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Research Paper

Enhanced hybrid CEEMDAN-GMDH regression model for forewarning sucking pests in cotton crops of Coimbatore, Tamil Nadu

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ABSTRACT

Effective pest management relies on early and accurate forecasting, yet current models struggle to capture regional specific complex relationship between weather conditions and pest incidence. This study addresses this gap by developing a robust crop pest forecasting model using the Group Method of Data Handling (GMDH) regression. We employed three decomposition techniques like Empirical Mode Decomposition (EMD), Ensemble Empirical Mode Decomposition (EEMD), and Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) to break down nonlinear data into Intrinsic Mode Functions (IMFs). These IMFs were then predicted using GMDH regression, incorporating weather variables as independent factors. The ensemble forecasts were constructed by aggregating the predicted IMFs. The study utilized pest incidence data from 2015 to 2023 for aphid, jassid, thrips, and whitefly pests. Findings indicated that the CEEMDAN-GMDH model outperformed others for forecasting the incidence of aphid, thrips, and whitefly pests, with improvements of 16.3%, 4.3%, and 13.6% over the univariate GMDH model, respectively. For jassid, the EEMD-GMDH model provided the best forecasts, despite CEEMDAN's superior decomposition capabilities. The study concludes that integrating decomposition methods, with GMDH regression provides a more reliable tool for predicting pest incidences in cotton crops, thereby aiding in better pest management strategies.

Keywords: Forewarning, Pest management, Machine learning, Sucking pests, Population dynamics, Decomposition techniques.

Bt cotton is a genetically modified cotton variety that exhibits good control of American Bollworms. Even though Bt cotton has been found successful in the management of bollworms, it has also invited sucking pests due to the reduction of pesticides at the early stages of cotton cultivation (Jeyakumar *et al.,* 2008). Also, the warm and humid climate of tropical areas provides ideal conditions for the proliferation of sucking pests. So, early warnings and forecasts based on weather models in tropical regions provide lead time for managing the impending pest attacks (Prasad and Prabhakar, 2012). The excessive use of pesticides and chemicals can be avoided by forecasting of pests which helps to reduce the damage to the environment and the production costs associated with pesticides and chemicals (Domingues *et al.,* 2022).

Studies have been carried out for forecasting crop pests using models like ARIMAX (Aswathi and Duraisamy, 2018), Regression models with weather indices (Kumar *et al.,* 2018), Markov chain (Chandi *et al.,* 2021), machine learning approaches (Vaidheki *et al.,* 2023). Real world raw data often contain noise (Yahya *et al.,* 2017). Hence, pre-processing the raw data before applying statistical or machine learning models for forecasting will yield better results. The divide and conquer strategy are a simple but effective way and breaks the complex data into a few relatively simple components and extracts the relevant features for future work (Li *et al.,* 2019).

Researchers have used the combined decomposition methods and machine learning or statistical models for forecasting nonlinear and non-stationary datasets in different fields like tourist arrivals (Yahya *et al.,* 2017), crude oil prices (Li *et al.,* 2019) and groundwater (Moosavi *et al.,* 2021). Many hybrid models using decomposition methods have used univariate statistical or machine learning models for forecasting. Since sucking pest incidence is influenced a lot by weather parameters, multivariate models would

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perform better than the univariate models. Also, studies have not been initiated in developing hybrid model using decomposition techniques and GMDH regression for pest forewarning. The Group Method of Data Handling (GMDH) regression model offers unique advantages over other machine learning techniques is a self-organizing polynomial neural network that automatically determines the optimal model structure by iteratively selecting and combining predictors based on external validation criteria. This capability eliminates the need for extensive manual feature engineering and hyper parameter tuning that models like XGBoost, LSTM and other few machine learning models require. Unlike LSTM, which is specifically designed for large-scale data, GMDH performs effectively even with small and medium sized data. Hence, a new hybrid model using decomposition methods and a multivariate forecasting model GMDH regression have been developed for forewarning cotton pest incidence.

MATERIALS AND METHODS

Data description

The weekly data of population dynamics of cotton pests such as aphid, jassid, thrips and whitefly (pests per three leaves) of Coimbatore were collected from various reports of the All India Coordinated Research Project (AICRP) of Cotton for the period of 2016-17 to 2022-23 for aphid and from year 2015-16 to 2022-23 for jassid, thrips, whitefly. Since crop pests are influenced by weather, weekly weather data of variables such as minimum temperature (°C), maximum temperature (°C), relative humidity morning (%), relative humidity evening (%), rainfall (mm) were used as independent variables for forecasting. Cotton is the winter irrigated crop in Coimbatore. Therefore, pest incidence and weather data from the month of August to December from the year 2016-17 to 2022-23 have been collected for the model development.

Group method of data handling (GMDH)

The group method of data handling involves a family of inductive algorithms in machine learning techniques which is a type of artificial intelligence (Ivakhnenko, 1968). Originally higher order regression polynomial such as modelling and classification were solved by GMDH method (Shabri and Samsudin, 2014).

The Ivankhneko polynomial is defined as follows;

$$Y = a_0 + \sum_{i=1}^{m} a_1 x_1 + \sum_{i=1}^{m}\sum_{j=1}^{m} a_{ij} x_i x_j + \sum_{i=1}^{m}\sum_{j=1}^{m}\sum_{k=1}^{m} a_{ijk} x_i x_j x_k + \cdots \quad (1)$$

The GMDH algorithm involves collection of data. After that, the input dataset is divided into training and testing datasets for constructing the algorithm and evaluate the performance. Fig. 1 shows the network of GMDH algorithm with m inputs and k layers.

GMDH regression

An R package GMDHreg was used for regression analysis using GMDH algorithm. The least squares method is used to estimate the polynomial coefficient. The external criteria in GMDHreg package to select the best model are Predicted Residual Error Sum of Squares (PRESS) and Index of Informational Complexity (ICOMP). In the present study, GMDH regression was performed

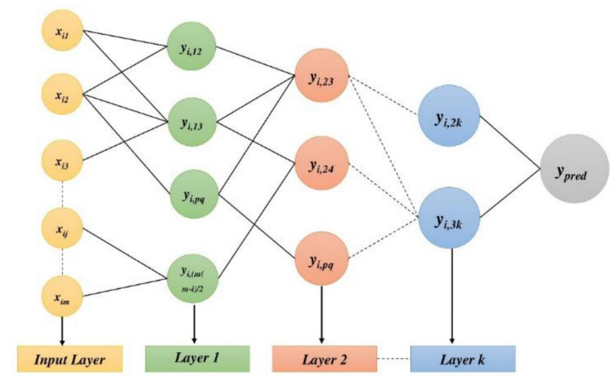

Fig 1: Network of group method of data handling (GMDH) algorithm

using combinatorial algorithm to forecast pest incidence using weather variables as independent variables. GMDH combinatorial is a classic algorithm that creates models for all possible combination of input and selects the final model from the generated set of models based on the selection criteria. In GMDH combinatorial regression, each pair of independent variables are taken as possible input, and the best combination is chosen for the model.

Empirical mode decomposition (EMD)

Empirical mode decomposition (EMD) introduced by Huang *et al.,* (1998) is a method applied to process non-linear and non-stationary datasets. EMD decomposes the original data into smaller components called intrinsic mode function (IMF) and residual. To decomposed by EMD, the data must satisfy the following criteria;

a) The sum of the maxima and minima must be zero.

b) the average of the envelopes must be equal to zero at all point of data (Gaci, 2016).

The EMD involves identification and interpolation of the local extrema using cubic spline to obtain the envelopes by calculating the average of upper and lower envelope $m(t)=[U(t)+L(t)]/2$. Then, subtract the average $m(t)$ from the original signal: $h_1(t)=x(t)-m(t)$. Replace the signal $x(t)$ by $h_1(t)$ and repeat the previous steps until it satisfies the two conditions of the IMF. The original signal is reconstructed by the following formula;

$$x(t) = \sum_{m=1}^{M-1} \mathrm{IMF}_m(t) + r_n(t) \quad (2)$$

where, M-1 is the number of IMFs.

Ensemble empirical mode decomposition (EEMD)

The effect of mode mixing is the major drawback of EMD technique. To overcome this, Wu and Huang, 2009 proposed EEMD which is noise assisted EMD. By including white noise in each iteration, it enables a better scale separation than EMD to the decomposed IMFs until the corresponding IMFs are obtained (Gaci, 2016; Moosavi *et al.,* 2021).

Table 1: Summary Statistics of Pest Incidence

Statistics	Aphids	Jassid	Thrips	Whitefly
Mean	5.08	5.45	3.29	0.76
Std. Deviation	5.32	5.04	4.06	0.93
Minimum	0.00	0.00	0.00	0.00
Maximum	28.60(2022-45)	18.64(2017-2)	14.94(2020-45)	4.37(2020-45)

Note: Numbers in the bracket indicates the year and SMW

Table 2: Results of BDS and ADF tests

BDS test results					
	Aphid			**Thrips**	
Dimension	BDS Statistic	p value	Dimension	BDS Statistic	p value
2	11.21	<0.01**	2	16.74	<0.01**
3	13.63	<0.01**	3	16.42	<0.01**
	Jassid			**Whitefly**	
Dimension	BDS Statistic	p value	Dimension	BDS Statistic	p value
2	16.39	<0.01**	2	15.82	<0.01**
3	15.15	<0.01**	3	15.27	<0.01**

ADF test results		
Pest	**Statistic**	**p value**
Aphid	-3.13	0.11
Jassid	-3.13	0.11
Thrips	-1.85	0.64
Whitefly	-2.58	0.33

Note: ** 1% level of Significance

Complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN)

In decomposition, although EEMD can improve accuracy, they may introduce new noise into the recovered signal which can cause mode mixing problems. To overcome this, the decomposition technique CEEMDAN was proposed by Torres *et al.,* (2011). Decomposition by CEEMDAN is performed by adding white noise to the original inflow data of EEMD as,

$$y(t) = x(t) + w_0 n^j(t) \tag{3}$$

where j=(1,2,…m) is the m^th ensemble, x(t) is the original data, w_0 is the white noise. The first IMF is defined as,

$$\widetilde{IMF_1} = \sum_{j=1}^{m} \frac{IMF_{j1}^{m}}{m} \tag{4}$$

Compute the remainder of original inflow data from the 1st IMF by the following equation;

$$r_1(t) = x(t) - \widetilde{IMF_1} \tag{5}$$

Then, white noise is added to the reminder calculated from the equation (5) as and decompose to obtain the second IMF. Repeat the previous steps until it meets the stoppage criterion. When the residual becomes a monetary function and cannot be decomposed by EMD, the process is terminated.

Hybrid models

Due to non-linearity and non-stationarity, the classical time series models are not suitable for forecasting the pest incidence. So, a novel hybrid model such as EMD-GMDH, EEMD-GMDH, CEEMDAN-GMDH which are the combination of decomposition methods and GMDH regression have been developed for forewarning the pest incidence. The process of proposed hybrid model is explained as follows;

Decomposition of the data: EMD, EEMD and CEEMDAN are used to decompose the pest incidence data to obtain k-IMFs and residual $r_n(t)$.

Individual forecasting: GMDH regression model is used to predict the IMFs and residual. In GMDH regression, the individual IMFs and residual are taken as response variables while weather variables are taken as explanatory variables. By using GMDH regression individual forecast values of the components are obtained.

Ensemble prediction: The forecasting result of all the IMFs and residual are aggregated to obtain the final forecast value.

Performance criteria: The results obtained from the proposed hybrid models are compared with univariate GMDH and GMDH regression results to evaluate the performance of the hybrid models.

Goodness of fit measures

The performance of the model is assessed using goodness of fit measures like root mean squared error (RMSE), mean absolute error (MAE), predicted residual error sum of square (PRESS).

$$Adj\ R^2 = 1 - \frac{SS_{res}/(n-p)}{SS_t/(n-1)} \tag{6}$$

where, is residual mean square and is total mean square.

Table 3: Statistical analysis of IMFs decomposed by EMD

Pests		Aphid			Jassid	
Component	Mean	Std. Dev	ADF	Mean	Std. Dev	ADF
IMF 1	-0.385	2.569	-5.038**	-0.027	2.094	-5.595**
IMF 2	-0.068	1.912	-4.557**	-0.483	3.616	-5.642**
IMF 3	0.116	2.237	-3.949*	-0.021	2.917	-4.007*
IMF 4	-0.079	2.515	-3.458*	-0.097	2.118	-3.502*
IMF 5	-0.197	1.578	-2.964	0.415	2.604	-3.54*
Pests		Thrips			Whitefly	
Component	Mean	Std. Dev	ADF	Mean	Std. Dev	ADF
IMF 1	0.007	1.537	-4.848**	-0.026	0.346	-5.104**
IMF 2	0.024	2.868	-6.829**	-0.023	0.476	-5.633**
IMF 3	-0.126	1.895	-4.286**	-0.041	0.555	-4.984**
IMF 4	-0.013	1.515	-3.789*	-0.031	0.343	-4.913**
IMF 5	-0.423	1.825	-2.545	0.019	0.391	-2.369

Note: * 5% level of significance; ** 1% level of significance

Table 4: Statistical analysis of IMFs decomposed by EEMD

Pests		Aphid			Jassid	
Component	Mean	Std. Dev	ADF	Mean	Std. Dev	ADF
IMF 1	-0.161	2.164	-6.779**	-0.057	1.606	-6.645**
IMF 2	-0.088	2.133	-5.28**	-0.262	2.116	-4.288**
IMF 3	0.163	2.438	-4.915**	-0.374	3.174	-4.189**
IMF 4	-0.089	1.497	-2.896	0.019	1.647	-4.891**
IMF 5	-0.132	0.651	-2.363	0.057	1.453	-0.971
Pests		Thrips			Whitefly	
Component	Mean	Std. Dev	ADF	Mean	Std. Dev	ADF
IMF 1	-0.023	1.264	-5.202**	-0.005	0.267	-5.718**
IMF 2	-0.165	1.806	-4.715**	-0.027	0.344	-5.920**
IMF 3	-0.049	2.143	-5.472**	-0.085	0.603	-4.436**
IMF 4	0.166	1.224	-2.465	0.007	0.34	-3.107
IMF 5	-0.022	0.973	0.601	0.002	0.339	-0.083

Note: * 5% level of significance; ** 1% level of significance

Table 5: Statistical analysis of IMFs decomposed by CEEMDAN

Pests		Aphid			Jassid	
Component	Mean	Std. Dev	ADF	Mean	Std. Dev	ADF
IMF 1	-0.163	2.157	-6.847**	-0.054	1.597	-6.708**
IMF 2	-0.007	0.518	-6.839**	-0.008	0.308	-8.418**
IMF 3	-0.206	1.989	-7.529*	-0.196	1.77	-4.743**
IMF 4	-0.099	2.802	-3.448*	-0.387	3.191	-4.044**
Pests		Thrips			Whitefly	
Component	Mean	Std. Dev	ADF	Mean	Std. Dev	ADF
IMF 1	-0.024	1.263	-5.168**	-0.005	0.267	-5.768**
IMF 2	-0.002	0.271	-8.53**	-0.101	0.103	-6.497**
IMF 3	-0.191	1.814	-4.985**	-0.007	0.326	-6.048**
IMF 4	-0.009	1.895	-6.328**	-0.164	0.684	-4.218**

Note: * 5% level of significance; ** 1% level of significance

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \quad (7)$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (8)$$

$$\text{PRESS Statistic} = \sum_{i=1}^{n}[y_i - \hat{y}_i]^2 \quad (9)$$

where, n- number of observations – actual value and – predicted value

Table 6: Goodness of fit measures for the models

Pests	Model	Adj R^2	RMSE	MAE	PRESS
Aphids	GMDH	0.26	5.479	3.395	3782.81
	GMDH regression	0.39	4.982	3.558	2912.56
	EMD-GMDH	0.42	4.806	3.462	2910.33
	EEMD-GMDH	0.41	4.807	3.676	2911.997
	CEEMDAN-GMDH	**0.56**	**4.709**	**3.473**	**2794.604**
Jassid	GMDH	0.24	5.415	3.842	4222.727
	GMDH regression	0.4	4.793	3.873	2952.439
	EMD-GMDH	0.59	4.523	3.619	2945.451
	EEMD-GMDH	**0.62**	**4.508**	**3.598**	**2927.298**
	CEEMDAN-GMDH	0.58	4.557	3.659	2990.67
Thrips	GMDH	0.64	3.693	2.455	1964.411
	GMDH regression	0.63	3.769	3.129	1859.694
	EMD-GMDH	0.66	3.587	2.933	1853.278
	EEMD-GMDH	0.66	3.548	2.927	1813.117
	CEEMDAN-GMDH	**0.67**	**3.542**	**2.883**	**1806.67**
Whitefly	GMDH	0.72	0.944	0.652	128.187
	GMDH regression	0.74	0.874	0.756	103.613
	EMD-GMDH	0.75	0.844	0.711	102.57
	EEMD-GMDH	0.75	0.845	0.718	102.814
	CEEMDAN-GMDH	**0.76**	**0.831**	**0.691**	**99.43**

RESULTS AND DISCUSSION

Summary statistics of pest incidence

Table 1 gives the summary statistics of sucking pest incidence of cotton crop. It is clear that the minimum incidence of all pests is 0.00. It implies that at many weeks there was no pest influence for the crop.

Non-linear and non-stationary tests

To check the nonlinearity and non-stationarity of the pest incidence, BDS test developed by Brock *et al.,* (1996) and Augmented Dickey-Fuller (ADF) has been used. The result of the tests is presented in Table 2. It clearly shows that p values for all pests in BDS test are significant at 1% level. Therefore, the null hypothesis assuming that the data are linear is rejected which shows that all pest incidence data are non-linear. In the Table 2, p values for all pests in ADF test is not significant at 5% level. So, we accept the null hypothesis which states that all pest incidence data are non-stationary.

Decomposing the data

The non-linear and non-stationary data is decomposed by using the methods EMD, EEMD and CEEMDAN to extract IMFs and residuals. By decomposing the data using EMD and EEMD 5 IMFs and one residual are obtained while decomposing using CEEMDAN 4 IMFs and one residual are obtained. The plots of IMFs and residuals decomposed using CEEMDAN are given in the Fig. 2. The curve becomes much smoother with decreasing frequency from IMF1 to residual.

The descriptive statistics and ADF test statistic of IMFs decomposed by EMD, EEMD and CEEMDAN are presented in Table 3, 4 and 5 respectively. Table 3 shows that the t-value of ADF test is less than the critical value for all IMF except IMF5 for aphid, thrips and whitefly while all the IMFs for jassid are significant at 5% and 1% level of significance. From the t-value of ADF test of the IMFs decomposed by EEMD (Table 4), it is clear that IMF4 and IMF5 are not stationary for aphid, thrips and whitefly. For jassid all the IMFs except IMF5 are stationary. The t-values of all IMFs decomposed by CEEMDAN (Table 5) seem to be significant at 5% level of significance for all pests. Therefore, it is clear that CEEMDAN performed better at decomposing the non-stable sequence into several stable sequences compared to EMD and EEMD. As mentioned in the methodology, CEEMDAN introduces adaptive white noise in a controlled manner at each decomposition stage, ensuring that mode mixing which is lacking in EMD and EEMD. Therefore, CEEMDAN improves forecasting not only by decomposing the signal into stationary IMFs, but also because it retains more accurate frequency information, enabling the forecasting model to capture underlying patterns more effectively.

Fitting of hybrid models

The GMDH regression is used to forecast the individual IMFs and residual and aggregated to obtain final forecast value. The goodness of fit metrics such as RMSE, MAE and PRESS statistic is presented in Table 6 to assess the hybrid model's performance. To assess the performance of hybrid models, univariate GMDH and GMDH regression models are developed and compared with hybrid models. The CEEMDAN-GMDH model has high Adjusted R^2 value and low RMSE, MAE, PRESS values for aphids, thrips and whitefly. This implies that the CEEMDAN-GMDH model outperformed other models in forewarning the pest incidence of Aphids, Thrips and whitefly. For aphids, CEEMDAN-GMDH performed better than other models for forecasting by 16.3% compared to univariate GMDH. For thrips and whitefly, CEEMDAN-GMDH performed

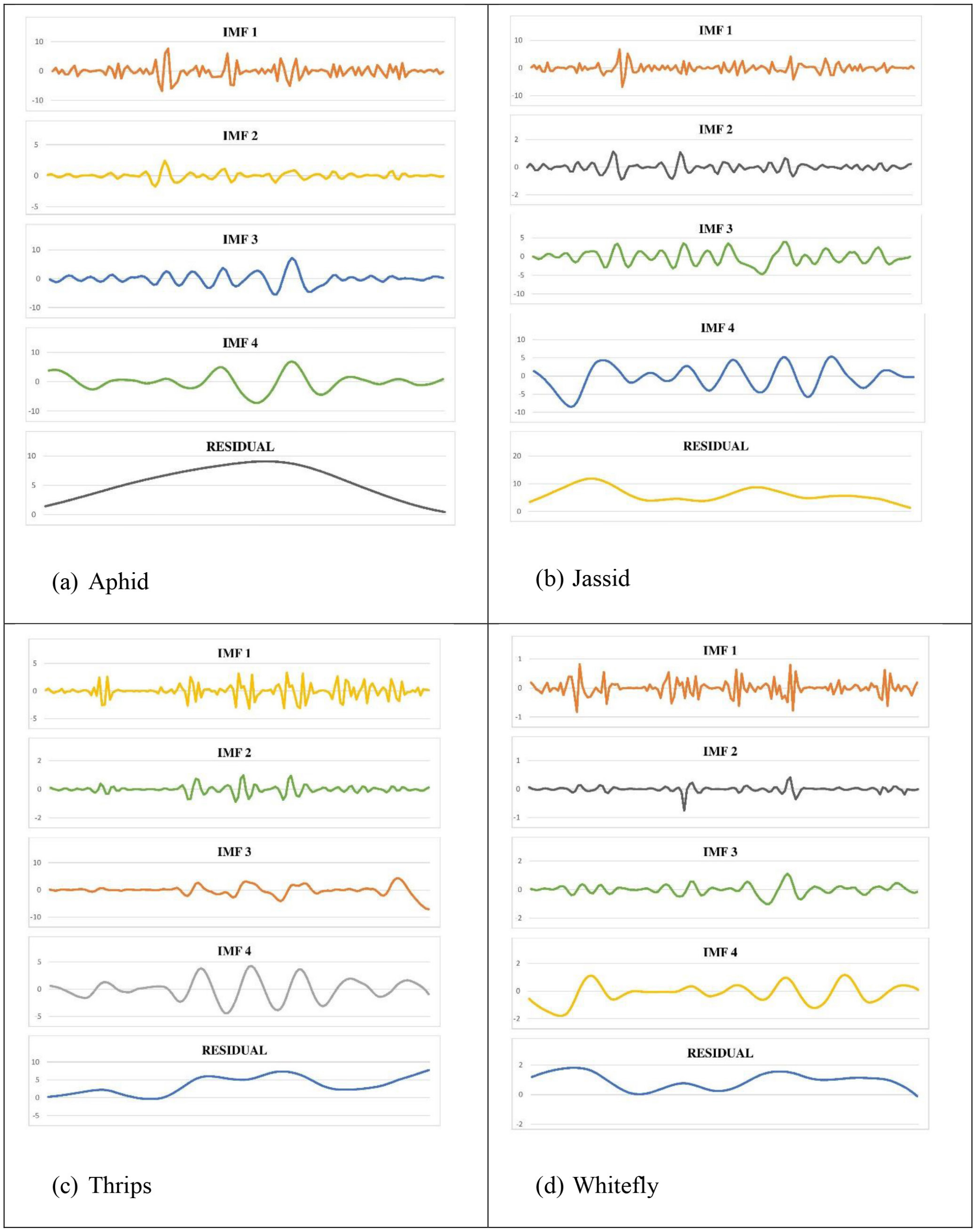

Fig 2: IMFs and residual plot of CEEMDAN for (a) Aphid, (b) Jassid, (c) Thrips and (d) Whitefly

4.3% and 13.6% better than GMDH respectively. Though, CEEMDAN performed better in decomposition, the model EEMD-GMDH performed better than other models for jassid by having high Adjusted R^2 and low error metrics. It performed 20.11% better than the univariate GMDH model for forewarning jassid.

From the results, it can be interpreted that CEEMDAN-GMDH performed better than other models for forecasting pest incidence of aphid, thrips and whitefly. Though, the goodness of fit measure value is similar in both EEMD-GMDH and CEEMDAN-GMDH for jassid, EEMD-GMDH performed better for forecasting pest incidence of jassid. The main reason is that the additional IMF generated using EEMD has carried meaningful signal components despite being non-stationary. It is clear that GMDH model after decomposition performed better than GMDH models before decomposition in forewarning cotton pests.

CONCLUSION

To enhance the forecasting technique for sucking pests of cotton, this study proposed hybrid models that combines the decomposition methods and machine learning model. The results revealed that CEEMDAN decomposed better than other two decomposition methods (EMD, EEMD). Hybrid model CEEMDAN-GMDH outperformed other models for forecasting pest incidence of aphid, thrips and whitefly while EEMD-GMDH performed better for jassid. The proposed CEEMDAN–GMDH hybrid model incorporated key weather parameters to capture the complex, non-linear influence of meteorological factors aligning with the agrometeorological principle that climate drives pest outbreaks. The weather-integrated approach enables early and accurate forewarning which helps in effective pest management decisions.

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Authors contribution**: N. Naranammal:** Conceptualization, Methodology, Visualization, Formal analysis, Writing-original draft, Data curation; **S.R.K. Priya*:*** Conceptualization, Writing-review and editing, Supervision, **Naveena. K**: Methodology, Writing-review and editing, Supervision.

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