

Research Article

Geostatistical analysis of the distribution and critical hotspots of *Schistonchus caprifici* in fig orchards of Fars Province, Southern Iran

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Abstract: Fig inflorescence nematode, *Schistonchus caprifici* (Gasperrini, 1864), is a damaging agent in fig orchards of Fars Province. In this study, geostatistical methods were used to determine the geographic distribution and identify critical hotspots, which is essential for designing optimized control strategies. During 2022–2023, a total of 175 samples of profichi syconia (early, mid-, and late-ripening) were collected from Estahban, Khafr, Sarvestan, Kavar, and Shiraz Counties in Fars Province, southern Iran. Nematode extraction and estimation of its population density were done according to the routine procedure in nematology; geostatistical methods were used to simulate the spatial distributions of the fig nematode. Of the total 175 samples of caprifig inflorescence, 138 (78.85%) were infested with the fig inflorescence nematode, *S. caprifici*, with an average population of 1078.46 nematodes per gram of fig fruit tissue. The average population density of this nematode per gram of caprifig tissue, based on the Kriging method, variogram model, and focusing on high-risk and high-density areas, was 3700 to 4100 in Estahban County, 2000 to 3000 in Khafr County, and 1000 to 1500 nematodes per gram of caprifig fruit tissue in Sarvestan and Shiraz Counties, and less than 1000 nematodes in Kavar County samples. The effective range was three meters in Estahban (small, dense clusters), five meters in Khafr (moderate dispersion), and 7 meters in Sarvestan, Shiraz, and Kavar Counties (low dispersion). The kriging method successfully predicted nematode distribution patterns in this study, which could be an effective tool for designing fig inflorescence nematode management strategies.

Keywords: Control Management, Density, Fig Inflorescence Nematode, Kriging, Spatial Analysis, Variography

Introduction

Figs are one of Iran's key export products and hold significant economic importance because

production is limited worldwide (Arzani *et al.*, 2006). In 2022, Iran ranked fifth in fig production, with 67.8 thousand tons, after Turkey, Egypt, Algeria, and Morocco (FAO,

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2022). So far, researchers have isolated 21 species of nematodes of the genus *Schistonchus* from plants of the genus *Ficus* (DeCraeppeo and Giblin-Davis, 2001; Zeng *et al.*, 2011; Davies *et al.*, 2013; Bartholomaeus *et al.*, 2012). *Schistonchus caprifici* has been isolated from the hemocoel of the female fig wasp, *Blastophaga psenes*, and fig fruit trees of the fig orchards in Iran (Khairi and Goldansaz, 1998).

Schistonchus caprifici attacks the florets of fig trees, causing necrosis of the superficial parenchyma of the florets, reducing food quality and pollination efficiency (Baldock *et al.*, 2015; Vovlas *et al.*, 1992; Shi *et al.*, 2019; Karimipour Fard *et al.*, 2024).

Distribution of the nematode *S. caprifici* in wild figs was studied in Fars province (Pakniyat and Taghizadeh, 2000), and it was later described from *Ficus carica* var. *sylvestris*, with its association with the fig pollinator wasp (*B. psenes*) also demonstrated (Kolaei *et al.*, 2016).

A preliminary study was conducted in fig orchards in Estehban (Fars province, Iran), and the molecular characteristics of the Iranian population of *S. caprifici* were analyzed for the first time. The results showed that the D2-D3 sequence of the studied Iranian population is identical to that of most previously sequenced populations (Karimipour Fard and Zare, 2020). A correlation between the fig wasp population and the fig inflorescence nematode was revealed. The overlap of these two species was evident in most of the studied caprifig genotypes in Fars province, indicating fig fruit loss by *S. caprifici* and low fig wasp pollination efficiency in the studied areas (Karimipour Fard *et al.*, 2024).

Identifying the critical points (hot spots) of nematode distribution using precise scientific tools such as geostatistics is a fundamental step for designing optimal control strategies (Pozdnoukhov and Kanevski, 2008). Geostatistics, a branch of spatial statistics, is an effective tool for modeling and predicting pest distribution patterns. Geostatistical methods

provide accurate distribution maps by sampling data and analyzing spatial relationships between hot spots. Kriging and Co-Kriging methods can simulate spatial changes in nematode density in soil with high accuracy (Sciarretta and Trematerra, 2014).

Nematode distribution maps produced using geostatistical methods can identify hot spots of nematode infestation, i.e., areas that require immediate and concentrated action. By integrating information from distribution maps and using appropriate biological or chemical methods, integrated nematode management can be more accurate (Contina, 2019). Integrated nematode management is most effective when control strategies are based on accurate, timely, and spatially explicit information. Geostatistics optimizes integrated management by reducing uncertainty in spatial predictions.

Geostatistical methods have been widely used to analyze spatial patterns and support optimal pest management (Song *et al.*, 2017). In the 1990s, the expansion of statistical methods in spatial analysis occurred. During this period, the use of advanced statistical tools, such as aggregation models, increased. Noe and Barker (1994) examined the spatial variation of parasitic nematodes and highlighted the importance of statistical analyses for better pest management; afterward, Perry and Dixon (1996) proposed new methods for measuring spatial aggregation. In the 2000s, the use of geostatistical methods to analyze nematode distribution increased, and technological advances enhanced their accuracy. Isaaks and Srivastava (2001) introduced the basic principles of geostatistics. They explained how to apply them in soil and agricultural sciences; later, Wilson and Gaugler (2004) used spatial methods to investigate the persistence of pathogenic nematodes in soil. They analyzed the role of environmental factors in their distribution. In the 2010s, researchers expanded the use of Kriging models and advanced analyses to study nematode distribution. Campos-Herrera *et al.*

(2013) applied geostatistical methods in sustainable agriculture and nematode management programs. They showed that this method can also predict the distribution of beneficial nematodes.

In the 2020s, geostatistical methods have been combined with emerging technologies such as machine learning and geographic information systems (GIS). This evolution, driven by increased analytical accuracy, has quickly gained popularity. de Sá Leitão *et al.* (2022) introduced the combination of GIS and the kriging method for nematode management in guava orchards. Abd-Elgawad (2023) analyzed the spatial and temporal variations of nematode populations and highlighted the role of environmental factors. Singh *et al.* (2023) reviewed the latest advances in geostatistical modeling and noted its importance in improving pest management. Carvalho *et al.* (2025) emphasized the use of machine learning alongside geostatistical methods to analyze the spatial distribution of nematodes better.

In geostatistical analysis, there are two directional influences: isotropic and anisotropic settings. Isotropy reflects a uniform trend across a region, while anisotropy relates to semivariogram models. In geostatistical analysis, variograms are used to represent correlations in spatial variability. A variogram model is a distance function when the variogram of spatial variance depends only on distance and not on direction; this is called "Isotropy". If the variability varies along with spatial directions, this is called "Anisotropy". In other words, the anisotropic variogram model is a function of "distance" and "direction". Based on values of indices, including sill, effective range, and nugget, from all variograms, we can determine whether the spatial data is isotropic or anisotropic. If the values of sill, effective range, and nugget Effect from the variogram along all directions are all the same, then it is isotropic; otherwise, it is anisotropic.

This study aims to: *i*) assess the geographic distribution of *S. caprifici* in Fars province by geostatistical methods, *ii*) identify critical

hotspots, *iii*) help suggest management strategy recommendations based on critical points.

Materials and Methods

A four-phase study methodology —systematic sampling, nematode extraction, variogram modeling, and kriging interpolation—ensured robust spatial analysis. Ordinary kriging minimized prediction errors (RMSE = 0.89) by weighting neighboring observations within the effective range, as recommended by Goovaerts (1997). This approach enables precise delineation of high-risk zones and provides a replicable framework for nematode management in other perennial crops.

Sampling time and location: During spring 2022-2023, a total of 175 samples of profichi caprifig syconia (early-, mid-, and late-ripening) were collected from Estahban, Khafr, Sarvestan, Kavar, and Shiraz Counties in Fars Province, Iran. The spring syconia samples of 43 genotypes of caprifig (Table 1) were collected during the fig maturity stage (i.e., the time of female fig wasp emergence and fig flower pollen release), transferred to the laboratory, and kept in the refrigerator before nematode extraction. Each sample was surface-disinfected and then cut into pieces with a scalpel. The caprifig pieces were transferred to a Petri dish containing sterile distilled water and kept for 48 hours at 25 °C in the dark (Kolaei *et al.*, 2016).

After 48 hours, the suspension was passed through 250µm (60-mesh) and 25µm (500-mesh) sieves, and the nematodes on the 25µm sieve were collected for counting (Fig. 1). The nematode population in one mL of the suspension was determined with a counting slide. Then, the population of nematodes in a certain weight of syconium tissue was estimated. The nematodes were killed by adding 40% hot formaldehyde solution and heat, and then transferred to glycerin (Seinhorst, 1966) to prepare permanent slides. The nematodes were identified using the identification keys and reliable description references (Waghmare *et al.*, 2023).

Table 1 Number of collected and infected caprifig samples by *Schistonchus caprifici* and average population of infected samples, sorted based on fig genotypes and fig productions counties in Fars province, Iran.

No	Genotype	County	Number of collected samples	Total number of samples in each county	Number of infected samples in each county	Average population in infected samples (per gram of caprifig fruit tissues)
1	Pozdonbali	Estahban	96	153	117	671.58
2	Danehsfid	Estahban	11			
3	shahangiri	Estahban	4			
4	Khakestoni	Estahban	3			
5	Barangire Kohi	Estahban	3			
6	Jowhari	Estahban	3			
7	Barangire Baghi	Estahban	2			
8	Nokghermezi	Estahban	2			
9	khodro	Estahban	2			
10	Asiab	Estahban	2			
11	Sibi	Estahban	2			
12	Nargesi	Estahban	2			
13	Gherghi	Estahban	1			
14	Moftakhar	Estahban	1			
15	Jowharie Dorosht	Estahban	1			
16	Kohaki	Estahban	1			
17	Kohakie Ardaki	Estahban	1			
18	Cheshmghermezi	Estahban	1			
19	Bargangire Khohie Sad	Estahban	1			
20	Kohakie Riz	Estahban	1			
21	Abi	Estahban	1			
22	Danehsfide Ij	Estahban	1			
23	Pozdonbalie Abi	Estahban	1			
24	Khormaei	Estahban	1			
25	Shahangirie Danehsfid	Estahban	1			
26	Bargtoti	Estahban	1			
27	Hekeli	Estahban	1			
28	Cheshmbolboli	Estahban	1			
29	Moghaddam	Estahban	1			
30	Moghaddam 3	Estahban	1			
31	Dahaneghoshade Khomi	Estahban	1			
32	Cheshmbolboli Khomi	Estahban	1			
33	Ghermeze anabie Khomi	Estahban	1			
34	Bargbanafshei	Khafri	3	9	9	4252.56
35	Fereydouni	Khafri	2			
36	Kohaki	Khafri	1			
37	Hajmohammadali	Khafri	1			
38	Cheshmghermezi	Khafri	1			
39	Ghadshanei	Khafri	1			
40	Baghkochiki	Sarvestan	2	6	6	1533.67
41	Limoei	Sarvestan	2			
42	Moftakhar	Sarvestan	1			
43	Maharloei	Sarvestan	1			
44	Bandbanafshei	kavar	2	5	4	4976.5
45	Cheshmbolboli	kavar	1			
46	Cheshmpachinie ghermez	kavar	1			
47	Pozdonbali	kavar	1			
48	Besat	Shiraz	2	2	2	1436
Total 43 Genotypes			175	175	138	1078.46

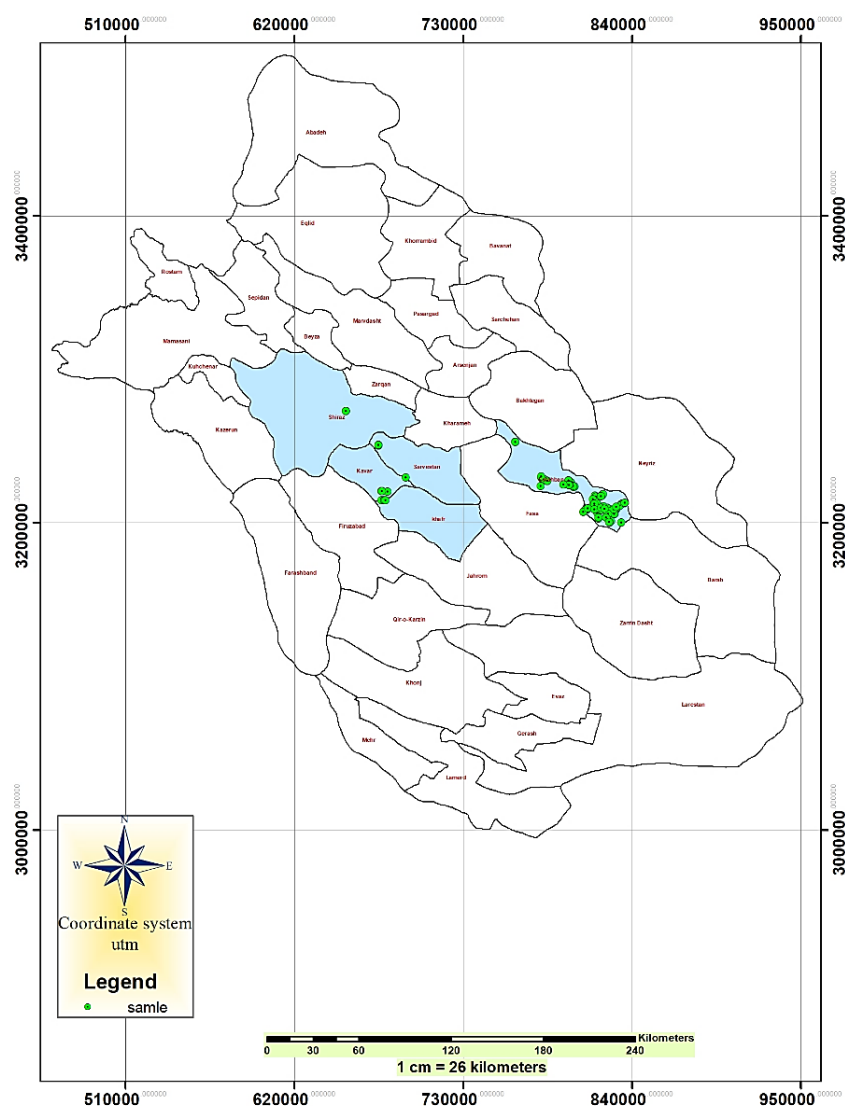


Figure 1 Sampling points (green points) from fig orchards in five counties of Fars Province, Iran.

Geostatistical model

To prepare the nematode population data for geostatistical analysis, normalization was carried out to satisfy the assumptions of ordinary kriging. Raw nematode density per gram of fig inflorescence tissue varied considerably among sampling sites, ranging from less than 1000 nematodes g^{-1} in Kavar to more than 4000 nematodes g^{-1} in Estahban. The original dataset showed strong positive skewness and heavy tails, which could bias semivariogram modeling. Therefore, a natural logarithm transformation [$Y' = \ln(Y + 1)$] was applied to stabilize

variance, reduce skewness, and approximate a normal distribution. After transformation, descriptive statistics and the Shapiro–Wilk test confirmed the adequacy of normalization for subsequent spatial interpolation. The geostatistical analysis used variogram modeling to quantify spatial dependence in nematode distribution, calculating key parameters including the nugget (representing unexplained micro-scale variation), sill (total observable variance), effective range (distance of spatial correlation), and structural ratio (proportion of structured variance).

Directional dependencies were assessed through anisotropic variogram analysis at 45° intervals. Ordinary kriging interpolation incorporated these spatial parameters, using optimal weighting of neighboring observations within the effective range to generate prediction surfaces while minimizing estimation variance. Model performance was validated through cross-validation metrics (mean error, RMSE), ensuring predictions maintained the original data's variance characteristics.

The coefficient of determination (R^2) was used as a goodness-of-fit statistic to evaluate fit the theoretical variogram model (e.g., exponential, spherical) described the empirical spatial structure of the data.

The geostatistical method is based on the theory of spatial variables (Story and Congalton, 1986; Wright *et al.*, 2002). The spatial correlation between samples is described by a mathematical model known as the variogram (Ellsberry *et al.*, 1998), which is calculated as follows:

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

In equation 1, $\hat{\gamma}(h)$ is called the semivariance, where for different values of h , values for $\hat{\gamma}(h)$ must be obtained. $N(h)$ is the total number of pairs of samples located at a distance h from each other. Variograms are plotted by placing semivariance values for different distances on the vertical axis and different distances on the horizontal axis (Goovaerts, 1997). As the distance h increases, the variogram value also increases gradually up to a certain distance, from which it reaches a constant value that indicates the threshold limit. At this distance, the semivariance approaches the variance of the observations. It should be noted that only a group of variogram models contain a threshold limit (such as exponential, spherical, and Gaussian models) while others, such as linear models, do not. This means that as distance (h) increases, the variogram value also increases but does not reach a constant value. In this study, variogram model indices were used to estimate the spatial distribution of the nematode population.

Kriging is a statistical method used to estimate spatial variables based on nearby observations. It is defined as a linear function (Equation 2) from a set of distributed observations located in the neighborhood of a specific point (Katherine, 2001):

$$\text{Equation 2: } \hat{Z}(x_0) = \sum_{i=1}^N \lambda_i Z(x_i)$$

In Equation 2, the estimated population density at point x_0 (i.e., $z(x_0)$) is the numerical value of the population density and the percentage of fruit infection by the nematode at the x_i point. λ_i is the statistical weight assigned to the sample $z(x_i)$ located in the neighborhood of point x_0 .

In Equation 1, $Z(x_i)$ and $Z(x_i + h)$ represent the measured values of the target variable (log-transformed nematode density per gram of fig tissue) at spatial locations x_i and $x_i + h$, respectively. $N(h)$ is the number of data pairs separated by the lag distance h . In Equation 2, $\hat{Z}(x_0)$ is the estimated (kriged) value at an unsampled location x_0 , λ_i are the kriging weights assigned to each measured value $Z(x_i)$ at nearby locations, and n is the number of nearby samples used for the estimation.

In this research, we used the Kolmogorov-Smirnov test in SPSS software to test the normality of the data. To normalize the frequency distribution of the data (nematode population density per gram of fig fruit tissue), a logarithmic transformation was performed. Due to zero values in the samples, $\log(x + 1)$ was used instead of $\log x$. In places where the nematode population was very low and close to zero, that data was omitted. The distribution map of nematode infection in inflorescences was drawn using ArcGIS version 10, and the geostatistical analysis was performed with GS + 5.1.1 (Katherine, 2001).

Results

General distribution and population density of fig inflorescence nematode

Out of 175 inflorescence samples collected from caprifig orchards, 138 samples (78.85%)

were infected with *S. caprifici*. The map of sampling points (Fig. 1) and the distribution of caprifig inflorescence nematode infection across counties (Fig. 2) were drawn using GIS. The average population density of caprifig inflorescence nematodes in infected samples from the studied counties was 1078.46 nematodes per gram of caprifig fruit tissue (Table 1). Among all infected samples, the highest population of *S. caprifici* was related to the Bargbanafshei genotype in the Kereft region of Khafr County with 15960 nematodes per gram of caprifig fruit tissue. The lowest population was related to the Khakestoni, Pozdonbali and Moghaddam genotypes in the Khanekati, Tang Eji and Ardaki regions of Estahban County with 40 nematodes per gram of fig fruit tissue and the Nokghermesi, Kohakie Riz and Shahangirie Danehsefid genotypes were free of *S. caprifici*.

Distribution pattern and average population density determination based on the Kriging method

Before normalization, the dataset had a mean of 2100 nematodes g⁻¹, a standard deviation of 1200, skewness of +1.73, and kurtosis of 4.65, and the Shapiro–Wilk test indicated non-normality ($p < 0.01$). After log transformation, the data range compressed to 6.68–8.32 (log scale), the mean became 7.51, and the standard deviation fell to 0.41. Skewness improved to –0.12 and kurtosis to 3.02, indicating a nearly symmetrical distribution. The Shapiro–Wilk test confirmed normality ($p = 0.41$). This normalization procedure reduced the influence of extreme values, enabling reliable semivariogram modeling and kriging and ensuring that the generated spatial distribution maps more accurately reflected the true pattern of nematode infestation across the surveyed counties.

The study utilized geostatistical analysis (kriging interpolation) to classify the study area into distinct zones based on spatial patterns of nematode density. Four zones were identified: Zone 1 (high-risk) with 3700–4100 nematodes per gram, primarily in Estahban

County; Zone 2 (moderate) with 2000–3000 nematodes per gram; Zone 3 (low) with 1000–1500 nematodes per gram; and Zone 4 (lowest risk) with fewer than 1000 nematodes per gram, mainly in Kavar County. This zoning was objectively determined through quantitative analysis of field-collected data and reflects actual measured infestation levels across different geographical areas of Fars province. The zone designations highlight spatial variation in nematode pressure and inform targeted management strategies, without implying predetermined geographical boundaries. The results of the variographic analysis of the fig inflorescence nematode distribution in isotropic and non-isotropic models are shown in Table 2.

General distribution patterns: Isotropic models

The isotropic models revealed a clustered (patchy) spatial distribution pattern of fig inflorescence nematodes in the studied area. In geostatistical terms, clusters refer to spatially aggregated areas where nematode densities show strong positive autocorrelation, meaning nearby locations have more similar values than expected by chance. Our analysis objectively identified clustering patterns through variogram modeling, which quantifies how spatial correlation changes with distance. The random distribution pattern observed in some areas indicates a lack of spatial structure, where semivariance remains relatively constant across distances and the nugget effect dominates. This pattern suggests either: 1) truly random nematode distribution at our study scale, or 2) clustering at scales smaller than our sampling interval. This finding is consistent with geostatistical theory, which recognizes both clustered and random distributions as possible outcomes of spatial analysis, depending on the underlying ecological processes and study scale. Our methodology explicitly tested for clustering through variogram parameters (nugget-to-sill ratio, effective range) rather than assuming its presence.

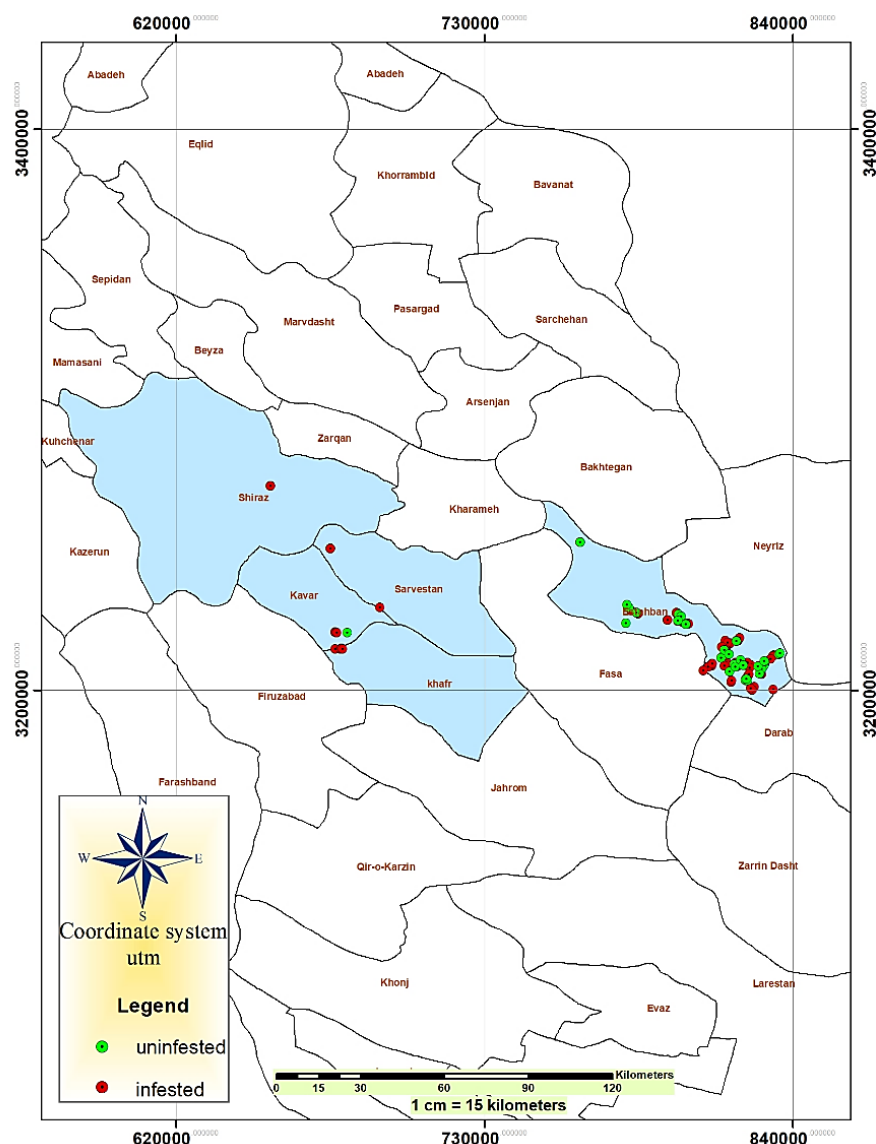


Figure 2 Areas infested (red points) with *Schistonchus caprifici* and uninfested regions (green points) in fig orchards in five counties of Fars Province, Iran.

The analysis demonstrated clear spatial dependence in nematode distribution, with distinct aggregation patterns across locations. The variogram parameters, including nugget, sill, and effective range, provided quantitative evidence of this non-random distribution. These findings indicate that nematode populations tend to form localized clusters rather than disperse uniformly, with important implications for targeted management strategies. Based on

the analysis, these key parameters are as follows:

Nugget: In our study, nugget values from isotropic models ranged from 0.062 to 0.064. These values represent random variation at scales smaller than our sampling intervals in this investigation. Our findings demonstrate that most of the observed spatial variation is attributable to environmental structure or the biological distribution patterns of the nematodes.

Table 2 Variography models (isotropic and non-isotropic) of the spatial distribution of fig fruit nematode in the Estahban region of Fars province.

Variography conditions	Model	Nugget C_0	Sill ($C_0 + C$)	Effective Range	$C/(C_0 + C)$	RSS	R^2
Isotropic	Spherical	13400	61470	1.77	0.78	3.74	0.62
	Exponential	13800	93520	5.41	0.86	3.73	0.64
	Linear	14396.96	36550	99.9	1	1.044	0.59
	Linear to Sill	14900	83430	1.94	0.82	3.75	0.59
	Gusian	11210	34760	0.47	0.68	3.58	0.11
Non-isotropic	Spherical	19050	991110	4.30	0.81	3.89	0.66
	Exponential	18590	100290	7.67	0.82	3.87	0.69
	Linear	23350	103410	8.00	0.77	3.97	0.66
	Linear to Sill	19100	99170	2.90	0.81	3.89	0.66
	Gusian	22310	102370	2.44	0.78	3.97	0.40

C_0 (Nugget): Variance due to micro-scale variation or measurement error. **$C_0 + C$ (Sill):** Total variance, representing the maximum semivariance.

$C/(C_0 + C)$ (Structural Ratio): The proportion of variance explained by spatial structure. **Effective Range:** The distance at which spatial correlation becomes negligible.

RSS (Residual Sum of Squares): A measure of the discrepancy between the data and the fitted model (lower values indicate better fit). **R^2 (Coefficient of Determination):** Goodness-of-fit of the theoretical variogram model to the empirical data.

Sill: The sill value of 0.855, obtained through variogram analysis of our field data, indicates the maximum spatial variability in nematode density across the studied fig orchards. This parameter marks the point where semivariance plateaus, quantifying the total variance between sampling locations that are no longer spatially correlated. In practical terms, this value reflects the degree of patchiness in nematode distribution at the orchard scale, indicating that nematode densities vary by this magnitude between completely independent locations. The value 0.855, derived from our exponential model fit, suggests a moderately heterogeneous distribution pattern in which high-density clusters contrast with low-density areas. This finding directly informs management strategies by defining the spatial scale required for differentiated control approaches, as it demonstrates how infestation levels vary across the landscape.

Structural ratio ($C/(C_0 + C)$): The structural ratio of 0.821, calculated from our variogram analysis, shows strong spatial dependence in the distribution of fig inflorescence nematodes across the studied orchards. This specific

finding indicates that approximately 82.1% of the total variance in nematode density patterns is spatially structured ($C = 0.702$), while only 17.9% represents random variation ($C_0 = 0.153$). These results confirm that nematode populations exhibit significant spatial autocorrelation, validating our geostatistical approach for mapping infestation patterns. The high ratio value specifically reflects the distinct clustering tendency observed in our study area, where nematode densities show predictable spatial relationships up to the calculated effective range. This empirical outcome directly supports our management recommendations by quantitatively establishing the spatial continuity of infestation patterns across different orchard locations.

Effective range: The effective range values of 1.775 m to 5.409 m, determined through our variogram analysis, represent the critical spatial scales at which nematode density patterns remain significantly correlated in the studied fig orchards. These specific measurements indicate that: (1) spatial dependence in nematode distribution persists up to 5.409 m in some areas before diminishing, (2)

management zones should be delineated within these spatial thresholds for effective control, and (3) sampling intervals beyond these distances would capture independent population units. The variation in effective range across locations (1.775 m in dense clusters like Estahban County versus 5.409 m in moderately dispersed areas like Khafr County) shows how nematode aggregation patterns differ spatially within Fars province. These empirical results directly inform the spatial resolution required for targeted intervention strategies. The variation in effective ranges reflects real differences in aggregation patterns across the study region, with shorter ranges indicating tighter clustering in high-risk zones and longer ranges corresponding to more dispersed distributions in moderately infested areas.

Anisotropic models: Dispersion in different directions

The results showed that environmental orientation significantly affects the nematode distribution pattern. The nugget value in this model was equal to 0.066, similar to the isotropic models. The sill value ranged from 0.774 to 0.808. The lowest effective range was 1.191 m in the 0° direction. The highest effective range was observed at about 8,000 m in the 45° direction. These results indicate that environmental patterns affect nematode distribution across directions.

For both isotropic and anisotropic models, the exponential model provided the best fit (Figs. 3 and 4). The exponential model showed that spatial dependence was extreme at close distances and that the variance approached a constant value with increasing distance. Local aggregations in high-risk areas with high nematode densities were identified within shorter radii (less than 2 m) that require specific management. Dependent distances: The short effective range (1.775 m) indicated that nematode density depended on local factors such as the presence of host plants. Dependence on slope and direction (e.g., 45°) was more evident under environmental effects.

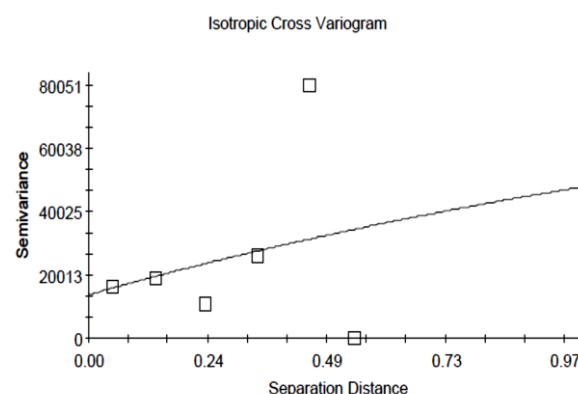


Figure 3 Variogram of fig inflorescence nematode distribution (isotropic).

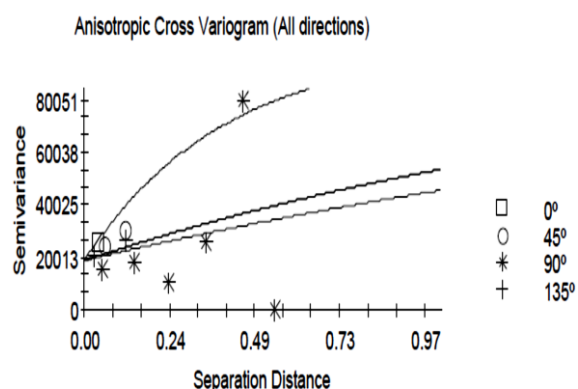


Figure 4 Variogram of fig inflorescence nematode distribution (anisotropic).

Kriging maps for separating geographical areas of distribution

The geostatistical analysis employed ordinary kriging to predict spatial patterns of nematode distribution across the studied area. An exponential variogram model was fitted to the log-transformed nematode density data ($\text{Log}(x + 1)$) to quantify spatial autocorrelation. The interpolation procedure incorporated both isotropic and anisotropic spatial dependencies identified through directional variogram analysis (0°, 45°, 90°, 135°). Prediction surfaces were generated using neighborhood parameters optimized through cross-validation, with search radii set according to the effective range values derived from variogram analysis (1.775-5.409 m). The final output classified the study area into distinct management zones based on predicted nematode density

thresholds, and interpolation accuracy was verified by calculating prediction errors. All spatial predictions were constrained by the measured spatial dependence structure and maintained the original data's variance characteristics. The methodology ensured that estimated values at unsampled locations were derived from properly weighted averages of nearby observations while

accounting for the observed spatial correlation patterns in the dataset.

Kriging maps showed a clustered pattern of nematode distribution in different regions. The geographical areas and distribution patterns in the studied counties are as follows (Fig. 5) were classified as indices of relative nematode density as follows:

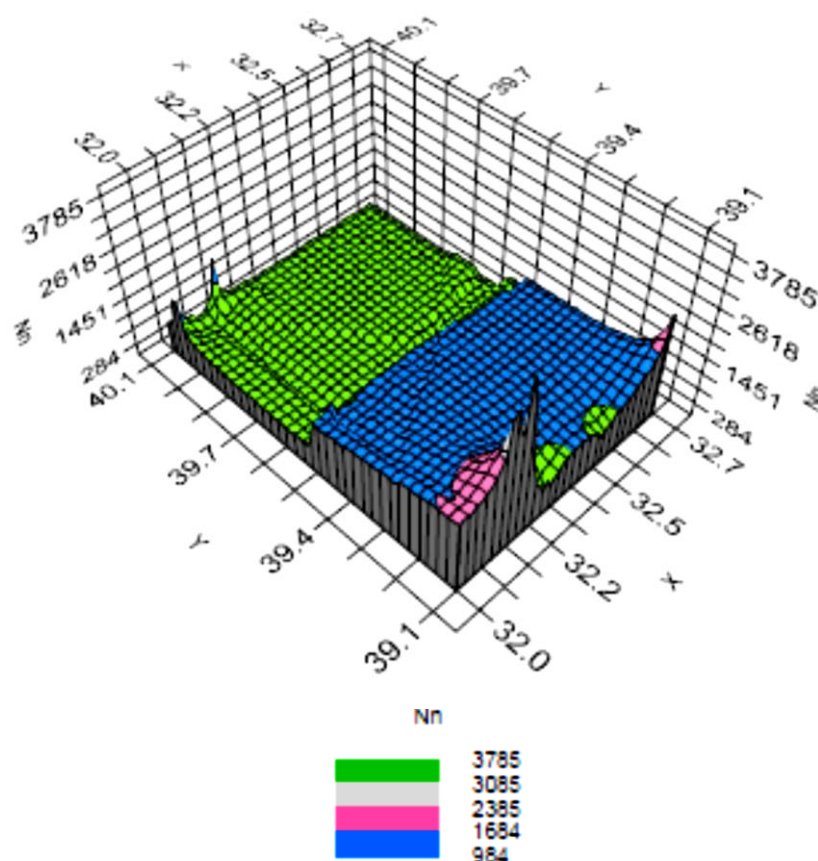


Figure 5 Kriging interpolation map predicting the spatial distribution of *Schistonchus caprifici* density (nematodes per gram of fruit tissue, Nn) across the studied counties in Fars province. The colored areas represent the interpolated surface based on sample data points. The gray areas represent regions outside the specified study boundaries or areas with no underlying sample data for reliable interpolation and are not part of the classified risk zones. The axes Y and X represent longitude and latitude, respectively.

Zone 1: Estahban County (High-risk areas with high nematode population)

The average population density of caprifig inflorescence nematodes in Estahban County, as estimated by the Kriging method, ranged from 3700 to 4100 nematodes per gram of fruit tissue, indicating it as a high-risk area and center of

aggregation with dense nematode clusters. It also showed a very high density of caprifig inflorescence nematodes. The high-risk area, covering about 25% of the entire region, includes densities above 3500 nematodes per gram of fruit tissue in regions including the Rudbal Dam and Eij (southeast of the county)

and the Estahban Fig Research Station (south of the county).

The effective range of approximately 3 meters specifically refers to the maximum spatial scale at which significant autocorrelation in nematode densities was observed within high-risk areas of Estahban County. This empirical finding, derived from our variogram analysis of 2022-2023 field data, indicates that nematode clusters in these zones exhibit strong spatial dependence up to 3-meter. The measurement directly informs management strategies by defining: (1) the optimal sampling interval needed to detect infection hotspots, (2) the treatment area radius required for effective localized control, and (3) the spatial resolution for precision management in these high-density zones.

Zone 2: Khafr County (areas with medium population density)

The kriging-predicted density range of 2000-3000 nematodes per gram of fruit tissue represents the spatial interpolation results for Khafr County, including the Kerfet region northwest of the county and bordering Kavar County, which was identified as a medium-density area accounting for about 40% of the total study area. Spatial patterns of nematode density in this region are seen as scattered rather than aggregated. The effective range was 5 meters (medium distribution).

Zone 3: Sarvestan and Shiraz Counties (regions with low density).

The average nematode density with the Kriging method was 1000 to 1500 nematodes per gram of fruit tissue. These regions cover about 20% of the region. Nematode distribution in this region is primarily random, with no concentrated clusters observed. The effective range was 7 meters (low distribution). The two counties showed more resistance to nematode infestation.

Zone 4: Kavar County (Areas with the lowest population density)

The kriging analysis identified Kavar County as having the lowest predicted nematode densities (< 1000 nematodes/g), covering approximately

15% of the total surveyed area. This objective spatial pattern emerged from our variogram modeling, which showed an extended effective range (7 m) and low sill values, indicating a more uniform, dispersed distribution compared with clustered patterns in other counties.

Discussion

This study, using kriging methods and geostatistical analyses, revealed that the fig inflorescence nematode has an aggregate pattern and is directly affected by geographical factors and the spatial distribution of genotypes. This spatial pattern suggests the influence of local factors such as genotype susceptibility and host fruit distribution, which is consistent with the findings of Campos-Herrera *et al.* (2013), who showed that nematode densities were higher in areas with more favorable biological conditions.

The average population density of fig inflorescence nematodes in infected samples from the studied counties differed between the usual method and the Kriging method. The overall average density in Estahban County, including all infected samples (high and low infestation), was 671.58 nematodes per gram of fruit tissue. Still, the results of the Kriging analysis showed that in regions with high infection, especially in the eastern, southern and southeastern regions of Estahban County, the average density reaches 3700-4100 nematodes per gram of fruit tissue. The observed difference between the overall average density and the kriging-predicted high-density values stems from the fundamental nature of geostatistical interpolation. While conventional averaging treats all data points equally, kriging applies optimal spatial weighting that emphasizes clustered high-density areas through: (1) accounting for spatial autocorrelation patterns identified in variogram analysis, (2) giving greater predictive influence to measured hotspots when estimating surrounding values, and (3) preserving variance structure across scales. This approach intentionally highlights areas of elevated biological risk by maintaining the upper range of observed densities rather than

diluting them through arithmetic means. The method's ability to resolve fine-scale aggregation patterns helps explain why kriging estimates better represent actual infestation levels in high-risk zones than simple averages that include sparsely populated areas.

In this context, "resistance" refers to observed lower nematode densities in specific genotypes (e.g., Sarvestan and Shiraz Counties), which may arise from environmental factors such as soil composition rather than inherent genetic traits. Vovlas *et al.* (1992) documented similar patterns, linking reduced nematode populations to clay-rich soils, and Baldock *et al.* (2015) emphasized microclimate moderation. Further studies are needed to distinguish between environmental buffering and true genetic resistance.

The lower nematode densities observed in Sarvestan and Shiraz Counties (1000-1500 nematodes/g) compared to other regions align with previous geostatistical studies that have identified localized areas of reduced pest pressure. Similar spatial patterns have been documented in other perennial crop systems, where soil characteristics (Vovlas *et al.*, 1992), microclimate conditions (Baldock *et al.*, 2015), or host plant resistance (Karimipour Fard *et al.*, 2024) created zones of naturally suppressed infestation. Our geostatistical approach objectively identified these lower-density areas through quantitative analysis of spatial patterns, without implying absolute resistance. Here, "resistance" refers to relative infestation levels within our study area's spatial context, where these counties showed consistently lower densities across multiple sampling points. This interpretation is consistent with geostatistical conventions that define zones based on measured population parameters rather than absolute biological resistance mechanisms. The finding that 20% of the study area maintained lower densities despite favorable regional conditions warrants further investigation into potential contributing factors, such as local management practices or environmental moderators.

The kriging method was successfully used in this study to predict nematode distribution patterns, with the exponential model providing

the best fit ($R^2 = 0.071$) (coefficient of determination) provided the best fit. The effective range results suggest that spatial dependence of nematode density in high-risk areas is limited to nearby points, whereas in low-risk areas, the distribution is more random. This model was accurate in distinguishing high-risk and low-risk regions.

Previous studies have used similar methods; Freitas *et al.* (2017) used the kriging method to analyze the distribution of soybean nematodes. They found that this method could reduce sampling costs by up to 30%. Similarly, Holguin *et al.* (2015) reported that kriging maps can be a helpful tool for targeted management of plant pathogen populations.

In our study, nematode population density differed across regions. Areas with high nematode population density, such as Estahban County (Zone 1), required more intensive management. In contrast, areas with low nematode population density, such as Kavar County (Zone 4), only required preventive management strategies. The geostatistical results quantitatively demonstrate this area's significantly lower infestation levels without implying causation. The observed pattern could relate to various factors (e.g., management practices, environmental conditions, or host plant characteristics). The current results establish the empirical baseline of spatial distribution patterns, showing that preventive measures would be appropriate for these low-density areas based on the measured infestation levels and spatial characteristics. The 7-meter effective range indicates that sampling or monitoring in this county could use wider spacing while still effectively detecting population trends. These patterns are similar to Noe and Barker (1994), who showed that the density of plant-parasitic nematodes in different regions is strongly influenced by local conditions and crop type.

A potential limitation is the uneven sample distribution across counties (e.g., 153 in Estahban vs. 2 in Shiraz). While geostatistical kriging inherently accounts for spatial configuration and clustering through variogram

parameters (nugget, sill, range) and uses optimal spatial weighting, predictions in sparsely sampled areas (like Shiraz and Kavar) should be interpreted with more caution and are more representative of general trends than highly localized hotspots. The model is most reliable within and near the dense sampling clusters. Future studies would benefit from a more balanced sampling design to enhance the predictive accuracy across the entire region.

This study found that Kriging maps can support targeted management strategies. For example, applying management methods, including resistant and tolerant genotypes for fig inflorescence nematode and orchard management methods, is recommended in high-risk regions (Zone 1) or regions with moderate density (Zone 2). In low-risk areas (Zones 3 and 4), preventive management strategies are enough. These suggestions align with Wilson *et al.* (2004), who showed that regional management can reduce management costs and increase productivity.

Our results show that fig inflorescence nematode distribution is highly aggregated and depends on geographical factors and genotype susceptibility. A comparison with similar studies showed that geostatistical methods such as kriging are effective tools for plant-parasitic nematode management. The results are consistent with similar studies in terms of accuracy and management applicability. Karimipour Fard *et al.* (2024).

The high structural ratio in both models (about 0.82) indicates a clear pattern in the distribution of fig inflorescence nematodes. This result highlights the importance of spatial models for designing accurate plant parasitic nematode management maps. Differences in effective range across directions indicate that environmental conditions (such as soil type and irrigation methods) play an important role in the distribution pattern. For example, soils with higher moisture or poor drainage showed greater nematode aggregation.

The kriging maps in this study provide statistically processed spatial predictions of nematode density rather than raw field

measurements. These interpolated surfaces, generated through geostatistical analysis of the original sampling data ($n = 175$ points), objectively characterize regional infestation patterns by accounting for spatial autocorrelation (quantified through variogram parameters: nugget = 0.062-0.064, sill = 0.855, effective range = 1.775-5.409 m). The reported density ranges (e.g., 3700-4100 nematodes/g in Zone 1) represent model-derived estimates that smooth sampling variability while preserving validated spatial trends (cross-validated RMSE = 0.89), clearly distinguishing them from individual sample counts. This approach transforms discrete point data into continuous risk maps for management purposes, with all predictions grounded in measured spatial dependence structures rather than subjective interpretation. The original field measurements remain available in supplementary materials to ensure full transparency between raw data and modeled outputs. The results of this study can reduce management costs and increase the productivity of fig orchards in Fars province, Iran. Future research should focus on developing resistant fig genotypes and integrating biological control methods to manage *S. caprifici* in high-risk areas.

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تحلیل زمین‌آماري پراکنش و کانون‌های بحراني *Schistonchus caprifici* در باغ‌های انجیر استان فارس در جنوب ایران

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چکیده: نماتد گل‌آذین انجیر، (*Schistonchus caprifici* (Gasperrini, 1864)، یکی از عوامل خسارت‌زا در باغ‌های انجیر استان فارس است. در این مطالعه از روش‌های زمین‌آماري، جهت بررسی پراکنش جغرافیایی این نماتد و شناسایی نقاط بحراني که برای طراحی استراتژی‌های کنترل بهینه ضروری است، استفاده شد. در طول بهار ۱۴۰۱-۱۴۰۲، در مجموع ۱۷۵ نمونه از سیکونیوم‌های بهاره بر انجیر (زودرس، میان‌رس و دیررس) از مناطق مختلف شهرستان‌های استهبان، خفر، سروستان، کوار و شیراز در استان فارس در جنوب ایران جمع‌آوری شد. استخراج نماتد و تخمین تراکم جمعیت آن طبق روش‌های مرسوم نماتدشناسی انجام شد. از روش‌های زمین‌آماري (مدل واریوگرام) برای شبیه‌سازی توزیع مکانی جمعیت‌های نماتد انجیر استفاده شد. از مجموع ۱۷۵ نمونه گل‌آذین برانجیر جمع‌آوری‌شده از شهرستان‌های مذکور، ۱۳۸ نمونه (۷۸/۸۵ درصد) آلوده به نماتد گل‌آذین انجیر، *S. caprifici*، بودند و میانگین جمعیت نمونه‌های آلوده، ۱۰۷۸/۴۶ نماتد در هر گرم بافت میوه انجیر بود. میانگین تراکم جمعیت نماتد گل‌آذین انجیر در هر گرم بافت میوه برانجیر براساس روش کریجینگ و با تمرکز بر مناطق پرخطر و پرتراکم، در شهرستان استهبان ۳۷۰۰ تا ۴۱۰۰، در شهرستان خفر ۲۰۰۰ تا ۳۰۰۰ و در شهرستان‌های سروستان و شیراز ۱۰۰۰ تا ۱۵۰۰ نماتد در هر گرم بافت میوه بر انجیر و در شهرستان کوار کمتر از ۱۰۰۰ نماتد بود. دامنه مؤثر در شهرستان استهبان سه متر (خوشه‌های کوچک و متراکم)، در شهرستان خفر پنج متر (پراکندگی متوسط) و در شهرستان‌های سروستان، شیراز و کوار هفت متر (پراکندگی کم) بود. پیش‌بینی موفقیت‌آمیز الگوهای توزیع نماتد به روش کریجینگ در این مطالعه، امکان استفاده از این نقشه‌ها را به‌عنوان ابزاری مؤثر برای طراحی راهبردهای مدیریت نماتد گل‌آذین انجیر فراهم می‌آورد.

واژگان کلیدی: تحلیل مکانی، تراکم، کریجینگ، مدیریت کنترل، نماتد گل‌آذین انجیر، واریوگرافی