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Research Article

Spatial-temporal analysis of wheat leaf rust disease (*Puccinia triticina* Eriks) in Southwestern Iran

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Abstract: Leaf rust is one of the most important diseases and influences the sustainable cultivation of wheat. Therefore, for the first time in Iran, the spatial pattern and temporal progress of this disease were assessed in five wheat cultivars, including Chamran 2, Star, Ofogh, Kavir, and Boolani, with different resistance levels in 2015-16 and 2016-17 cropping years. In both years, disease progress curves (DPC_S) showed a sigmoid-like shape, and the rate curves had an obvious inflection point, both the features of Gompertz and logistic models. Plots of transformed, predicted disease intensity values and residual patterns indicated that disease intensity data fit closely with Gompertz and logistic models. Gompertz and logistic models with a bit of variation gained R^2 above 90 % in all cultivars. Based on the results, there is no direct relationship between cultivar resistance and best-fitted models, as in both years, logistic and Gompertz models fitted properly with disease intensity data for all cultivars. In the Gompertz model, the mean rate of increase (rG) per unit of disease in the resistance (Chamran 2) and susceptible (Boolani) cultivars were 0.052 and 0.09, respectively, and in the logistic model (rL) were 0.12 and 0.144, respectively. Results indicated that in the first weeks after the appearance of the disease symptoms, the spatial pattern of diseased plants was aggregated, and the amount of the *dispersion* index and *lloyd's Index of Patchiness* in the first and second years were 8.9, 9, and 1.3, 1.2, respectively. Three weeks after data collection, the spatial pattern became random.

Keywords: wheat, leaf rust, spatial pattern, temporal progress, dispersion index

Introduction

According to the researchers' prediction, wheat production in the world should be increased by 60% by 2050; meanwhile, 20 to 30% of wheat will be reduced by environmental factors and pests (Prasad *et al.*, 2017). Wheat leaf rust (WLR: caused by *Puccinia triticina* Eriks) is one of the most important yield-limiting diseases in Iran and

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worldwide. It influences the sustainable cultivation of wheat (Teferi, 2015). Severe epidemics of the WLR resulted in significant yield losses and have become a serious economic problem in the world (El Jarroudi *et al*., 2014; Ordonez and Kolmer, 2007). Plant resistance, environmental conditions, pathogen race, agricultural practices, and infected plant's growth stage affect the rate of yield loss (Singh *et al*., 2001; Martinez *et al.*, 2005). The damage of WLR from traceable amounts ranging up to 80 % (Dadrezaei and Torabi, 2016; Dadrezaei *et al*., 2018; Hasanzadeh *et al*., 2020), and the occurrence severe outbreak in the early growth stages result in plant death (Wiik, 2009). In heavy epidemic years, losses due to WLR in plots of spring wheat cultivars were 5 to 40%, depending on the resistance of the cultivar (Kolmer *et al*., 2014); even under suitable environmental conditions, yield losses may reach up to 70% (Oerke and Dehne, 1997; Roelfs *et al*., 1992). The importance of rusts is still increasing due to the rapid emergence of new races and quick adaptation of pathogen populations to resistant cultivars (Chen, 2005).

WLR is borderless and is found worldwide, affecting wheat production (Buck *et al*., 2007). Due to the gradient of horizontal distribution and cultivation of susceptible plants, inoculum carried easily by the wind causes a significant problem for local use of fungicides and also considerable damage (Fitt *et al*., 1987). Therefore, for efficient regional control, reducing labor time, and improving the spraying time, understanding the epidemiology of WLR is essential (Pethybridge *et al*., 2005). Epidemiology could lead to specific managerial suggestions and conceptual creativities in disease management (Madden, 2006), including the analysis of the spatial pattern and temporal progress of disease in host plant populations. Epidemiologists use the disease temporal statically progress models, and indexes of spatial patterns to predict, understand, compare, and describe the epidemics, which can lead to improving disease control strategies. Many studies have assessed disease intensity over time (Madden, 2006) to evaluate cultivars with different levels of resistance and spraying levels (Madden and Hughes, 1995). For this purpose, disease intensity must be assessed a minimum of five times to obtain an integrated measure of the rate of disease progress during an epidemic (Stevenson and Jeger, 2015). Gompertz, logistic, and monomolecular models are the most common models for fitting Disease progress curves (Campbell and Madden, 1990).

About 71 % of cultivated crops in Iran are dedicated to cereals, constituting 24 % of total crop products. The southwest Iran (Khuzestan Province) holds the fourth place in the wheat cultivation area; nevertheless, it is the first wheat producer (Hasanzadeh *et al*., 2019). The climate of this province (warm and humid) is suitable for the WLR disease. Although awareness of the accurate time and place of the appearance and development of the WLR disease is necessary for planning and efficient use of fungicides, basic epidemiological studies have not been available yet. Therefore, we studied the spatial and temporal dynamics of WLR disease to select and introduce the most appropriate model to describe temporal disease progress and the local and regional spatial of disease distribution. The results of this epidemiological research would be a step forward to help producers make management strategies to improve performance (along with reducing damage). Eventually, the knowledge generated through this epidemiological research could complement the previous studies and provide a basis for future research to use the accumulated knowledge in the control of WLR.

Materials and Methods

Seed and inoculum preparation

The Agriculture Research Center in Khuzestan Province provided all the used seeds in both field experiments. Seed rates used for cultivars Chamran 2, Ofogh, Star, Kavir and Boolani were 156, 152, 156, 164 and 160 kg ha^{-1}, respectively. Currently, except Boolani, all the wheat cultivars are cultivated on a large scale in Khuzestan province. The area under

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cultivation of these cultivars reaches 40%, and more than half of it belongs to the Chamran 2 cultivar. Plots were cultivated on the field, and all the current cultivation operations were performed.

Puccinia triticina Eriks' primary inoculum indigenous to Khuzestan province was collected during 2015 and 2016 from wheat nurseries located at Seed and Plant Improvement Institute in Karaj province to avoid additional cultivation operations. Collected urediniospores were stored in tubes and put into a desiccator for 24 hours to be dried, and then placed in deep freeze vials and stored at -80 °C. Before using spores in the experiment, the frozen vials were incubated in a 40 °C water bath for two minutes (Watkins et al., 2001).

Field experiments

Temporal analysis

Five winter wheat cultivars including Chamran 2 (resistant), Star (semi-resistant), Ofogh (semi-resistant), Kavir (semi-susceptible), and Boolani (susceptible) were cultivated in December 2015 and 2016 in the Agricultural and Natural Resource Center of Khuzestan province in Ahvaz (Fig. 1). The experiments were conducted in one treatment with four repeats as the Randomized Complete Block design (RCBD). Each repeat included six rows of wheat with 6 m length and 1.2 m width. The distance between rows and in rows was 25 and 5 cm, respectively. All around the studied farm, the susceptible cv. Boolani was cultivated as the spreader.

Inoculation was carried out according to Eslahi and Mojerlou, (2016). Four grams of *urediniospores* were thoroughly mixed with 20 g of talc powder and poured on the wet leaves of the wheat plants in the plots and susceptible cv. Boolani was planted on the borders of the experimental plot and between treatments. The farm's borders were covered with transparent polyethylene for 48 hours. To ensure infection establishment, inoculation was continued at intervals of one week until the appearance of the first symptoms. The growth stage in which the first inoculation was done during 2015-16 and 2016-17 were recorded according to the Zadoks growth scale (Zadoks *et al*., 1974) (Table 1). Due to the importance of meteorological data in the prevalence and development of rusts, rainfall, and temperature data will be used to analyze the results.

Spatial analysis

Local susceptible winter wheat cv. Boolani was cultivated in December 2015 and 2016 in the Agricultural and Natural Resource Center of Khuzestan province in Ahvaz (Fig. 1). The experimental plot size was 10 m × 10 m (100 m^2). The distance between rows and in rows was 25 and 5 cm, respectively. For obtaining the areal infection center, one side of the farm (1 m × 10 m) was inoculated in February at GS27 growth stage (Zadokas scale). Inoculation was carried out according to Eslahi and Mojerlou, (2016). The inoculated area was covered by transparent polyethylene for 48 hours. The assessment of spatial patterns was performed 12 days after the first appearance of the symptoms in the inoculated area. By applying 0.6 square quadrats, the four-stage assessment was conducted with a one-week interval. In each evaluation, 35 quadrats in different plot spots were assessed randomly. Disease intensity was measured using Stevenson's method (Stevenson and Bowen, 2015).

Analysis

Temporal analysis

Assessment of leaf rust

Disease intensity (%) was measured according to a modified scale of Cobb (Peterson *et al*., 1948). Since the first appearance of symptoms, the disease was assessed and continued every three days seven times.

Data analysis

Disease intensity (%) was evaluated with various disease progress models, from the simplest to the most complex, including linear, monomolecular, exponential, logistic, and Gompertz (Table 2). The EPIMODEL software program was used to regression analysis and visually fit the WLR disease severity data to the five models mentioned above (Nutter *et al*., 2015).

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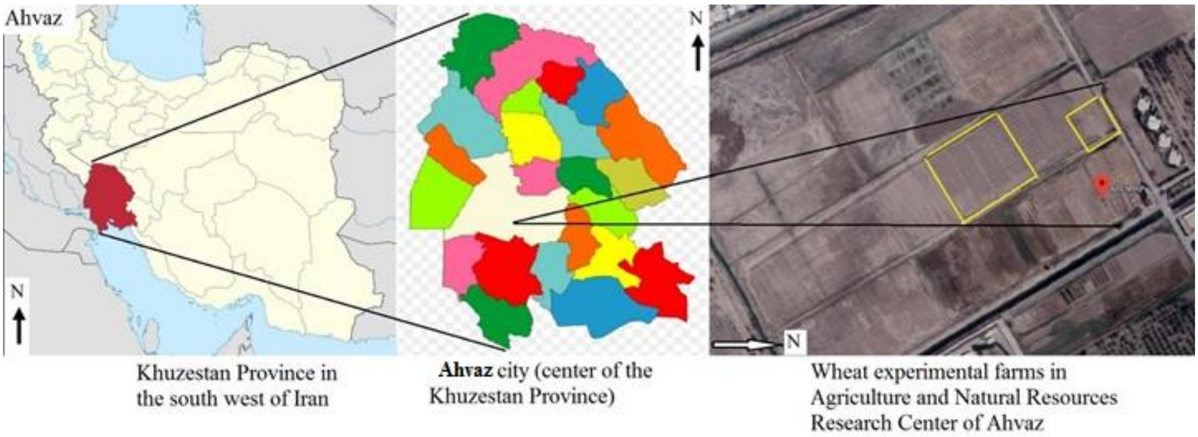

Figure 1 Map of Khuzestan province and field experiment which was conducted to the analysis of Wheat leaf rust (*Puccinia triticina* Eriks.) disease temporal and spatial progression in winter wheat cultivars Chamran 2, Star, Kavir, Ofoq, and Boolani in Agriculture and Natural Resources Research Center of Ahvaz, Khuzestan province, Iran.

Table 1 Date of cultivation, inoculation and harvesting of winter wheat cultivars[a] Chamran 2, Star, Kavir, Ofoq and Boolani in Agriculture and Natural Resources Research Center of Ahvaz, Khuzestan Province, Iran in 2015-2016 and 2016-2017.

Year	Date of cultivation	Frist date of inoculation	Number of inoculation	Growth stage at first inoculation	Date of harvesting
2015-2016	2 Dec	22 Jan	4	GS 27	1 May
2016-2017	3 Dec	20 Jan	4	GS 27	2 May

Table 2 Five disease progress models commonly used to describe temporal disease progress (Nutter *et al*., 2015).

Model	Integrated expression	Absolute rate equation	Linearized equation
Linear	$y = y_0 + rt$	$\frac{dy}{dt} = r$	$y = y_0 + rt$
Monomolecular	$y = 1 - (1 - y_0)\exp(-r_M t)$	$\frac{dy}{dt} = r_M(1 - y)$	$\ln\left(\frac{1}{1-y}\right) = \ln\left(\frac{1}{1-y_0}\right) + r_M t$
Exponential	$y = (y_0)\exp(r_E y)$	$\frac{dy}{dt} = r_E y$	$\ln(y) = \ln(y_0) + r_E t$
Logistic	$y = \frac{1}{1 + [(1 - y_0)/y_0]\exp(-r_L t)}$	$\frac{dy}{dt} = r_L y(1 - y)$	$\ln\left(\frac{y}{1-y}\right) = \ln\left(\frac{y_0}{1-y_0}\right) + r_L t$
Gompertz	$y = \exp\{[\ln(y_0)]\exp(-r_G T)\}$	$\frac{dy}{dt} = r_G y[-\ln(y)]$	$-\ln[-\ln(y)] = -\ln[-\ln(y_0) + r_G t$

**The EPIMODEL computer program uses the linearized forms of each model to transform disease intensity assessments and compute model parameters and regression statistics.

Fitness of models

Based on the residual distribution patterns, shapes of the disease rate and progress curves, and plots of predicted, transformed disease intensity values, one of the most appropriate models was chosen for *y* transformations and describing the epidemic. The fitness of different models was examined by coefficients of determination (R^2) and standard error of the *y* estimate (SEEy = root MSE).

Spatial analysis

Measuring Dispersion Index (D)

Analysis of spatial pattern is performed by runs and based on the calculation of the index of dispersion, *D* (Stevenson, 2015) in rows and

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grasses like wheat, respectively (Stevenson, 2015). The dispersion index was used to determine the spatial pattern of WLR in the field (Stevenson, 2015).

$$D = S^2/\bar{X}$$

S^2 is the variance of the samples; $\bar{X}$ is the mean of the infected plants. If $D = 1$, indicating that the pattern of disease plants is random. If $D > 1$, the pattern of disease plants is aggregated, and if $D < 1$, the pattern of disease plants is regular. The chi-square test is used to test significant deviation from randomness. If $P < 0.05$, the null hypothesis of randomness will be rejected (evidence of aggregation). If $P > 0.05$, the null hypothesis of randomness cannot be rejected (no evidence of aggregation).

Measuring Lloyd's Index of Patchiness (*LIP*)

The following formula was used for Lloyd's Index of Patchiness (Bez, 2000).

$$LIP = 1 + [(S^2 - \bar{X})]$$

S^2 is the variance of the samples; $\bar{X}$ is the mean of the infected plants. This method is based on the calculation of dispersion index *D, which is* known as the relation between the variance and mean. If *LIP* = 1 the pattern of disease plants would be random. If *LIP* > 1, the pattern would be a cluster; if *LIP* < 1, the pattern would be regular.

Results

Meteorological data analysis

On February, March, and April, flag leaf emergence and development and seed filling period, the rainfalls and average monthly temperatures in Khuzestan province in 2015 were 33.3, 41.1, and 26.6 mm, and 16.8, 20.3, and 26.5 °C, respectively. In 2016 the rainfalls in February, March, and April were 4.7, 38.3, and 26.4 mm and the average monthly temperatures were 17, 21, and 25.9 °C.

Results indicated less rainfall during the growing season of 2016-17 than in 2015-16, and during February and March, which is the time of the symptoms' appearance, the rainfall rate was almost half that of the other periods. Comparing meteorology data for February, March, and April indicates that in 2015-2016, weather temperature was one to two °C higher than in 2016-2017 (Fig. 2). Regarding the meteorological factors, the weather conditions were more suitable for the leaf rust development in 2015-16 than the following year.

Temporal analysis

2015-16 cropping year

Concerning the wheat cultivars, the disease intensity of WLR was assessed 39-47 days after inoculation (Fig. 3). Disease temporal progress analysis was done with EPIMODEL software by fitting different models to severity data (Table 2). Based on the results linear, exponential, logistic, and Gompertz models received the highest R^2 in all cultivars (Table 3). In cultivar Chamran 2, the disease progress curve (DPC) showed between logistic, Gompertz, linear, and sigmoid-like shapes related to the linear models, the inflection points of DPC occur before the time when y = 50% (Fig. 4). The rate curve has a prominent peak (special for Gompertz and logistic models); therefore, we can rule out the linear, and exponential models, the rate curve of these models is a horizontal line (Fig. 4). Plots of transformed, predicted disease intensity values ($\hat{y}*$), indicate that Gompertz and logistic models provide a close fit to the data, and residual patterns are not decisive (Fig. 5). The Gompertz model, compared to the logistic model showed a higher R^2 and less SEEy (Table 3). According to the results, the Gompertz model was selected as the most appropriate model. In cultivars Kavir, Boolnai, and Star, the logistic model was chosen as the best-fit model to describe WLR progress in field condition of Khuzestan province, due to the highest R^2 (Table 3), shape of DPC and rate curve (Fig. 4), residual distribution pattern (Fig. 4) and the simplicity of the model. In the Ofoq cultivar based on the above criteria, the Gompertz model was selected as the most acceptable

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model compared to the logistic model, with a little difference.

2016-17 cropping year

Based on the wheat cultivars, the disease intensity of WLR disease was assessed 40-49 days after inoculation (Fig. 3). In cultivar Chamran 2, DPC showed Gompertz, logistic, and curve-like shapes related to the exponential models (Fig. 6). Rate curve has an obvious peak; therefore, we can rule out the exponential models (Fig. 6). Plots of transformed, predicted disease intensity values ($\hat{y}*$), indicate that Gompertz and logistic models provide a close fit to the data (Fig. 7). Still, the residual distribution pattern of the logistic model was more random (Fig. 6). The logistic model compared to the Gompertz model showed a higher R^2 (Table 3). The logistic model was selected as the most appropriate based on the evidence. In cultivars Kavir, Boolnai, and Star, the Gompertz model was chosen as the best-fit model to describe WLR progress in field condition of Khuzestan province, due to the highest R^2 (Table 3), the shape of DPC and rate curve, residual pattern (Fig. 6). Same as the previous year, in Ofoq cultivar logistic model compared to the Gompertz model was chosen as the most acceptable model.

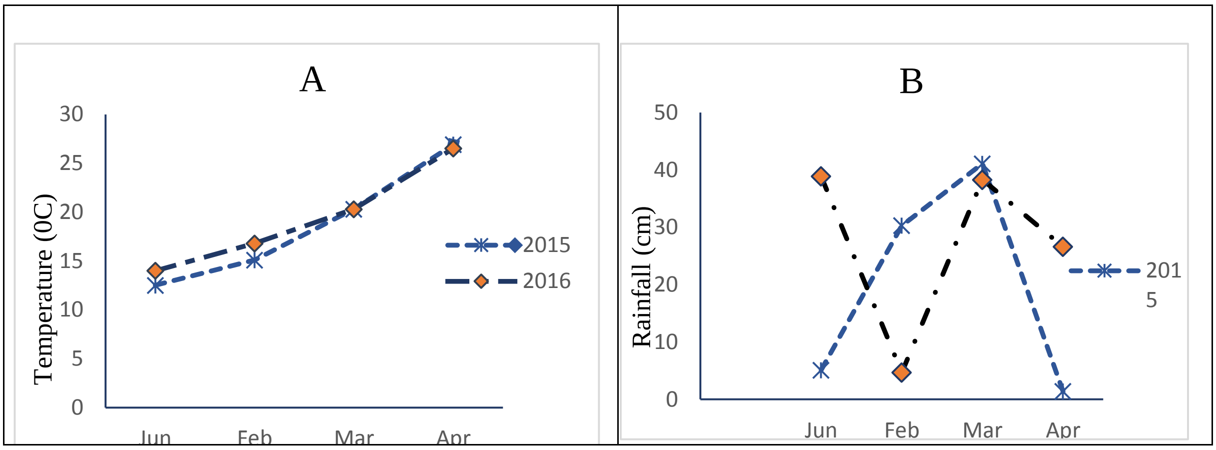

Figure 2 A and B Monthly mean temperature (°C) and total rainfall (cm) of the two growing seasons of 2015-16 and 2016-17 in Ahvaz city (Center of Khuzestan Province).

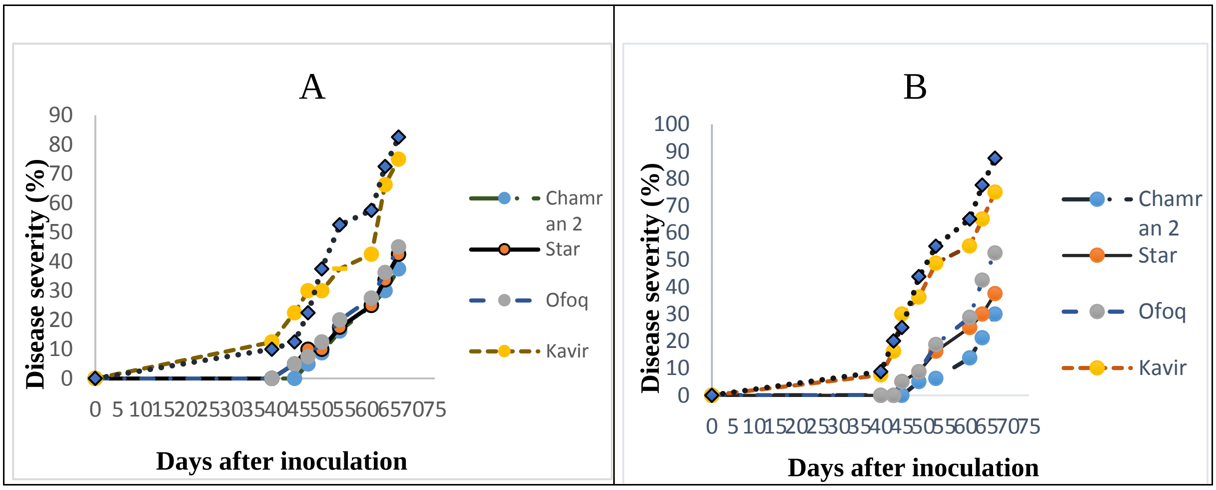

Figure 3 Percentage of visible leaf disease severity based on method of Cobb (Peterson et al., 1984).
**A & B 2015-16 and 2016-17 growing years respectively.

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Table 3 Regression statistics (SEEy and R^2) and model parameters (slope, intercept) values of disease progress evaluated for linearized equations of the linear, monomolecular, exponential, logistic, and Gompertz disease progress models in winter wheat cultivars Chamran 2, Star, Kavir, Ofoq and Boolani in agricultural and natural resources research center of Khuzestan Province, Iran in 2015-16 and 2016-17.

Cultivar**	Model*	2015-16				2016-17			
		R^2 (%)	SEEy	Intercept	Slope	R^2 (%)	SEEy	Intercept	Slope
Chamran 2	LI	0.914	0.028	-0.075	0.012	0.772	0.051	-0.115	0.013
	M	0.896	0.037	-0.096	0.014	0.732	0.07	-0.153	0.016
	E	0.929	0.045	-4.605	0.125	0.878	0.276	-4.142	0.101
	L	0.852	0.46	-4.702	0.121	0.868	0.324	-4/295	0.12
	G	0.912	0.128	-1.708	0.053	0.835	0.158	-1.692	0.051
Kavir	LI	0.826	0.09	0.111	0.02	0.942	0.055	0.096	0.023
	M	0.776	0.211	0.018	0.041	0.915	0.130	0.008	0.045
	E	0.787	0.281	-1.864	0.057	0.769	0.380	-2.094	0.073
	L	0.824	0.431	-1.845	0.098	0.878	0.418	-2.085	0.118
	G	0.817	0.29	-0.78	0.064	0.926	0.199	-0.861	0.074
Boolani	LI	0.943	0.063	0.062	0.027	0.945	0.059	0.089	0.028
	M	0.884	0.201	-0.09	0.058	0.898	0.222	-0.109	0.069
	E	0.8	0.383	-2/204	0.08	0.817	0.338	-2	0.075
	L	0.902	0.435	-2.295	0.144	0.929	0.378	-2/109	0.139
	G	0.923	0.248	-1.003	0.1	0.939	0.242	-0.953	0.09
Ofoq	LI	0.94	0.035	-0.03	0.016	0.886	0.063	-0.128	0.022
	M	0.907	0.061	-0.07	0.022	0.825	0.118	-0.23	0.032
	E	0.91	0.243	-3.157	0.089	0.907	0.273	-3.537	0.108
	L	0.932	0.26	-3.231	0.111	0.919	0.329	-3.767	0.141
	G	0.947	0.11	-1.303	0.053	0.907	0.181	-1.601	0.071
Star	LI	0.903	0.042	-0.025	0.014	0.906	0.038	-0.059	0.015
	M	0.87	0.066	-0.06	0.019	0.887	0.054	-0.098	0.019
	E	0.92	0.210	-3.086	0.082	0.886	0.258	-3.4	0.091
	L	0.928	0.245	-3.147	0.101	0.902	0.288	-3.498	0.11
	G	0.925	0.121	-1.269	0.049	0.915	0.123	-1.407	0.051

* LI = Linear, M = Monomolecular, E = Exponential, L = Logistic, G = Gompertz.
**Chamran 2, Star, Kavir, Ofoq and Boolani are, respectively, resistance, semi-resistance, semi-resistance, semi-susceptible, susceptible.

Spatial analysis

Measuring *D* and *LIP* Indexes

Results indicated that in the first week after the appearance of the symptoms, the spatial pattern of diseased plants or pathogen propagules was aggregated, and the *D* index was 8.9 and 9.9 in the first and second years, respectively (Table 4). As the disease intensity was higher than 15% in each quadrat, the Chi-Square test cannot be used to determine the fit of goodness. These results continued into the second and third week of the data collection, and the *D* index was 1.6 and 2.04 for the first and second years of study, respectively. *LIP* index results showed that the spatial pattern was aggregated in the first week after the symptoms appeared, and this approach continued until the third week of data collection (Table 4). After 20 days, the spatial pattern became random, as expected. Our data showed that the spatial pattern of WLR was aggregated at first, and both indexes showed the same results. Two-year results showed that the dispersion process and the disease's models are similar and aggregated.

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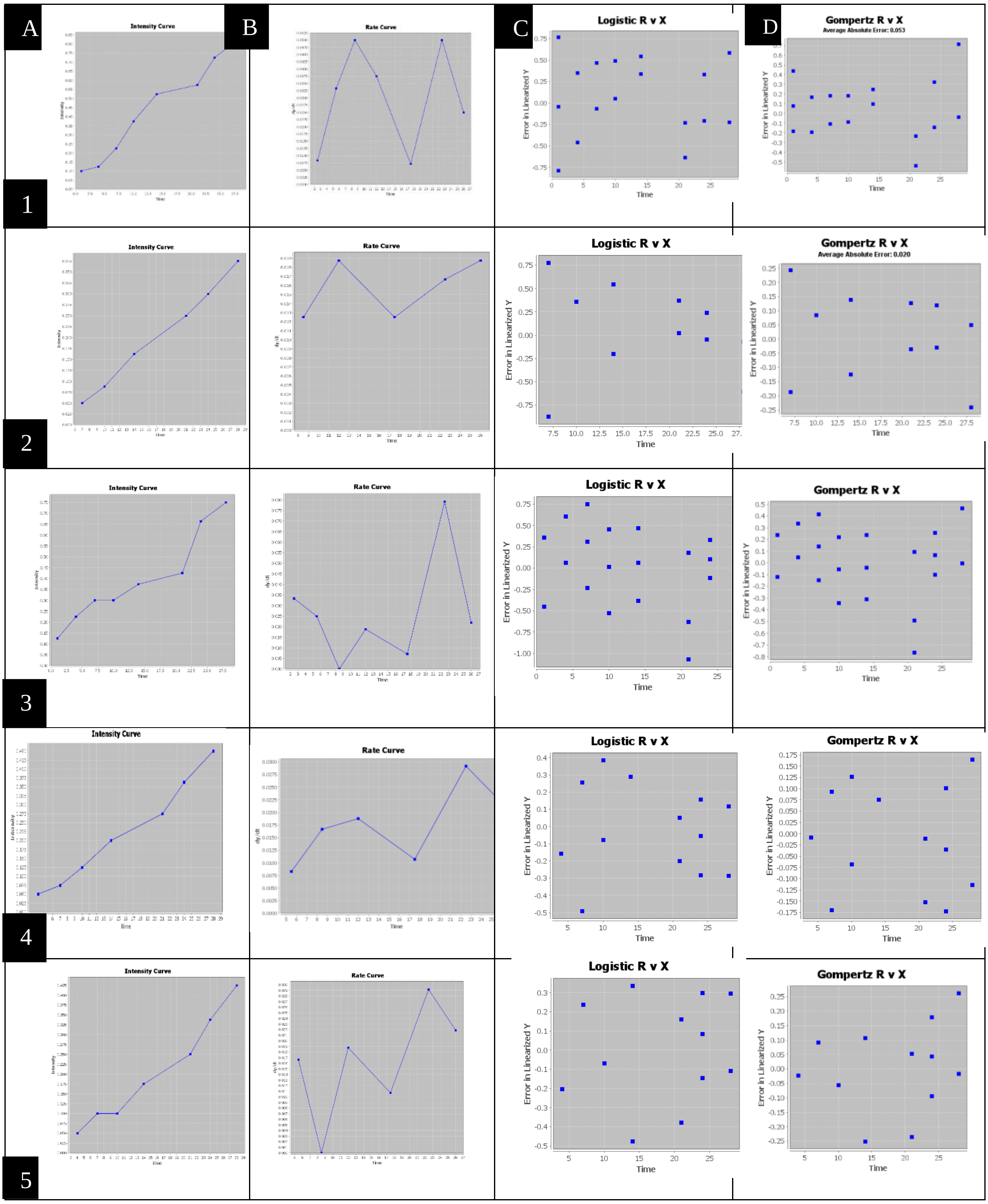

Figure 4 Column A - Disease progress curve (nontransformed disease intensity ***y***, expressed as proportions, vs. time ***t***). Column B - The rate curve (the estimated rate of change of nontransformed ***y*** between pairs of times (***dy/dt***) against time ***t***. Column C and D - The residuals vs. independent variable show the residual errors (i.e., differences between predicted and actual disease intensity) from transformed regression models vs. time in logistic and Gompertz models, respectively. Graphs in rows 1, 2, 3, 4, 5 are related to cultivars Boolani, Chamran 2, Kavir, Ofoq, and Star, respectively in 2015-16.

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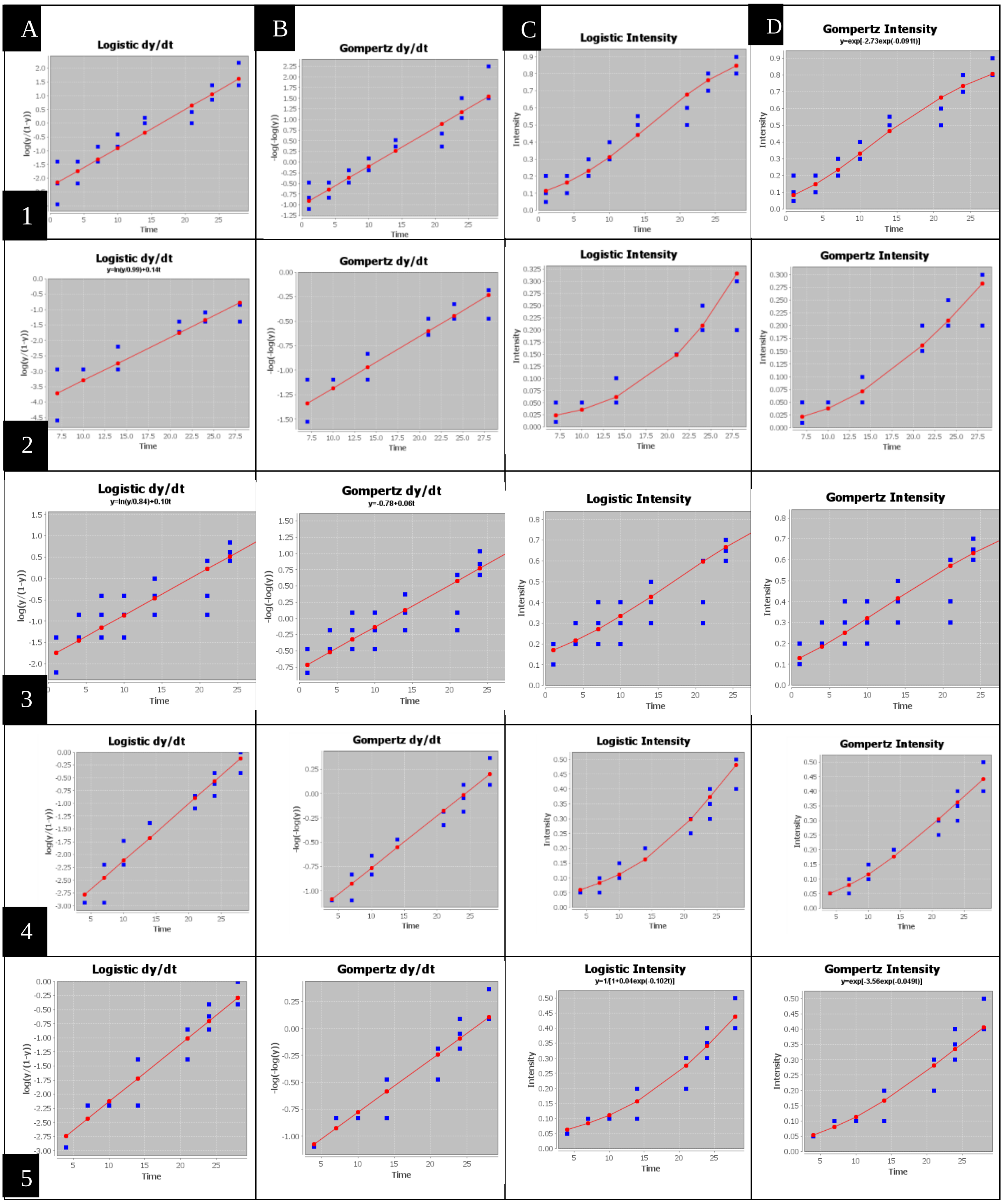

Figure 5 Column A and B - Linearized graph display model-transformed disease intensity data points against time, and predicted regression lines for linearized Logistic and Gompertz models, respectively. Column C and D - The back-transformed graph shows predicted regression lines for Logistic and Gomperts growth models, respectively, with predicted *y** values back-transformed to proportions and plotted with original disease intensity assessments. Graphs in rows 1, 2, 3, 4, 5 are related to cultivars Boolani, Chamran 2, Kavir, Ofoq, and Star, respectively in 2015-16.

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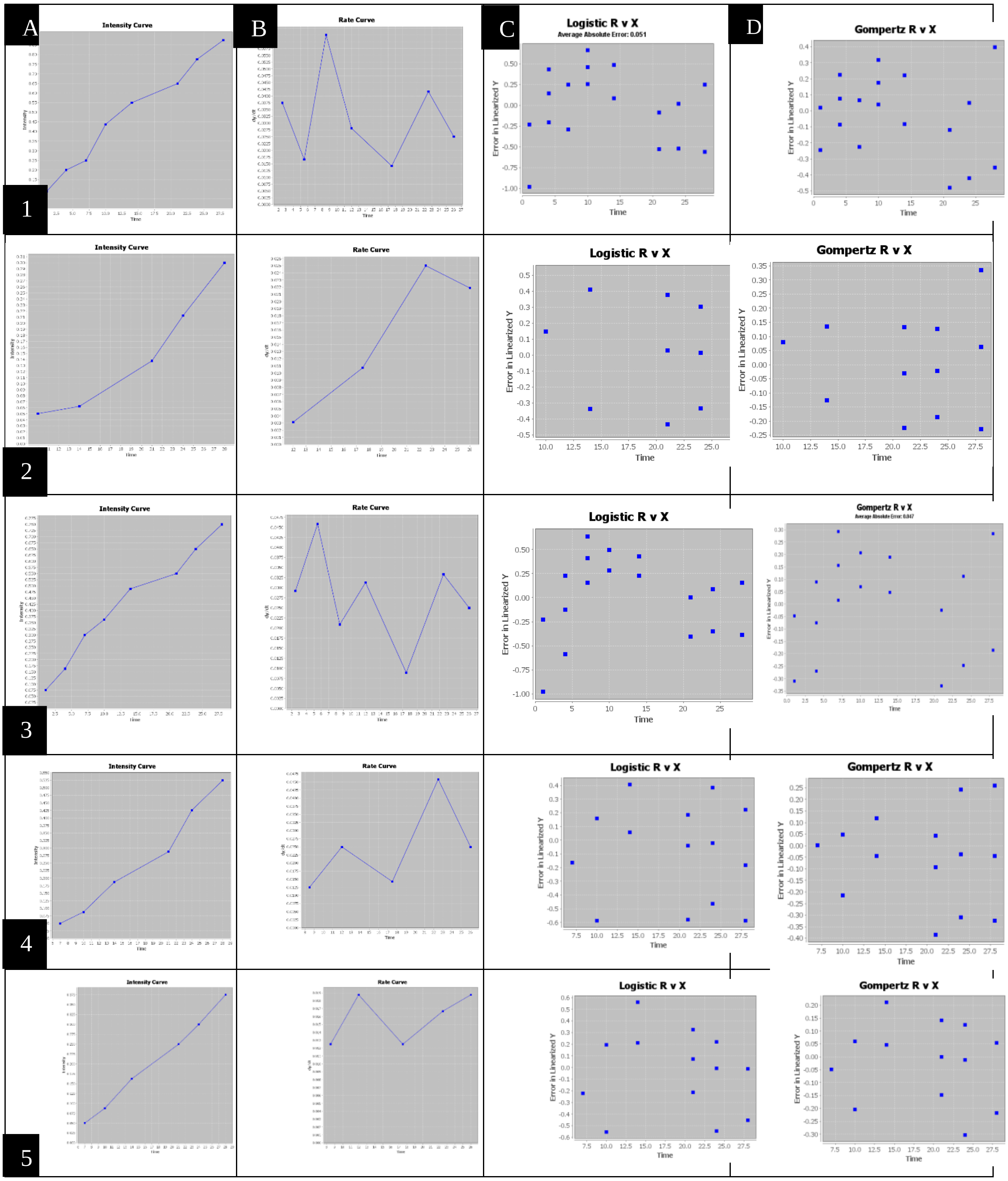

Figure 6 Column A - Disease progress curve (nontransformed disease intensity ***y***, expressed as proportions, vs. time ***t***). Column B - The rate curve (the estimated rate of change of nontransformed ***y*** between pairs of times (***dy/dt***) against time ***t***. Column C and D- The residuals vs. independent variable show the residual errors (i.e., differences between predicted and actual disease intensity) from transformed regression models vs. time in Logistic and Gompertz models, respectively. Graphs in rows 1, 2, 3, 4, 5 are related to cultivars Boolani, Chamran 2, Kavir, Ofoq, and Star, respectively in 2016-17.

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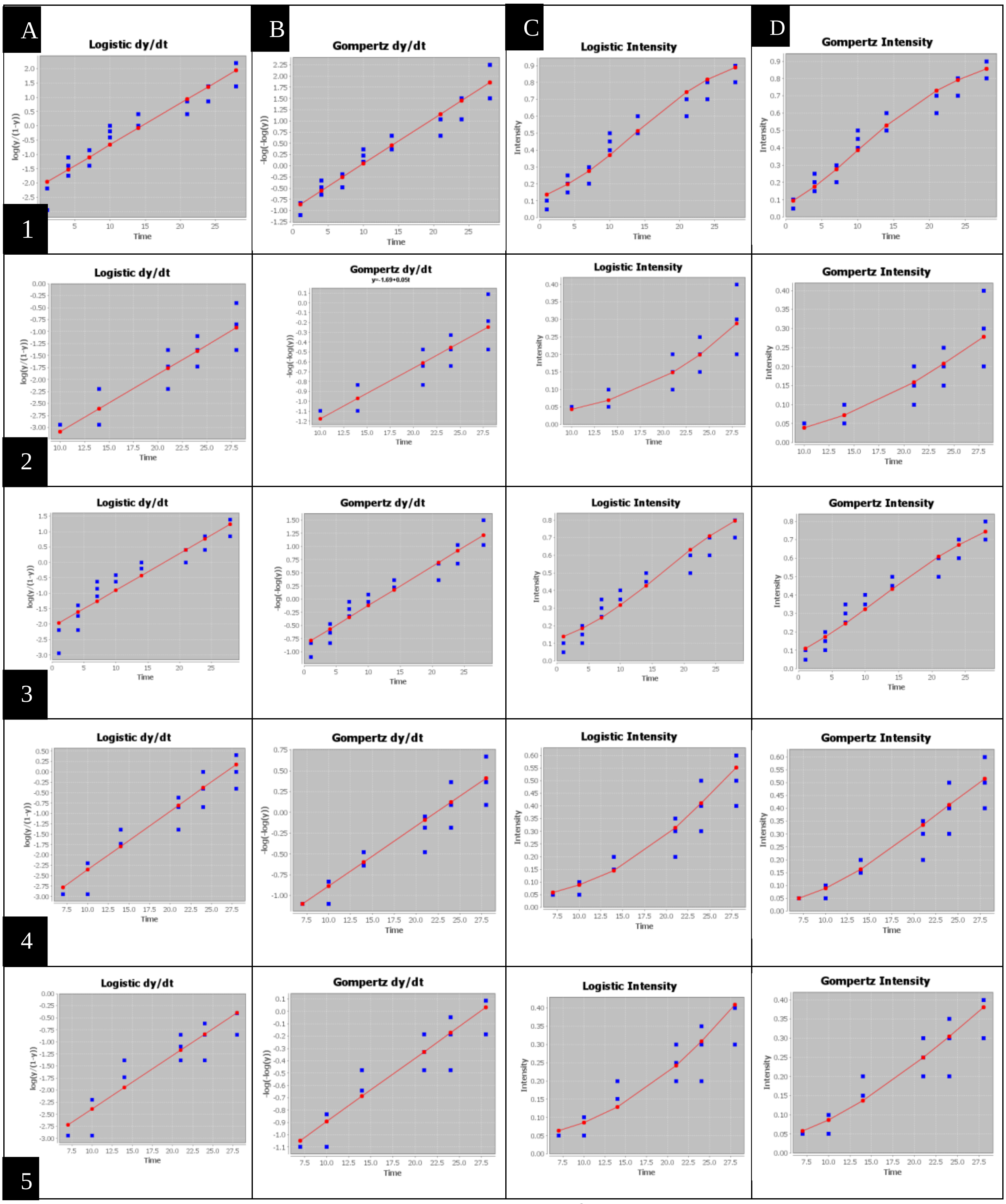

Figure 7 Column A and B - Linearized graph display model-transformed disease intensity data points against time, and predicted regression lines for linearized Logistic and Gompertz models, respectively. Column C and D - The back-transformed graph shows predicted regression lines for Logistic and Gomperts growth models, respectively, with predicted *y** values back-transformed to proportions and plotted with original disease intensity assessments. Graphs in rows 1, 2, 3, 4, 5 are related to cultivars Boolani, Chamran 2, Kavir, Ofoq, and Star, respectively in 2016-17.

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Table 4 The results of measuring *D* and *LIP* indexes of Wheat leaf rust (WLR) *Puccinia triticina* Eriks during the 2015-16 and 2016-17 growing seasons.

Days after symptoms appearance	2015-16 cropping season					2016-17 cropping season				
	$S^{2\,b}$	$\bar{X}^{c}$	*D*	*LIP*	Pattern [d]	S^2	$\bar{X}$	*D*	*LIP*	Pattern
12	231.9	25.9	8.9	1.30	Aggregated	308.5	31.1	9.9	1.20	Aggregated
19	190.8	48.3	3.9	1.00	Aggregated	278.7	59.7	4.6	1.06	Aggregated
26	112.0	69.0	1.6	1.00	Aggregated	173.3	84.8	2.0	1.01	Aggregated
33	36.1	73.5	0.4	0.99	even	90.2	47.6	0.5	0.99	Even

a. The dates in which the severity of the disease is taken based on the modified index of Cobb (Peterson *et al*., 1948), b. The variance of severity data., c. The means of severity data, d. The spatial patterns of WLR in each date, D: Dispersion Index, LIP: Lloyd's Index of Patchiness.

Discussion

According to global distribution maps of the disease, Iran, especially the southwest (Khuzestan province), is one of the key lands of WLR disease, and symptoms of the disease occur every year in different areas (Chai *et al*., 2016; Roelfs *et al*., 1992). In Iran, this disease placed after the yellow rust and was reported as an epidemic in different parts of the country (Torabi *et al*., 1995; Mohammadi *et al*., 2023), but in Khuzestan province is primarily important (Dadrezaei and Torabi, 2016; Dadrezaei and Nazari, 2015; Pouralibaba *et al*., 2021). Due to favorable weather conditions and the prevalence of rust, this province, one of the country's most important hubs of wheat production, was selected as the main monitoring center for WLR in Iran. This study proves previous studies about disease distribution in Khuzestan province. According to regional monitoring of WLR in Khuzestan Province from 2014 to 2017 (Hasanzadeh *et al*., 2019), depending on climate conditions and geographical situation, the first symptom of the disease occurred in late March until mid-February irregularly between GS39 to GS57 growth stages. However in experimental plots, the disease has been epidemic in both years and developed significantly until the end of the growth season, which demonstrated the importance of the presence of external inoculation sources and the inherent potential of this province for the prevalence of large epidemics. In compound-interest diseases such as WLR, unlike the simple-interest ones, primary inoculum did not have any significant effect on the epidemic establishment, and disease results from hundreds of parallel secondary cycles that develop epidemics (Agrios, 2005). Proper management of this disease requires an accurate understanding of disease development and epidemiology (Chen, 2017). Using epidemiological studies, it is possible to present how a disease in the host population and the effect of the disease pyramid factors in its development leads to valuable and effective strategies for disease management (Xu, 2006). One of the main aspects of epidemiological studies is a temporal analysis of disease to evaluate factors affecting disease (Xu, 2006), which is considered several decades later in quantifying disease progression. For instance, Ware *et al.* (1932) and Ware and Young (1934) presented curves demonstrating the effect of cultivar resistance and fertilizer treatment of flax wilt dynamic. Wander Plank also applied parameters of disease progress models for treatment comparison of disease development (Xu, 2006). Each curve, drawn based on disease intensity data, presents a dynamic image of disease in time and is called the "signature of" an epidemic (Campbell and Madden, 1990). The regression statistics of this research showed that every disease progression model fitted properly on all studied cultivars with WLR disease intensity data. However, as expected, disease progress and rate curves fit properly with the logistic and Gompertz models. The disease progress curve had a sigmoid shape, and the rate curve had an obvious inflection point, characteristic of the logistic and Gompertz models. Zadoks (1961) showed that the logistic model is the best for predicting wheat yellow rust as a polycyclic disease. Most of the foliage and airborne diseases, such as septoria leaf blotch of tomato (Parker *et al*., 1997), Cercospora leaf blotch of corn (Ward *et al*., 1997), and sugarcane

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Cercospora leaf blotch (Madanian *et al*., 2004) are the polycyclic and logistic model presented the best fit for describing the epidemic. Also, Gompertz model compatibility, previously affirmed in the peach rusty spot (Furman *et al*., 2003), citrus canker (Gottwald *et al*., 1989), grapevine leafroll-associated virus 3 (Habili and Nutter, 1997), and pea powdery mildew (Viljanen -Rollinson *et al*., 1998). According to our results, there is no direct relationship between cultivar resistance/susceptibility and appropriate models, as in both years, logistic and Gompertz models, with a little difference, fitted properly with the disease intensity data of all cultivars. Noteworthy, the biological nature of the disease could not decisively determine the special model with appropriate statistical data to describe a disease epidemic. For instance, fusarium head blight of wheat (FHB), behaves as a polycyclic disease in nature while due to the special time/phenology stage (anthesis) to infection on wheat, known as a monocyclic disease (Wiese, 1991). So, the epidemiological study's results showed that FHB, like most polycyclic diseases, fitted with the logistic and Gompertz models instead of the monocyclic disease model (monomolecular) (Taiely *et al*., 2006). Therefore, the same fitness of disease intensity data with monocyclic and polycyclic disease models and the compatibility of the polycyclic disease with the monocyclic disease model and vice versa is possible (Arneson, 2001).

The model aims to fit with disease severity data and determine the proper one by using the estimated parameters (r and y_0) to formulate equations to determine disease intensity at a specific time. This compares epidemics to developed cost-effective and integrated management programs (Xu, 2006). Due to a diverse unit of model parameters, it is essential to analyze epidemics with the same models (Nutter *et al*., 2015). In the case of the polycyclic disease epidemic, the impact of all affecting factors on the disease pyramid is reflected in the rate of disease progression. The comparison of changes in the rate of two epidemics could be related to the special change during that epidemic. The modified line rate of Gompertz and the logistic model differ regarding plant disease. In this study, in the resistant cultivar Chamran 2, r_G was 0.053 and 0.051in the 2015-2016 and 2016-2017 crop seasons, respectively. Also, in susceptible cultivar Boolani, it was 0.09 in 2015-2016 and 0.1 in 2016-2017. In Chamran 2, the resistant cultivar, r_L was 0.121in the 2015-2016 crop season and 0.12 in 2016-2017; in Boolani, the sensitive cultivar, r_L was 0.144 in 2015-2016 crop season and 0.139 in 2016-2017. Gompertz model rate is lower than 1 in most diseases (rG < 0.1) (Berger, 1981); as the rate of 0.961 was recorded for asparagus Cercospora blight (Conway *et al*., 1987) and 0.008 for dutch elm and yokka rust disease (Berger, 1981). In canola, Sclerotinia stem rot epidemic in Iran r_G ranged from 0.003 to 0.077 (Aghajani and Safaie, 2010). According to the Gompertz model, the rate of disease progress in the susceptible cultivar, Boolani, was almost twice as resistant cultivars, Chamran 2. Still, in the logical model, it was lower than Gompertz.

The first step to understanding the ecological process of disease is identifying their spatial pattern (Fortin *et al*., 2002). The spatial pattern of pathogen, vector, and disease distribution demonstrated the effect of environmental heterogeneity on pathogen dispersion, which could be depicted by statistical analysis. However, when spatial pattern analysis aims to explain the basic process according to outcomes, only statistical models might not be enough. Still, such methods could be used to formulate ecological theories that no statistical tools could evaluate- and also to affirm the basic processes (Madden, 2006). The information on the distribution pattern of disease is important for several reasons. Knowing the aggregative degree of disease pattern directly helps determine required and effective sampling units (based on infection rate) to evaluate the average necessary intensity and establish proper management strategies. In addition, the released distribution pattern gives direct insight into the distribution mechanism and the spatiotemporal dynamic of disease, which is essential in defining optimal control tactics (Stevenson, 2015).

In this study, the aggregative spatial disease pattern obtained during two experimental years

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was consistent with a single pathogen life cycle. This pattern represents the pathogen's infectious and polycyclic behavior and demonstrates that the pathogen has a vector (Madden *et al*., 2007). Wheat rusts such as WLR, a polycyclic disease could be distributed rapidly in optimal conditions. After a 7-10-day latent period, each uredinium could produce 30,000 spores daily for 20 days (Singh *et al*., 2002). This explanation showed the explosive nature of the disease in favorable environmental conditions and the ability to transfer to distant areas by wind, animals, and human activities (Roelfs *et al*., 1992).

The wheat rust epidemic is affected by three components of an epidemic triangle similar to other diseases: pathogen, host, and environment. In the presence of the pathogen and susceptible host, environmental conditions play a key role in the effectiveness and severe occurrence of the epidemic (Chen, 2005). In several studies, the role of the vector as one component of environmental conditions was evaluated to create a spatial pattern and physical distribution of spore or disease agents at far and near distances. Also, the actual data were used to validate theoretical predictions of spore transformation (Teferi, 2015). Hilker *et al.* (2017) applied mathematical models to analyze the dispersion of maize lethal necrosis virus disease agent on maize in Africa to predict the management effect on disease agent and vector distribution. In another experiment, the incidence of an aggregative pattern of bacterial wilt in rows of a commercial farm demonstrated the effect of irrigation on disease extension (Wimer *et al*., 2011).

Today's researchers benefit from parameters such as traveled distance, temperature, relative humidity, direction, and wind speed to determine and define spatial patterns of the pathogen at lower distances. Such information helps understand the spore dispersion in long distances, model distribution routes, and predict the start of an epidemic (Ojiambo *et al*., 2017). Tracing the possible route of the rust and predicting the spreading path could be performed according to maps and the direction of air flows. The main masses and air flows affecting Iran included: 1- Sudan perception system 2- Mediterranean moist air mass 3- Siberian cold air mass 4- Southern warm and wet masses (active in summer) 5- Saudi Arabian dry and warm air mass (Dadrezaei *et al*., 2018). Mediterranean and Sudanese air masses play a critical role in the transmission and distribution of urediniospores in wheat farms. The combination of Sudanese and Mediterranean low-pressure air mass causes the strengthening of the Sudanese low pressure and receiving moisture from the Red Sea, Arabian Sea, and the Persian Gulf, resulting in heavy rain in this region. When the direction of air flows and the rise and the motion of rusts are examined carefully, the conformity of rusts movement direction and air flows is observed. Mediterranean air mass affected wheat fields during growth season. Also, in the years when the Sudanese masses are acting, rusts are more active and induce regional or global epidemics due to humidity and heavy rain. During these days, rusts occur severely in the south and southwest Iran from 2012 to 2014. Regional monitoring of WLR disease in southwest Iran (Khuzestan Province) (Fig. 8) depicted the activeness of this disease according to the route of Sudanese air Mass (Hasanzadeh *et al*., 2019). The results of epidemiological studies of wheat rusts in the past decade have revealed that the Khuzestan province has always been one of the first areas to experience a rust outbreak (Dadrezaei et al., 2018).

Considering to the air masses way and reviewing the history of the rust epidemic in Iran, like the trans-regional dispersion of yellow rust in an epidemic of 1980 in the CWANA region (North Africa, Central Asia, and West Asia countries), it could be found that it is the same way which caused pathogenic yellow rust race spore transformation to resistant wheat cultivars carrying a resistance gene *Yr9* in the 1990s (Dadrezaei *et al.*, 2018). The area under the cultivation of these cultivars was more than 20 Million hectares, and the activity of both air masses caused the yellow rust epidemic in CWANA region and induced a 1 billion dollar loss. In 1993, wheat yield loss in Iran due to this epidemic was 1.5 million tons, estimated to be 1 million tons annually in 1995 (Torabi *et al*., 1995).

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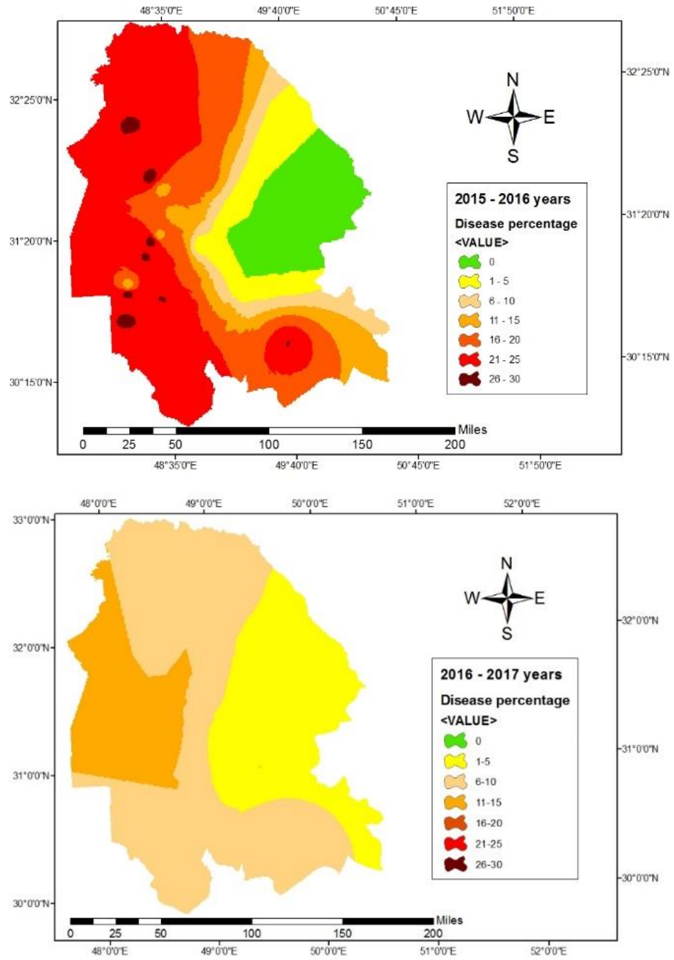

Figure 8 GIS map shows the severity of symptoms (%) and pattern of the spread of wheat leaf rust disease in Khuzestan province in 2015-16 and 2016-17 growing years. Areas with different severity of symptoms are shown in different colors.

The emergence of a new race of cereal rust by weather trends from Northeast Africa to Iran similar to the yellow rust race with pathogenicity for wheat cultivars carrying *Yr27* gene was a typical example of the continental motion of this disease (Afshari, 2004). Although the progress direction of rusts is not observable, the transition and diffusion path of rust spores from northeastern Africa and West Asia by Sudanese airflow could be compared by dust motion pictures and cloud masses in this route, which occurred during recent years.

Considering the climate conditions in Khuzestan province, especially in these two years, it is understood that 2015-16 is more conducive than 2016-17 with a very slight difference. However, the compressive view of the epidemic that occurred in both years concludes that the weather in Khuzestan Province is favorable for this disease. Furthermore, because of the aggregative spatial pattern of WLR, in the case of Sudanese and Mediterranean perception system entrance and cultivating the susceptible cultivar, transmission of spores from internal and external infection spots with system motion is possible. The heavy epidemic will happen and could impose severe damage due to high moisture content and heavy perception. Therefore, the

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logistic and Gompertz growth models for predicting disease development during the season and management strategies mainly established based on resistant cultivars and fungicides (Hasanzadeh *et al*., 2020) are needful and necessary.

Compliance with ethical standards

Conflict of interest: The authors declare that the research was conducted without any commercial or financial relationships that could be construed as a potential conflict of interest.

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آنالیز فضایي-زماني بیماري زنگبرگي گندم (*Puccinia triticina* Eriks) در جنوب غربي ایران

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چکیده: زنگبرگي یکي از مهمترین بیماریهای گندم میباشد و کشت پایدار آن را تحت تأثیر قرار میدهد. ازاینرو برای اولین بار در ایران، الگوي فضایي و پیشرفت زماني این بیماري در پنج رقم گندم شامل چمران۲، استار، افق، کویر و بولاني با سطوح مختلف مقاومت طي سالهای ۹۵-۱۳۹٤ و ۹٦-۱۳۹۵ مورد ارزیابي قرار گرفت. در هر دو سال منحني پیشرفت بیماري (DPCs) حالت سیگموئید داشته و منحنی نرخ داراي يك نقطه خمیدگي واضحی بود که هر دو از ویژگیهای مدلهای لوجیستیک و گمپرتز میباشد. پلاتهای تغیر یافته، مقادیر شدت بیماري پیشبینی شده و الگويهاي باقيمانده نشان دادند که مدلهای لوجیستیک و گمپرتز برازش نزدیکي را با دادههاي شدت بیماري فراهم ميکنند. R^2 مدلهاي لوجیستیک و گمپرتز در تمام ارقام بالاي ۹۰ درصد بوده و ارتباط مستقیمي بین سطوح مقاومت ارقام و مدل مناسب وجود نداشته و هر دو مدل برازش مناسبي با دادههاي شدت بیماري در تمام ارقام را نشان دادند. میانگین نرخ افزایش بیماري در مدل گمپرتز (rG) در رقم مقاوم و حساس بهترتیب برابر با ۰/۰۵۲ و ۰/۰۹ و در مدل لوجیستیک (rL) بهترتیب برابر با ۰/۱۲ و ۰/۱٤٤ بود. در اوایل بیماری، الگوي پراکنش فضایي گیاهان بیمار تجمعي بوده و مقدار شاخصهاي *D* و *LIP* در سال اول و دوم بهترتیب برابر با ۸/۹ - ۹ و ۱/۳-۱/۲ بود. الگو تجمعي پس از ۲۰ روز تبدیل به الگوي تصادفي گردید.

واژگان کلیدی: گندم، زنگبرگی، الگوی فضایی، الگوی زمانی، شاخص پراکندگی

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