both mean and maximum severity of early blight for all locations wherein higher values represent lower prediction performance and *vice versa*. It was noticed that RMSE values for SVR were invariably lower that for MLR in all cases. It was interesting to note that the location Bengaluru (KA) with highest mean and maximum severity of the disease amongst locations had lower RMSE for maximum over mean severity under both models indicating the better prediction of maximum over mean severity at higher levels of the disease.

Machine learning technique, viz. SVR has been applied for modelling and forecasting of maximum and minimum severity of early blight in tomato in five locations in India. For models building, the weather factors MaxT & MinT (°C), RHM & RHE (%), SS (h/d), Wind (km/h), RF (mm) and RD were considered. Along with SVR, MLR has also been applied and empirical comparison is carried out in terms of RMSE. It is seen that SVR outperforms the usual MLR model in terms of RMSE for prediction of both maximum and minimum severity of early blight in tomato in studied locations. SVR model thus can be a better substitute for MLR. Better prediction of early blight using SVR is expected to strategize management interventions during crop

Table 3 RMSE values in relation to MLR and SVR models predicting mean and maximum severity of early blight across locations

Location	Mean severity		Maximum severity	
	MLR	SVR	MLR	SVR
Rajendranagar (TS)	12.9	11.8	15.7	12.6
Bengaluru (KA)	37.3	31.5	36.1	26.9
Rahuri (MH)	4.9	4.1	5.1	4.9
Raipur (CG)	6.6	4.5	8.7	7.7
Ludhiana (PB)	0.5	0.2	1.0	0.4

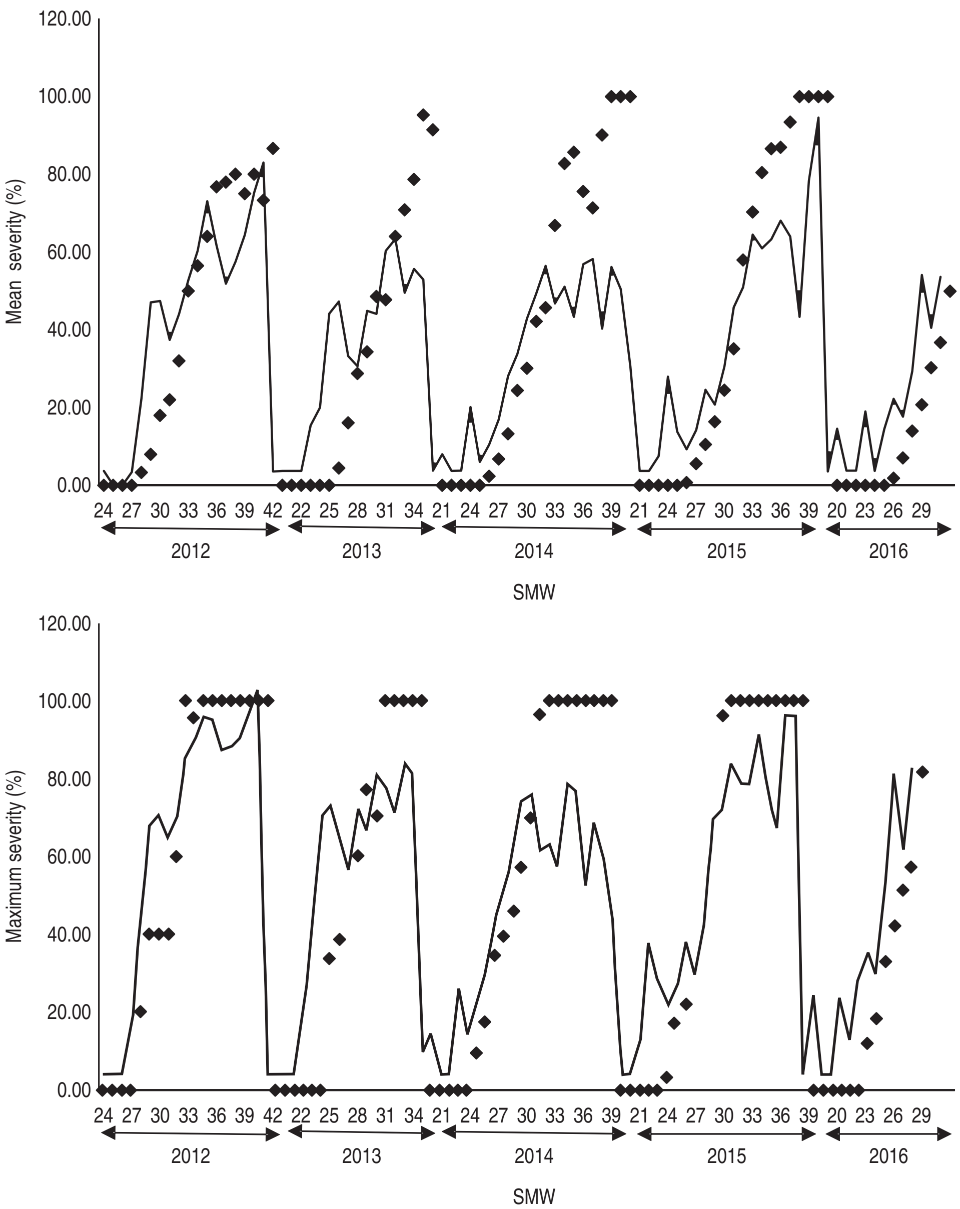

Fig 3 Actual vs. fitted plot of mean severity (upper plot) and maximum severity (lower plot) by SVR model [Location: Bengaluru (KA)].

seasons at different locations in the coming years. Such an advanced approach can also serve as a template for other locations of the same disease or for other crop pests for different locations.

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