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Research Article

Decision-making system for the management of date inflorescence rot disease caused by *Mauginiella scaettae*

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Abstract: The inflorescence rot is an essentially high impact (or damaging) disease of date palm. The current research was carried out to help develop a decision-making system in Abadan, Khorramshahr, Shadegan, Ahwaz, Mahshar, and Behbehan regions of Khuzestan province Iran based on climatic and geostatistical models using five-year data from 2011 to 2015. Samples were taken randomly from 10 date palm trees within one orchard in each of 33 villages. The disease started in March, and the damage reached its peak values in April. The forecasting model of damage factors has been significant at levels 1 and 5%. The model nuggets for disease in Abadan-Khorramshahr, Shadegan, Ahwaz, Mahshar, and Behbehan regions were 2.1, 1.1, 0.09, 2.60, and 0.27 km, respectively. These results show that the disease damage estimation errors were low at distances less than within sampling space. The effective ranges of variograms were 4.9. 8.3, 9.1, 5.1, and 4.2, respectively, indicating the disease distribution in the region. The sill of models were 0.41, 0.46, 0.46, 0.29, and 0.58, respectively, indicating that correlations between the damage data were at the lowest level and could be monitored at distances more than these thresholds. Findings are fundamental steps in creating a decision-making system in the date palm protection network. Therefore, it could be concluded that the date inflorescence rot disease can be monitored, forecasted, and controlled correctly before the maximum damage occurs.

Keywords: date palm, inflorescence rot, monitoring, forecasting, Integrated management

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Introduction

Date palm is an important economic crop in different countries (FAOSTAT, 2018). Date palm inflorescence rot is one of the most important diseases in date palm plantations. The disease is caused by the fungus *Mauginella scattae* Cav. (Rabab *et al*., 2019). Of course, other microorganisms such as *Alternaria alternata* Fries, *Thielaviopsis paradoxa* (De Seynes) Höhn (Al-Sharidi and Al-Shahwan, 2003), and *Serratia marcescens* Bizio bacterium in Iraq, Basra, and Kuwait (Hameed, 2012) have been reported to cause inflorescence rot. Date palm inflorescence rot is very severe in date palm plantations with saline, heavy, and poorly drained soils, especially in areas with long winters and rainy springs. This disease reduces or stops the growth and even maturity of the male inflorescence (Zaid *et al*., 2002).

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The disease progression depends on weather conditions, especially the amount of rainfall in February and March. If the rainfall in winter is low and the weather is hot and dry, the inflorescences will grow faster. Any delay in the growth of inflorescences within leaf sheaths increases the chances of fungus penetrating them (Abdullah *et al*., 2005). The severity of date palm diseases is affected by climatic conditions in the ecosystem of date palm fields. Any interpretation of the causes of harmful factors fluctuations is significant with climatic factors such as temperature and humidity (Latifian and Zare, 2003). It has been proved that climate change affects disease in the date palm agricultural ecosystems (Latifian, 2001).

Designing a monitoring and forecasting system is necessary to improve the management strategy of date palm inflorescence rot. Establishing this system is possible by using mathematical models (Latifian and Solymannejadian, 2002). In general, there are two methods in the models' application for disease forecasting. Thermal data and multivariate regression models are used in the first method (Russo, 2000; Russo *et al*., 1993). In the second method, data are obtained from the synoptic meteorological station of the region (Schaub *et al.*, 1995; Sharov, 1996). In addition, multivariate regression models based on population relationships of pests or their injuries have been used to create forecasting models with climatic factors, for date palm spider mite *Oligonychus afrasiaticus* McGregor (Latifian, 2014), *Batrachedra amydraula* Myer (Latifian and Zare, 2003), and date bunch fading (Latifian and Rahkhodaei, 2020). In addition, geostatistical models have been used as a new tool to monitor and determine the distribution range of plant diseases in integrated control management (Ellsbury *et al*., 1998). Many attempts have been made to determine specific patterns of distribution of pathogens, but they have not considered the geographical sampling of locations to determine distribution patterns (Journel *et al*., 1978; Story *et al*., 1994).

Recent advances in this field, including geostatistical models, have significantly reduced the existing problems (Dent, 1995; Goovacts, 1997). The geostatistical method has been used in establishing the system of monitoring and distribution of important pests and diseases of date palm, including *B. amydraula* (Latifian and Solymannejadian, 2002), *O. afrasiaticus* (Latifian, 2014), the horned beetles *Oryctes*species. (Ghaedi *et al*., 2020) and date bunch fading (Latifian and Rahkhodaei, 2020). Date palm growers use these systems at the field scale to make economic decisions about pest control treatments. Forecasting systems based on assumptions about the pests' interactions with the host and environment were designed (Latifian, 2017). It is speculated that combining the forecasting model based on meteorological models and pest monitoring based on geostatistical models could be practically utilized as a computer program for decision-making systems in integrated pest management (Al-Shawaf *et al*., 2012). Designing a forecasting and monitoring system is very important to overcome its integrated management problems, including the calendar of control time and the lack of an accurate decision-making system. Accordingly, this study aimed to achieve a forecasting and monitoring system of this date palm disease.

Materials and Methods

This research was conducted in the Khuzestan province of Iran. The samples were selected randomly according to multi-stage geographical cluster sampling method from 33 date palm plantations in Abadan and Khorramshahr (10), Shadegan (8), Ahwaz (6), Behbahan (5), and Mahshahr (4). First, the cities of Khuzestan province were divided according to the geographical location and date palm cultivation area. Then the villages were selected as the sampling site of each city, as shown in Fig. 1.

Meteorological data

Meteorological data were collected through the meteorological station of the region and used in designing the model. For this purpose, 33 climatic parameters were used as described in Table 1. Meteorological data were collected from Abadan, Ahwaz (agriculture), Bandar Mahshahr, Behbahan, and Shadegan synoptic stations from which the average distance of selected plantations was 21, 19, 36, 27, and 31 km, respectively.

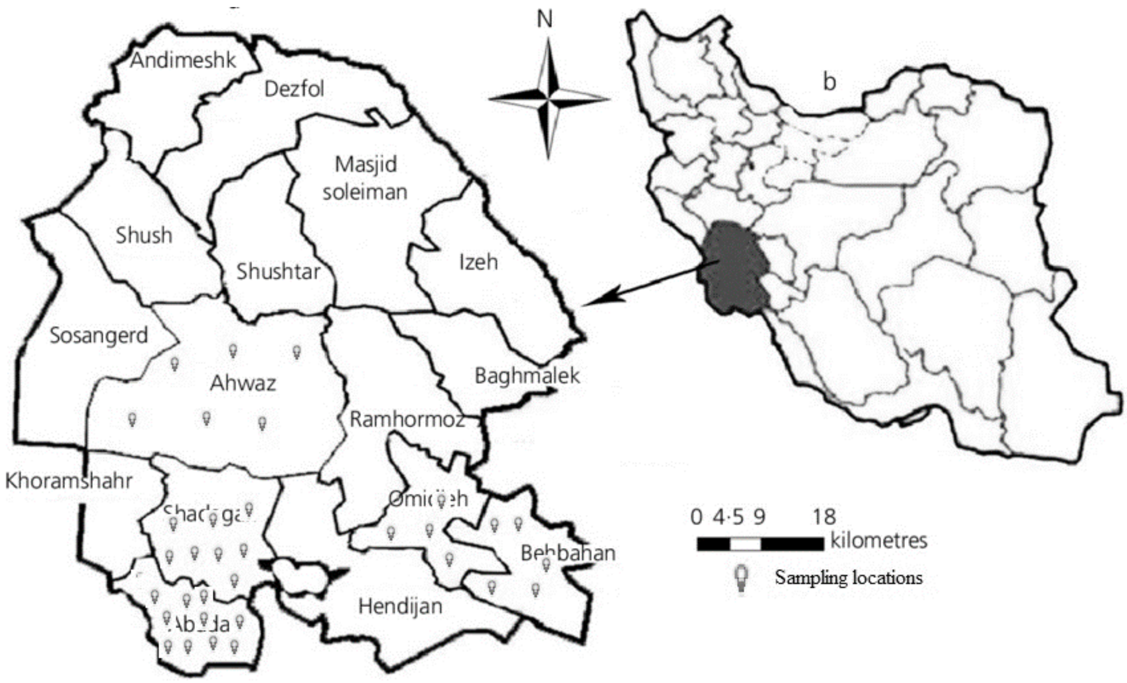

Figure 1 Distribution map of sampling areas of date palm inflorescence rot disease in Khuzestan province, Iran.

Table 1 Climatic parameters used in forecasting models of date palm inflorescence rot disease.

Meteorological index	Symbol	Meteorological index	Symbol
Average spring temperature	X_1	Total last winter rainfall	X_{17}
Average summer temperature	X_2	Total spring rainfall	X_{18}
Average last winter temperatures	X_3	Total summer rainfall	X_{19}
Average last autumn temperature	X_4	Number of rainy months	X_{20}
Average last year temperature	X_5	Total rainfall in March	X_{21}
Maximum temperature in last February	X_6	Total rainfall in April	X_{22}
Maximum temperature is last March	X_7	Average last year relative humidity	X_{23}
Maximum the year temperature	X_8	Average humidity of the wettest months	X_{24}
The highest temperature in the warmest month of the year	X_9	Average humidity in the driest month	X_{25}
Minimum temperature in the coldest month	X_{10}	Average humidity of last autumn	X_{26}
Temperature in the heaviest rainy month	X_{11}	Relative humidity in last winter	X_{27}
Temperature in the least rainy month	X_{12}	Average spring humidity	X_{28}
Total last year rain	X_{13}	Average summer humidity	X_{29}
Rain of the rainiest month	X_{14}	Average humidity of last February	X_{30}
Temperature in the lowest rainy month	X_{15}	Average humidity last March	X_{31}
Total rainfall in autumn last	X_{16}	Total rainfall in March	X_{32}
Average April Humidity	X_{33}		

Estimation of disease damage

One date palm plantation was randomly selected and sampled in each village to estimate the inflorescence disease damage percentage during the season. Ten date palm trees were selected in each plantation randomly, and the number of healthy and diseased inflorescences counted and the damage of the disease percentage calculated. Then the disease severity index was determined for each plantation by using the following formula (Steel and Torrie, 1980).

$$\text{Disease severity index (DSI)} = \frac{0*P0+1*P1+2*P2+3*P3+4*P4+5*P5}{N(G-1)}$$

P_0 to P_5 = total number of inflorescences observed in each grade of disease symptoms examined in each plantation. G = number of grading = 6 and N = total number of inflorescences observed. An observational scale based on the symptoms of the disease was used to score the infected inflorescence as follows: 0: no symptoms, 1: 0-20%, 2: 21-40% inflorescence, 3: 41-60%, 4: 61-80%, and 5: 81-100% of inflorescence was infected (Steel and Torrie, 1980).

Forecasting model

The effects of climatic factors on the disease damage fluctuations were evaluated by calculating the correlation coefficient between the disease damage and meteorological statistics. The incidence of the disease damage was modeled as a function of climatic factors using multivariate regression. Climatic factor coefficients were estimated in different months before reaching the maximum damage. Factors with small coefficient values were eliminated. Curve Expert (1.4) and SPSS (18) software were used for estimations. The models were designed separately for the data of each region (Manion 2003; Andrewarth and Brich, 1953).

Monitoring model

The geostatistical method was used for tracking (Story *et al*., 1994; Wright *et al*., 2002). If (Z) is the damage value, the difference between the damage values of two points with a particular distance h was estimated with [Z (xi) -Z (xi + h)]. Differences in the amount of damage at point X and all other points whispered h was necessary to monitor the disease. Whenever it is assumed that there are a total number of N (h) sample pairs at a distance h from each other, the semivariance was calculated with these hypotheses.

$$\hat{\gamma}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(xi) - Z(xi+h)]^2$$

The above equation $\hat{\gamma}(h)$ is called semivariance. This function should be obtained based on disease information in sampled plantations (Journel *et al*., 1978). The variogram is the most common geostatistical tool in spatial analysis in which the diagram of spatial structure variance is plotted as a function versus h (distance). The interval at which the semivariance reaches a constant is called the effect range. The amplitude of effect is the distance at which most of the samples do not affect each other. Such a distance determines the correlation limit of disease damage and the allowable limit of sampling distance. Most variograms show sudden and rapid changes at very short intervals so that the semivariance is not zero at the origin. The variograms do not pass through the coordinate center of the axis of semivariance. This value is called the sudden effect or the nugget effect. The effect of a piece is due to factors such as changes in disease damage at intervals less than the shortest sampling distance and disease damage errors (Goovaets, 1997). Spherical, exponential, linear, linear to the sill, and Gaussian models were fitted separately for each region data (Manion, 2003). The sum of residual squares (RSS = Residual sums of squares) and the coefficient of explanation R was used to select the best model. Models with minimum RSS and maximum R were selected (Karimzadeh *et al*., 2011). Kriging is a map of estimating spatial variables and is a linear function of a set of distributed observations located in the vicinity of a sampling point (Goovaets, 1997; Wright *et al*., 2002).

$$\hat{Z}(x.) = \sum_{i=1}^{N} \lambda i Z(xi)$$

In this regard, the estimated amount of disease damage at point x., Z (xi) is the numerical value of the disease damage at point $X_{1,}$ and λ_I are the statistical weight of the sample Z(xi) located in the neighborhood of point x. In this equation, n indicates the number of samples. In Kriging, a set of samples is given a statistical weight so that their linear composition is unbiased and has the least variance among other linear estimators (Katherine, 2001). Kolmogorov-Smirnov test, one of the most important statistical tests in SPSS software, was used to test the normality of data. A logarithmic conversion was performed to bring the data frequency distribution closer to normal. Due to zero values in the samples, Log (x + 1) was used instead of Log x. In places where the disease severity was very low and at zero, data was removed from the data list. Geostatistical analyzes were performed with GS^+ 5.1.1 software (Katherine, 2001).

Results

Seasonal fluctuations of inflorescence rot disease damage

Seasonal fluctuations of disease damage in study areas are shown in Fig. 2. The peak of disease incidence damage and severity varied in different regions. The disease damage started in March and gradually increased in severity with the weather's warming every year. So that around mid-April to early May, the disease reached its maximum, and then the disease severity decreased gradually.

Forecasting model

Step 1: Examine the correlation relations

The correlation results of damage inflorescence rot disease with climatic factors are shown in Table 2. Based on the results of the indicators X_{11} (temperature of the rainiest month of the year), X_{15} (least rainy month of the year), X_{18} (total spring rainfall), X_{20} (number of rainy months), X_{26} (average humidity of the driest months of the year) and X_{29} (average spring humidity) and inflorescence rot damage it appears that there was a strong correlation between climatic factors and disease progression. Correlation coefficient parameters X_{11}, X_{15} and $X1_8$ equivalent to -0.64, 0.5, 0.53 for Khorramshar and Abadan, X_{15}, X_{18} and X_{29} equivalent to 0.53, 0.56 and -0.7 for Shadegan, X_{11}, X_{15} and X_{20} equivalent to -0.7, 0.7 and -0.89 for Mahshahr, X_{20}, X_{26} and X_{29} equivalent to 0.67, -0.67 and -0.63 for Behbehan, and X_{11}, X_{15} and X_{18} equivalent to -0.6, 0.9 and 0.7 for Ahwaz, respectively. Therefore, climatic factors can be used in modeling disease forecasting.

Step 2: Determine multivariate regression relationships

The fitting data of the multivariate regression model are listed in Table 3. Based on the results of the fitted regression model, the significance in Mahshahr (F = 2.79), Ahwaz (F = 1.66), and Behbahan (F = 0.37) is at the 1% level and in Abadan-Khorramshahr (F = 0.36) and Shadegan (F = 0.36) at the 5% level.

According to Table 3, the forecasting models of the inflorescence rot disease were fitted as shown in Table 4.

Monitoring model

Step 1: Fit the geostatistical model

Disease distribution variography (Table 5) showed a significant fit in different regions of Khuzestan province. The nugget effect in this model in Abadan and Khorramshahr, Shadegan, Mahshahr, Ahvaz, and Behbahan regions was equal to 2.1, 1.1, 0.09, 2.6, and 0.27, respectively, which indicates a low-intensity estimation error. The injuries were less than the sampling distance in the areas. The variogram range in Abadan and Khorramshahr, Shadegan, Mahshahr, Ahvaz, and Behbahan regions was 4.9, 8.3, 9.1, 1.5, and 4.2 km, the highest correlation and the lowest heterogeneity remain in the data at longer distances. The model threshold in Abadan and Khorramshahr, Shadegan, Mahshahr, Ahvaz, and Behbahan regions were equal to 0.41, 0.46, 0.46, 0.29, and 0.58, respectively, which indicates a ratio of the

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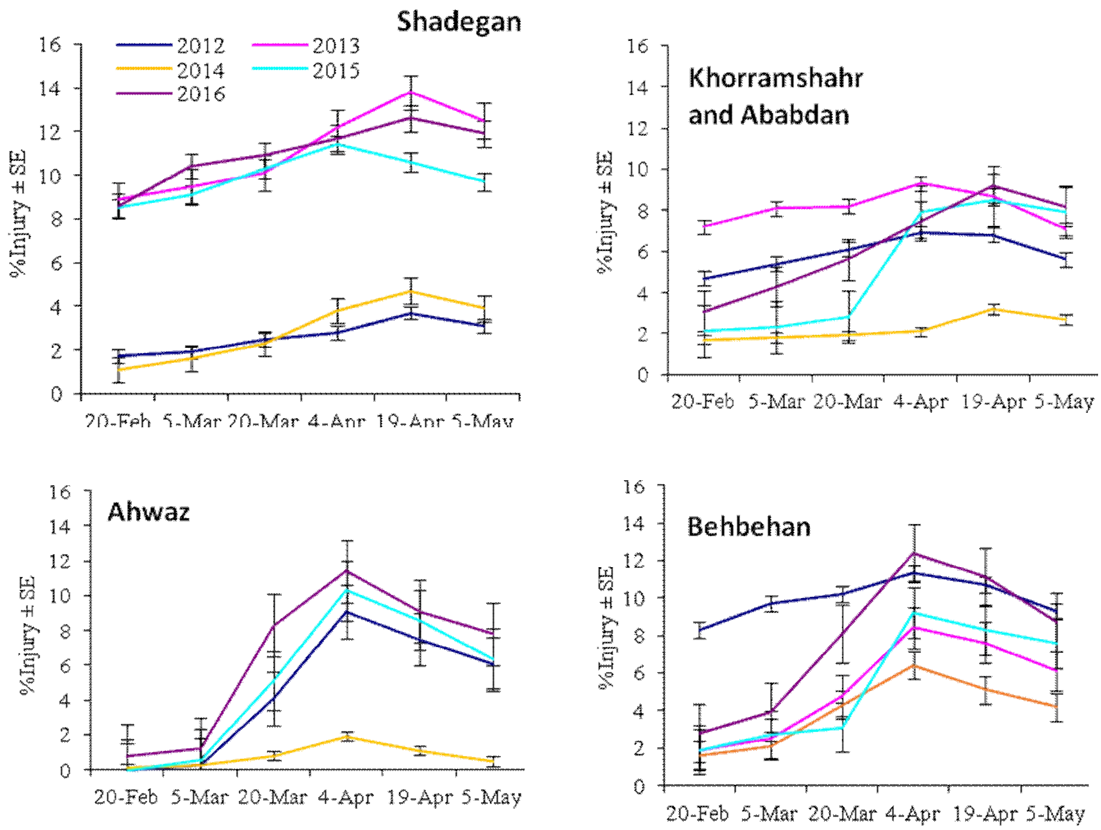
study area that the severity of inflorescence rot was detectable with error equivalent to nuggets or less.

Step 2: Kriging map

The kriging maps were obtained for planning the management of inflorescence rot disease control. The disease kriging maps in different areas are shown in Fig. 3 to estimate the severity of inflorescence rot damage in the study areas. According to Kringing maps, four groups of damage zones (Pathosystems) were considered, including the following groups.



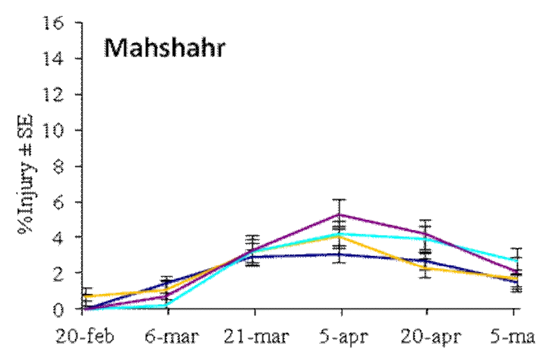


Figure 2 Seasonal fluctuation of date palm inflorescence rot disease damage in different regions of Khuzestan province, Iran.

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Table 2 Correlation of seasonal variations of date inflorescence rot damage with meteorological parameters.

Area Name	Meteorological Parameter	Correlation coefficient	t(N-1)	Significance Level
Khorramshahr and Abadan	X11	-0.64	-0.75	0.50
	X15	0.5	-0.75	0.50
	X18	0.53	-0.75	0.50
	X20	-0.1	-0.17	0.87
	X26	0.1	0.17	0.87
	X29	-0.2	-0.35	0.74
Shadegan	X11	-0.5	-1	0.39
	X15	0.53	-0.5	0.62
	X18	0.56	0	1
	X20	-0.4	-0.75	0.50
	X26	-0.5	-1	0.39
	X29	-0.7	-1.69	0.18
Mahshahr	X11	-0.7	-1.69	0.18
	X15	0.7	1.69	0.18
	X18	0.4	0.75	0.50
	X20	-0.89	-3.46	0.04
	X26	-0.43	0	1
	X29	0.4	0.75	0.50
Ahwaz	X11	-0.6	-1.29	0.28
	X15	0.9	3.57	0.037
	X18	0.7	1.69	0.18
	X20	-0.6	-1.29	0.28
	X26	0.7	1.69	0.18
	X29	0	0	1
Behbehan	X11	-0.3	0.54	0.62
	X15	0.3	0.54	0.62
	X18	0.56	0.54	0.62
	X20	0.67	1.56	0.21
	X26	-0.67	0.54	0.62
	X29	-0.63	-1.29	0.28

Table 3 Regression Model Variables of Prediction of date palm inflorescence rot disease.

Area name	Independent variables	Coefficients of factors	Standard error
Khorramshahr and Abadan	Intercept	43.75	85.95
	X11	-2.98	9.20
	X15	0.41	87.10
	X18	0.45	6.62
Shadegan	Intercept	49.80	48.28
	X11	-2.60	3.103
	X15	4.68	5.59
	X18	0.19	0.41
Mahshahr	Intercept	11.43	5.52
	X11	-0.21	0.19
	X15	0.03	0.13
	X20	-2.01	1.26
Ahwaz	Intercept	-161.39	120.82
	X11	-10.56	6.95
	X15	5.18	3.97
	X18	0.15	1.01
Behbehan	Intercept	56.66	5.77
	X20	4.00	0.41
	X26	-1.51	0.21
	X29	-0.42	0.05

The first pathosystem consists of white areas on the map that included low-risk areas. In this group, the degree of damage was less than 26%. The second pathosystem included the pale gray area of the map, which includes areas of moderate risk. In this group, the degree of damage varied between 26 and 37%. The third pathosystem included the gray area, which includes high-risk areas. In this group, the degree of damage varied between 37 and 48%. Finally, the fourth pathosystem included black areas, which include very high-risk areas. In this group, the degree of infection was higher than 48%. These areas showed the hot spots in each region. Disease control in such regions is essential at the beginning of the season to prevent its spread to other regions and reduce disease severity. Therefore, accurate adjustment of disease monitoring and forecasting in these areas is critical.

Table 4 The forecasting models of the inflorescence rot disease.

Area Name	Forecasting model	Explanation coefficient (R^2)	Standard error
Khorramshahr and Abadan	$I = 0.45X_{18} + 0.41X_{15} - 2.98X_{11} + 43.75$	0.72	3.50
Shadegan	$I = 0.19X_{18} + 4.68X_{15} - 2.6X_{29} + 49.8$	0.81	5.40
Behbehan	$I = 4X_{20} - 1.51X_{26} - 0.42X_{29} + 56.66$	0.96	2.40
Mahshahr	$I = 0.83X_{11} + 2.01X_{15} - 2.6X_{20} + 43.75$	0.82	3.05
Ahwaz	$I = 0.15X_{18} + 0.03X_{15} - 0.21X_{11} + 11.43$	0.89	2.70

Table 5 Spatial variogram models of date palm inflorescence rot disease in Khuzestan province, Iran.

Areaname	Fit model	Nugget	Sill	Range
Khorramshahr and Abadan	Spherical	2.4	0.58	6.4
	Exponential	2.1	0.41	4.9
	Linear	2.6	0.49	9.3
	Linear to Sill	2.7	0.56	7.5
	Gaussian	4.3	0.86	15.3
Shadegan	Spherical	8.6	0.37	4.9
	Exponential	8.5	0.42	5.3
	Linear	9.1	0.76	8.7
	Linear to Sill	9.2	0.33	7.5
	Gaussian	1.1	0.46	8.3
Mahshahr	Spherical	0.11	0.58	7.7
	Exponential	0.19	0.97	6.9
	Linear	0.12	0.37	2.4
	Linear to Sill	0.12	0.77	7.1
	Gaussian	0.09	0.46	9.1
Ahwaz	Spherical	2.6	0.29	5.1
	Exponential	2.6	0.21	2.6
	Linear	2.7	0.68	2.4
	Linear to Sill	2.9	0.31	5.2
	Gaussian	3.4	0.86	3.4
Behbehan	Spherical	0.27	0.58	4.2
	Exponential	0.32	0.63	5.1
	Linear	0.58	0.58	8.7
	Linear to Sill	0.49	0.58	4.2
	Gaussian	0.42	0.98	5.3

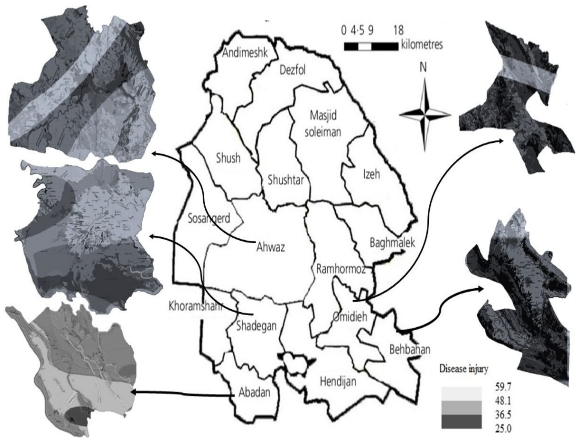

Figure 3 Kriging map of the distribution of date inflorescence rot disease in Khuzestan Province, Iran.

Discussion

The coefficients of explanations were higher than 0.7, and the detection errors were less than 25% in all forecasting and monitoring models fitted in this study. This error indicates the applicability of the models in the date palm care network of the region. Knowledge of the spatial behavior of date palm inflorescence rot is primarily crucial for designing the correct sampling pattern. If the spatial structure of disease damage is unknown in the study area, the best model for reducing variance is the geostatistical method. Because samples are taken from all parts of each region, the most information is obtained. Before this study, there was no information on the scale of the disease's spatial dependence in the selected plantations in each studied region.

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In this study, the effect value of the nugget was substantial at some times of sampling. As can be deduced from the semivariance definition, theoretically, the nuggets' effect value should tend to zero. However, in practice, non-zero nuggets are found in abundance in the data, which could be due to various factors such as non-uniformity of plantation areas, extensive sampling network selected, or sampling error (Liebhold *et al*., 1991). It might be possible that nugget values would be reduced if smaller sample networks were selected. However, due to the size of the sampling area, it was not possible to select smaller networks because the sampling cost would increase significantly.

Different models are used to develop integrated disease management systems for correct decision-making (Madden and Ellis, 1988; Dent, 1995). The most practical of these is the model of changes in phenological adaptation to climatic conditions. In phenological prediction models, periodic biological events of diseases related to seasonal changes in climatic conditions and host growth are studied, and the relationships obtained are used to forecast disease (Mawby and Gold, 1984; Gendi, 1998; Gaston, 2003). Results of the current study indicate the continuous occurrence of this disease under the conditions of date palm plantations in the Khuzestan province of Iran (Fig. 1). Kriging maps showed the occurrence of the disease with different severity of the damage, but low-risk areas were less in number in the whole area (Fig. 2). The prevalence of this disease varies from year to year, but it is present in the fourth group of pathosystems every year. A clear correlation was observed between the severity of disease damage and climatic parameters by analyzing the maps in the fourth pathosystem. Therefore, the expanse of high and medium risk areas has increased with the increase of the disease severity.

The performance of regression models showed a good fit for each year. The correlation test showed that the temperature of the rainiest month of the year, rainfall of the rainiest month of the year, total spring rainfall, number of rainy months, average humidity of the driest month of the year, and average spring humidity were effective in forecasting the disease severity. Our findings show that temperature and humidity have been of great importance in disease prevalence in combination with geostatistical maps. Studies on date pests and diseases have had similar results. For example, studies on the complication of date bunch fading have shown that climatic factors that lead to increased disease severity included the temperature of the rainiest month of the year, total rainfall during autumn of last year, average relative humidity in the previous year, and the average humidity for the driest month of the year (Latifian, 2014; Latifian and Zare, 2003; Latifian and Solymannejadian, 2002). The effects of moisture on the severity of the two diseases are opposite to each other. Therefore, the disease severity of date palm inflorescence rot and date bunch fading increase in higher and lower humidity years, respectively. Comparison of our findings with similar studies shows that in most cases, logistics models of the relationship between climatic factors and pest population parameters (Gaston, 2003) and multivariate linear regression models in forecasting damage changes due to various climatic factors (Latifian and Solymannejadian, 2002; Latifian and Zare, 2003) have been effective. The disease can be forecasted before the maximum damage occurs, and the control can be adequately planned with these models.

Comparison of the indicators used in this disease monitoring with similar studies that have used climatic regression models for this purpose (Young and Kwang-Hyung, 2019; Caffarra *et al*., 2011) shows that the geostatistical models have been successful in expressing the distribution and detection of inflorescence rot disease in the studied region. Spatial distribution in integrated pest management is called Site-specific integrated pest management or Precision IPM, which relies on applying disease distribution maps (Park *et al*., 2007; Sciarretta and Trematerra, 2014). IPM programs require a practical approach to disease risk analysis. Therefore, evaluation of disease development indicators, crop growth phenology (host), and environmental impacts of control management methods are essential to assess and predict disease distribution along with climate data and variables (Ojiambo *et al*., 2017). However, restrictions on the use of spatial distribution data and monitoring technologies at the level of agricultural ecosystems have been obstacles to developing decision-making systems in integrated pest management, which statistical and modeling methods can make it possible to achieve (Devadas *et al*., 2015; West and Kimber, 2015; Mahlein, 2016).

In general, determining the plant disease severity is an essential requirement under management at the spatial scale for practical use in these models. There is also a need for new patterns and models to integrate forecasting and monitoring disease spreads at the spatial scale (Newberry *et al*., 2016). The findings of this study are an essential step in creating a decision-making system in the date palm care network. Every year, high costs are paid to control this complication in Iranian date palm plantations, which in addition to the costs of economic damage, lead to socio-economic problems (West and Kimber, 2015). Therefore, reducing costs and, at the same time, effectively managing this complication will bring many economic and social benefits. Location-specific complication management is a way to achieve these goals. The results of this study provide crucial information on the ecology of inflorescence rot disease and can also be used in the management of the site. In conclusion, the following measures in the integrated management of palm disease care network are critical:

1) Compilation of other practical factors in disease monitoring and forecasting, including phenological adaptation to crop growth conditions and effects of soil properties, are necessary to complete the model.

2) Determining strategies and algorithms for controlling, monitoring, and forecasting the complication to determine the risk of an outbreak, determining the affected areas and the level of economic damage caused by the complication.

3) Establishing an intelligent system for forecasting complication monitoring services, including data collection and processing, and services to manage date palm plantation areas (periodic pathology map).

4) Providing the necessary information to control the complication in managing date palm protection in the region. The outputs of the models obtained from this study provide plant protection decisions to the government, phytosanitary clinics, commercial companies supplying complication control inputs, and date palm growers.

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سیستم تصمیم‌گیری در مدیریت بیماری پوسیدگی گل آذین خرما *Mauginiella Scaettae*

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چکیده: بیماری پوسیدگی گل آذین توسط عامل بیماری *Mauginiella Scaettae* از مهم‌ترین بیماری‌های نخل خرما می‌باشد. هدف از انجام این پژوهش ایجاد سیستم تصمیم‌گیری در مدیریت بیماری با استفاده از مدل‌های آب و هوایی و زمین آماری برای پیش‌آگاهی و ردیابی بیماری در استان خوزستان بود. نمونه‌برداری برای جمع‌آوری داده‌ها از ۳۳ روستا به‌مدت ۵ سال در منطقه خوزستان انجام شد. برای برآورد شدت خسارت بیماری از هر روستا یک نخلستان به‌صورت تصادفی انتخاب و در طول فصل نمونه‌برداری انجام شد. نتایج نشان داد که خسارت بیماری از حدود فروردین ماه آغاز و با گرم شدن هوا بر شدت آن به‌تدریج افزوده گردید. مدل رگرسیون برازش شده برای پیش‌آگاهی در کلیه مناطق در سطح ۱ و ۵ درصد معنی‌دار بود. واریوگرافی پراکنش پوسیدگی گل آذین خرما نشان داد که میزان اثر قطعه در این مدل در مناطق آبادان و خرمشهر، شادگان، ماهشهر، اهواز و بهبهان به‌ترتیب معادل ۲/۱، ۱/۱، ۰/۰۹، ۲/۶ و ۰/۲۷ بوده و نشان‌دهنده خطای برآورد شدت آسیب بیماری در فواصل کم‌تر از فاصله نمونه‌برداری بود. دامنه واریوگرام به‌ترتیب معادل ۴/۹، ۸/۳، ۹/۱، ۵/۱ و ۴/۲ کیلومتر بود و در فواصل بیش‌تر از این حد کم‌ترین هم‌بستگی بین داده باقی می‌ماند. آستانه مدل به‌ترتیب معادل ۰/۴۱، ۰/۴۶، ۰/۴۶، ۰/۲۹ و ۰/۵۸بود که نشان‌دهنده نسبتی از ناحیه مورد مطالعه می‌باشد که با خطای معادل نوگت یا کم‌تر از آن، بیماری قابلیت ردیابی داشت. نتایج این پژوهش گامی اساسی در ایجاد سیستم تصمیم‌گیری در شبکه مراقبت نخیلات است.

واژگان کلیدی: خرما، پوسیدگی گل آذین، پیش‌آگاهی، ردیابی، مدیریت تلفیقی

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