



مقاله پژوهشی

کاربرد سیستم های اطلاعات جغرافیایی (GIS) در نقشه برداری پراکنش شپشک آردآلود پنبه (*Phenacoccus solenopsis*) در فضای سبز شهری

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چکیده

شپشک آردآلود پنبه (*Phenacoccus solenopsis* (Hemiptera: Pseudococcidae) یکی از آفات مهم و مهاجم در فضای سبز شهری استان خوزستان است که خسارت های جدی به گیاهان زیتنی به ویژه ختمی چینی (*Hibiscus rosa-sinensis*) وارد می کند. این پژوهش با هدف بررسی الگوی پراکنش مکانی این آفت در فضای سبز شهر دزفول طی سال های 2024-2025 و با بهره گیری از روش های زمین آماری انجام شد. به منظور پایش جمعیت آفت، در دو منطقه شهری، 30 بوته ختمی چینی انتخاب و جمعیت پوره ها و حشرات بالغ در بازه های دوهفته ای شمارش گردید. داده های به دست آمده پس از آزمون نرمال بودن، با مدل های زمین آماری شامل واریوگرام و کریجینگ تجزیه و تحلیل شدند. نتایج نشان داد که الگوی پراکنش جمعیت شپشک آردآلود پنبه به طور عمده از نوع تجمعی بوده و وابستگی مکانی قوی (DD بیش از 70%) بین داده ها وجود دارد. مدل های نمایی و کروی بهترین برازش را با داده ها داشتند و دامنه تأثیر مکانی بین 20 تا 200 متر متغیر بود. این نتایج نشان می دهد که استفاده از روش های زمین آماری می تواند ابزاری کارآمد برای پایش بینی تراکم آفت، بهینه سازی طرح های نمونه برداری و کاهش هزینه های مدیریت در فضای سبز شهری باشد. در مجموع، یافته ها اهمیت مدیریت تلفیقی و مکان ویژه آفات را در کاهش خسارات زیست محیطی و اقتصادی ناشی از این گونه مهاجم برجسته می سازد.

واژه های کلیدی: شپشک آرد آلود پنبه، زمین آمار، کریجینگ، توزیع مکانی، ختمی چینی



Research article

Utilization of Geographic Information Systems (GIS) for Mapping the Distribution of the Cotton Mealybug (*Phenacoccus solenopsis*) in Urban Green Spaces

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Abstract

The cotton mealybug, *Phenacoccus solenopsis* (Hemiptera: Pseudococcidae), is a highly invasive pest that poses serious threats to ornamental plants in urban green spaces. This study aimed to determine the spatial distribution pattern of *P. solenopsis* populations on Chinese hibiscus (*Hibiscus rosa-sinensis* L.) in Dezful, southwestern Iran, during 2024–2025 using geostatistical methods. A total of 30 hibiscus plants were sampled in two urban areas, and nymph and adult mealybug densities were recorded bimonthly. Geostatistical analyses including variogram modeling and kriging were applied to characterize spatial dependence and generate distribution maps. Results showed that the population of *P. solenopsis* exhibited an aggregated distribution with strong spatial dependence ($DD = 0.70–0.99$). Exponential and spherical models provided the best fit to the data, with effective ranges varying between 20 and 200 m. Kriging maps revealed distinct hotspots of infestation across the study sites. These findings highlight the efficiency of geostatistical tools for predicting pest distribution and identifying high-risk areas. The study demonstrates that integrating spatial analysis into monitoring programs can optimize sampling design, reduce costs, and improve site-specific management strategies for *P. solenopsis* in urban green spaces.

Keywords: cotton mealybug, geostatistics, kriging, spatial distribution, hibiscus



Introduction

The Chinese hibiscus, *Hibiscus rosa-sinensis* L. (Malvaceae), is a perennial ornamental shrub of global horticultural significance, prized for its vibrant flowers and widespread cultivation in tropical and subtropical urban landscapes, including those in Iran's Khuzestan Province. Beyond its aesthetic value, this species possesses considerable medicinal importance, featuring prominently in traditional herbal practices (Khristi & Patel, 2016). However, the health and ornamental quality of *H. rosa-sinensis* are increasingly compromised by infestations of the cotton mealybug, *Phenacoccus solenopsis* Tinsley (Hemiptera: Pseudococcidae). *P. solenopsis* is a highly invasive and polyphagous pest, with a documented host range exceeding 200 plant species (Fand & Suroshe, 2015). Urban environments, characterized by high plant density, moderated microclimates, and environmental stressors, provide ideal conditions for its proliferation (Boushi *et al.*, 2022). The pest inflicts both direct and indirect damage: direct sap-feeding stunts growth, reduces vigor, and can cause plant mortality, while the excretion of honeydew promotes sooty mold growth, which impairs photosynthesis and diminishes aesthetic

value (Dhawan *et al.*, 2009; Nagrare *et al.*, 2011). The threat posed by *P. solenopsis* is projected to intensify under climate change, necessitating the development of robust monitoring and management protocols (Boushi *et al.*, 2022; 2025).

A foundational step in devising such strategies is a precise understanding of the pest's spatial distribution. Geostatistics provides a powerful analytical framework for this purpose, enabling the quantification and modeling of spatial continuity in ecological data (Liebhold *et al.*, 1993). The core of this methodology involves variography and kriging. The semi-variogram, a fundamental tool, quantifies spatial autocorrelation by modeling the variance between sample points as a function of the distance that separates them (Isaaks & Srivastava, 1989). It is calculated as:

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

where $\gamma(h)$ is the semivariance at lag distance h , $N(h)$ is the number of sample pairs separated by h , and $z(x_i)$ is the measured value at location x_i .

This modeled spatial structure then informs kriging, an optimal interpolation technique that provides unbiased, minimum-variance estimates of values at



unsampled locations, ultimately generating predictive distribution maps (Goovaerts, 1998). The accuracy of kriging is contingent upon the strength of spatial dependence, a property derived from the variogram model (e.g., spherical, exponential), which is frequently observed in insect population studies (Liebhold *et al.*, 1993).

A number of researchers have utilized geostatistical approaches to investigate the spatial distribution patterns of insects. For example, Ghahremani *et al.* (2023) examined the distribution of aphids and lady beetles in alfalfa fields in Karaj, employing geostatistical analysis to assess their degree of spatial dependence. The obtained degree of spatial dependence (DD) exceeded 50%, indicating an aggregated distribution pattern. Similarly, Shayestehmehr (2014) studied the spatio-temporal relationships between the spotted alfalfa aphid (*Therioaphis maculata* Buckton) and the seven-spotted lady beetle (*Coccinella septempunctata*) in alfalfa fields of Hamedan, reporting aggregated distributions for both species. This application extends to predator-prey dynamics in other systems, as demonstrated by Park and Obrycki (2004), who used geostatistics to reveal a strong spatio-temporal concordance between corn leaf aphids and lady beetles in corn fields. Beyond mapping current infestations,

the method's predictive capacity is evidenced by its use in forecasting pest emergence; Park and Telfson (2005) successfully employed kriging to model the spatial pattern of corn rootworm emergence, facilitating the potential for targeted preemptive management. The foundational importance of a well-defined spatial structure for such analyses is paramount, a principle underscored by Utset *et al.* (1998), who established that sampling intervals based on variogram ranges are critical for accurate spatial mapping. In the United States, Wright *et al.* (2002) analyzed the spatial distribution and damage intensity of the European corn borer, *Ostrinia nubilalis* (Hübner, 1796), using geostatistical methods, providing estimates of patch effect, range, and sill for various sampling periods. Likewise, Garcia *et al.* (2017) investigated the spatial distribution of fruit fly species (*Anastrepha spp.*) in an urban area containing forested patches, identifying their spatial distribution patterns and concluding that geostatistics offers an effective tool for sampling design and management of fruit fly populations. More recently, geospatial technologies have been increasingly integrated with geostatistical approaches for monitoring sap-sucking pests. For example, Costa *et al.* (2024) applied geotechnologies, including GIS, geostatistical interpolation, and remotely sensed vegetation indices, to investigate the spatial and temporal dynamics of



mealybug infestations in black pepper plantations in southern Bahia, Brazil. Their results demonstrated that spatial prediction maps derived from kriging effectively identified infestation hotspots and supported site-specific pest management. Similarly, Soares et al. (2020) analyzed the spatiotemporal dynamics of the green peach aphid, *Myzus persicae*, in bell pepper fields using geostatistical techniques and showed that pest populations exhibited distinct spatial aggregation patterns that could be exploited for targeted monitoring and integrated pest management. In another study, Garcia et al. (2017) employed geostatistical analyses to characterize the spatial distribution of fruit flies (*Anastrepha* spp.) in urban landscapes, concluding that spatial prediction models are valuable tools for optimizing sampling strategies and improving pest management decisions across heterogeneous environments.

Given the escalating impact of *P. solenopsis* on urban greenery, this study employs a geostatistical approach to characterize its spatial population structure within the urban green spaces of Dezful. The resulting distribution maps are intended to elucidate infestation patterns and provide a scientific basis for implementing site-specific Integrated Pest Management (IPM), thereby promoting more precise and sustainable pest control.

Materials and Methods

This study was conducted during 2024–2025 in the urban green spaces of Dezful, located in southwestern Iran. To monitor the population density of the cotton mealybug, *Phenacoccus solenopsis*, on ornamental plants, 30 Chinese hibiscus (*Hibiscus rosa-sinensis*) plants were selected from two areas within the city. Adult and nymphal mealybugs were counted and recorded twice per month on each plant throughout the study period. The geographical coordinates (longitude and latitude in meters) of each sampling plant were determined using GPS and remained unchanged during the entire sampling period.

For statistical analysis, Microsoft Excel 2013, SPSS version 19, and GS+ version 5.1 were used. The normality of the data for each sampling date was evaluated using the Kolmogorov–Smirnov test. When the data did not meet the assumption of normality, appropriate transformations (e.g., reciprocal transformation) were applied before geostatistical analysis.

Geostatistical analysis was then performed separately for each sampling date to characterize the spatial distribution of the mealybug population across the



study area. Experimental semivariograms were calculated based on the geographical coordinates and mealybug density at each sampling point, and several theoretical models (e.g., spherical, exponential, and Gaussian) were fitted to the data. The model providing the highest coefficient of determination (R^2) and the lowest residual sum of squares (RSS) was selected as the best-fitting model. The selected semivariogram model was subsequently used for ordinary kriging interpolation to generate spatial distribution maps of *P. solenopsis* population density.

From the best-fitted semivariogram, the nugget effect (C_0), sill ($C_0 + C$), and range were extracted to describe the spatial structure of the population. The degree of spatial dependence (DD) was calculated using the following equation:

$$DD = \left(\frac{C}{C_0 + C} \right) 100$$

where C_0 is the nugget effect, C is the structural variance, and $C_0 + C$ represents the sill of the semivariogram. According to Karimzadeh et al. (2011), DD values of <25% indicate weak spatial dependence, 25–75% indicate moderate spatial dependence, and >75% indicate strong spatial dependence. Finally, kriging interpolation maps were produced to visualize the spatial distribution and

identify infestation hotspots of *P. solenopsis* within the urban green spaces of Dezful.

Results

The results of the geostatistical analyses are summarized in Table 1, with the corresponding kriging maps presented in Figure 1. Variogram modeling indicated that the spatial distribution of *Phenacoccus solenopsis* populations was best explained by the exponential model on 10 sampling dates and by the spherical model on 7 dates. Nugget-to-sill ratios were consistently low, indicating strong spatial dependence throughout the sampling period. The Degree of Dependence (DD) ranged from 0.70 to 0.99, confirming a highly aggregated spatial distribution pattern.

The effective range, which defines the spatial radius of autocorrelation in mealybug counts, varied between 20 and 200 m, suggesting fluctuations in the scale of population aggregation across sampling dates. Model robustness was supported by coefficients of determination (R^2) ranging from 0.60 to 0.96 (Table 1).

The kriging maps provided a visual representation of these results (Figure 1), revealing clear and persistent

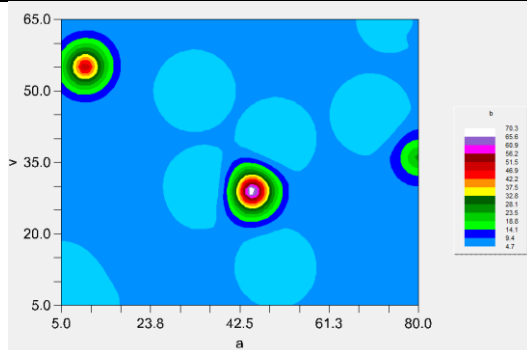


hotspots of infestation across the urban green spaces of Dezful. These maps highlighted localized areas of high mealybug density surrounded by regions of lower infestation, thereby confirming the aggregated nature

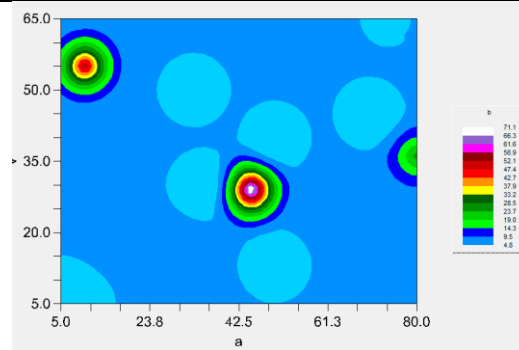
of population distribution detected by the statistical models.

Table 1. Geostatistical characteristics of *Phenacoccus solenopsis* population in the landscape of Dezfoul County.

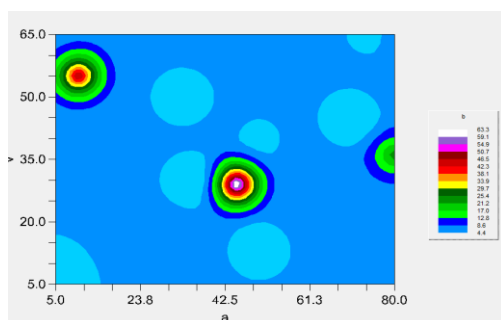
Sampling date	Model	nugget	Sill	Effective range (m)	DD (%)	R ²
25 April 2024	Exponential	1.7	10.7	102.2	0.833	0.78
9 May, 2024	Exponential	1.6	11.3	105.6	0.859	0.73
24 May, 2024	Exponential	3.1	11.1	190.4	0.716	0.79
6 June, 2024	Exponential	2.4	8.3	20.9	0.708	0.89
20 June, 2024	Exponential	3.5	11.3	160.8	0.690	0.79
4 July, 2024	Exponential	2.1	10.6	120.9	0.803	0.89
18 July, 2024	Exponential	0.01	10.9	127.2	0.999	0.90
2 August, 2024	Spherical	2.6	11.1	142.9	0.763	0.63
16 August, 2024	Spherical	2.2	14.4	185.8	0.845	0.90
30 August, 2024	Spherical	1.0	12.1	123.7	0.911	0.86
13 Sep., 2024	Spherical	0.1	11.1	100.6	0.987	0.90
27 Sep., 2024	Exponential	1.0	10.0	100.7	0.892	0.89
11 Oct., 2024	Exponential	3.3	11.5	125.2	0.706	0.88
25 Oct., 2024	Spherical	0.2	12.1	190.1	0.976	0.82
8 Nov., 2024	Spherical	1.0	11.1	123.2	0.89	0.93
22 Nov., 2024	Exponential	1.9	10.19	146.23	0.86	0.89
7 Dec., 2024	Spherical	0.01	13.2	200.5	0.999	0.96



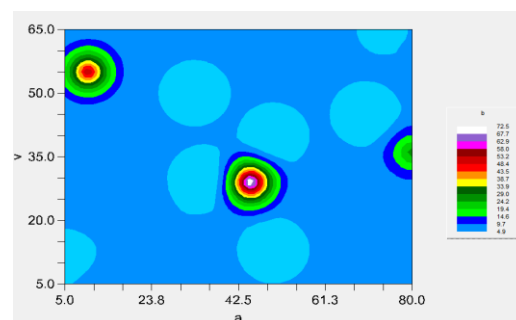
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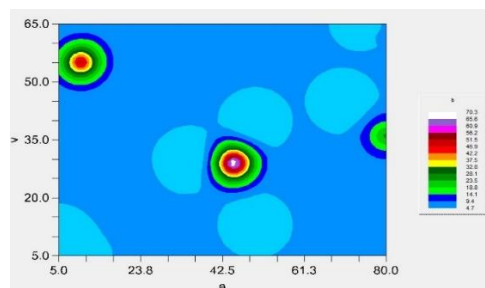
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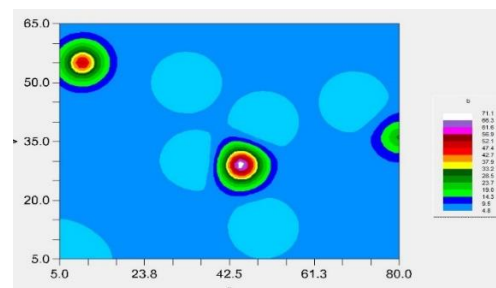
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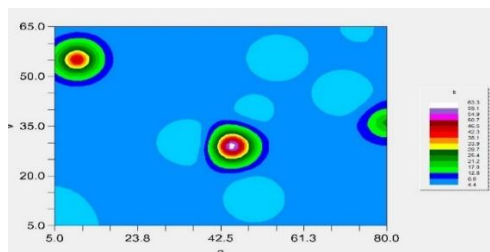
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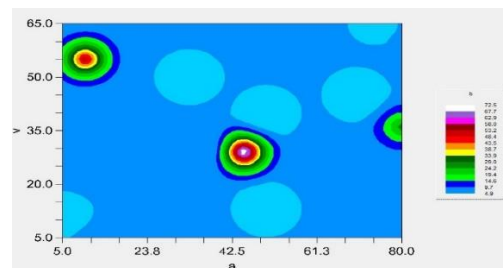
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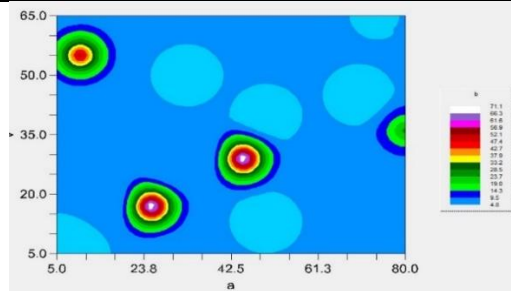
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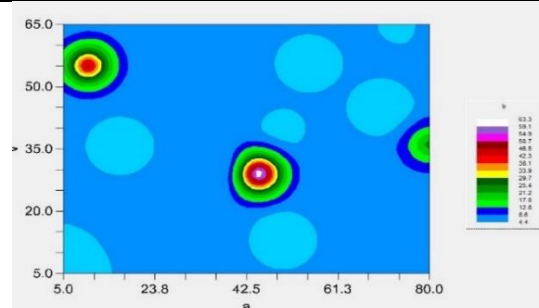
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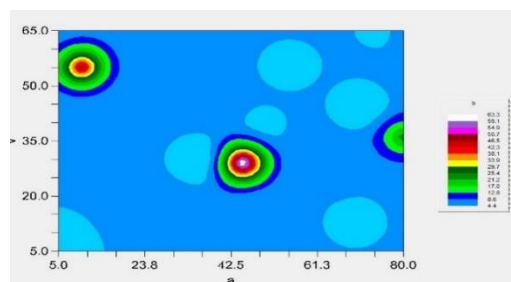
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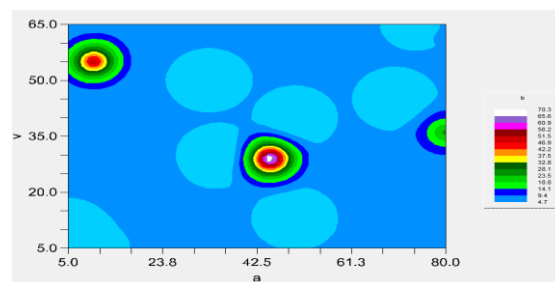
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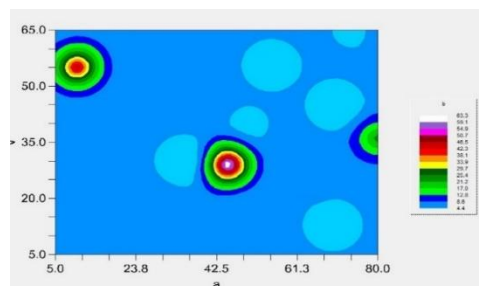
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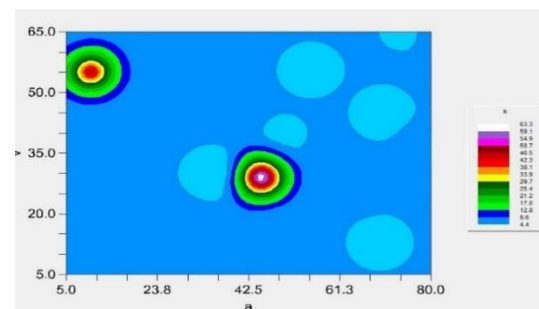
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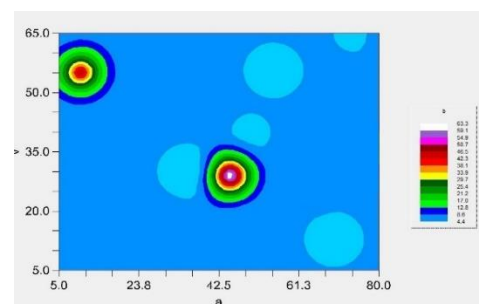
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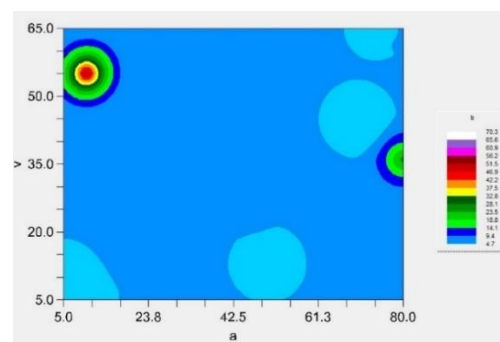
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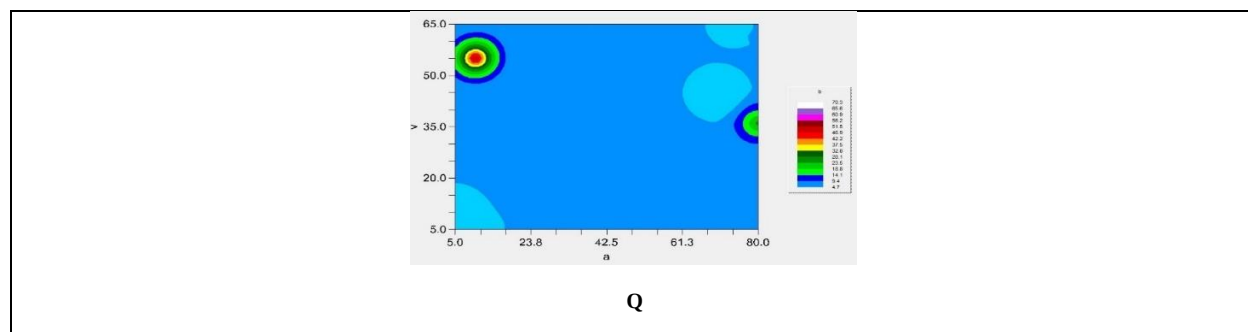


Figure 1. Kriging interpolation maps illustrating the spatio-temporal distribution and density hotspots of *Phenacoccus solenopsis* populations on *Hibiscus rosa-sinensis* in the urban green spaces of Dezful, Iran. Sampling dates: (A) 7 Dec. 2024; (B) 22 Nov. 2024; (C) 8 Nov. 2024; (D) 25 Oct. 2024; (E) 11 Oct. 2024; (F) 27 Sep. 2024; (G) 13 Sep. 2024; (H) 30 Aug. 2024; (I) 16 Aug. 2024; (J) 2 Aug. 2024; (K) 18 Jul. 2024; (L) 4 Jul. 2024; (M) 20 Jun. 2024; (N) 6 Jun. 2024; (O) 24 May 2024; (P) 9 May 2024; (Q) 25 Apr. 2024.

Discussion

This study provides clear evidence that *P. solenopsis* populations in the urban landscape of Dezful exhibit a strongly aggregated spatial distribution. Such clustering is consistent with the spatial ecology of many insect pests, reflecting the influence of heterogeneous environmental factors on population dynamics (Liebhold *et al.*, 1993). Similar aggregated patterns have been reported for gypsy moth egg masses (Liebhold *et al.*, 1993), root weevils in alfalfa (Karimzadeh *et al.*, 2015), and several aphid species (Mohiseni *et al.*, 2007), as well as fruit flies in urban forest fragments (Garcia *et al.*, 2017). Furthermore, the application of geostatistics to predator-prey systems, as demonstrated by Park and Obrycki (2004) with corn leaf aphids and lady beetles, confirms that

such aggregation is a fundamental ecological pattern that can be precisely quantified.

The exponential and spherical models provided the best description of spatial dependence, aligning with previous geostatistical studies on insects (Ellsberry *et al.*, 1998; Garcia *et al.*, 2017). These models are particularly effective at capturing the gradual increase in variance with distance, a common property of biological systems. However, the persistent non-zero nugget values observed in this study suggest the presence of unexplained variance at scales smaller than the sampling interval. Such micro-scale variation may result from patchy distribution of suitable microhabitats within hibiscus plants (e.g., leaf axils, plant age), the influence of natural enemies, or potential sampling error (Liebhold *et al.*, 1993; Boushi *et al.*, 2025).



The effective ranges, which varied from 20 to 200 m, have important implications for monitoring and pest management. Shorter ranges indicate localized clustering, likely driven by limited crawler dispersal or isolated heavily infested plants, while longer ranges may reflect broader dispersal facilitated by wind, human activity, or gradual population expansion. These findings are in line with Utset et al. (1998), who established that sampling intervals should not exceed 75% of the effective range to ensure accurate spatial characterization. Based on our results, effective monitoring of *P. solenopsis* requires a flexible grid system with intervals between 15 and 150 m, adjusted according to population density and seasonal dynamics. This approach aligns with the predictive framework of Park and Telfson (2005), who used similar spatial parameters to forecast corn rootworm emergence hotspots, demonstrating how range analysis directly informs proactive management.

Kriging maps provided a visual confirmation of statistical results and served as a valuable decision-support tool. By identifying clear hotspots of infestation, these maps enable a transition from broad, calendar-based pesticide applications to site-specific Integrated Pest Management (IPM). Concentrating monitoring and control efforts—such as targeted

insecticide sprays, releases of biological control agents like *Cryptolaemus montrouzieri*, or horticultural oil treatments—within high-risk areas can enhance control efficacy while reducing management costs, pesticide use, and non-target impacts (Reay-Jones, 2012; Rijal et al., 2014).

Despite these advances, high nugget variance may limit the accuracy of kriging predictions (Rendu, 1981). This limitation highlights the need for denser sampling in areas of high variability and for incorporating ecological covariates into spatial models. Factors such as host plant vigor, ant activity, and microclimatic variation likely play significant roles in shaping mealybug aggregation and should be integrated into future geostatistical analyses.

Overall, our findings confirm that geostatistical methods provide robust and practical tools for understanding pest spatial ecology, optimizing monitoring networks, and supporting precision IPM programs. By combining spatial analysis with ecological insights, pest management strategies can become more sustainable, efficient, and environmentally sound.

In conclusion, the strongly aggregated distribution of *P. solenopsis* populations in Dezful's urban



greenspaces underscores the high value of geostatistics and GIS in modern pest management. The methodology moves beyond simple density estimates to reveal the underlying spatial structure of infestations, providing a scientific basis for optimizing sampling design and implementing targeted control. The kriging maps offer a clear visual guide for proactive intervention. Future efforts to combine these spatial models with detailed ecological data will further enhance the predictive power and practical application of IPM strategies, safeguarding the health and aesthetic value of urban landscapes against this invasive pest.

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References

BOUSHI, S., L. RAMEZANI and S. ZARGHAMI, 2022. Biology of *Phenacoccus solenopsis* Tinsley on *Hibiscus rosa-sinensis* in the urban landscape of Dezful, Southwest Iran. *Plant Protection (Scientific Journal of Agriculture)*, 43(3): 75–86. <https://doi.org/10.22055/PPR.2020.16542>

BOUSHI, S., L. RAMEZANI and S. ZARGHAMI, 2025. Population dynamics of *Phenacoccus solenopsis* Tinsley (Hemiptera: Pseudococcidae) and its natural enemies on Chinese hibiscus (*Hibiscus rosa-sinensis*) in urban landscapes of Dezful, Khuzestan Province, Southwestern Iran. *Plant Protection (Scientific Journal of Agriculture)*, 48(3), 27–41. <https://doi.org/10.22055/PPR.2025.50249.1823>

COSTA, J.A., et al., 2024. Geotechnologies applied in the monitoring of mealybug in the black pepper cultivation in the South of Bahia. *Revista Sustinere*, 12(2): 761–780. <https://doi.org/10.12957/sustinere.2024.74369>

DHAWAN, A.K., K. SINGH, A. ANAND and S. SARIKA, 2009. Distribution of mealybug, *Phenacoccus solenopsis* Tinsley in cotton with relation to weather factors in southwestern districts of Punjab. *Journal of Entomological Research*, 33(1): 59–63.

ELLSBURY, M.M., W.D. WOODSON, S.A. CLAY, D. MALO and J. SCHUMACHER, 1998. Geostatistical characterization of the spatial distribution of adult corn rootworm (Coleoptera: Chrysomelidae) emergence. *Environmental*



Entomology, 27(4): 910–917.

<https://doi.org/10.1093/ee/27.4.910>

FAND, B.B. and S.S. SUROSHE, 2015. The invasive mealybug *Phenacoccus solenopsis* Tinsley, a threat to tropical and subtropical agricultural and horticultural production systems: A review. *Crop Protection*, 69: 34–43. <https://doi.org/10.1016/j.cropro.2014.12.001>

GARCIA, A.G., M.R. ARAUJO, K. URAMOTO, J.M.M. WALDER and R.A. ZUCCHI, 2017. Geostatistics and GIS to analyze spatial distribution of *Anastrepha* spp. in urban forest fragments. *Environmental Entomology*, 46: 1189–1194. <https://doi.org/10.1093/ee/nvx145>

GHAHREMANI, M., R. KARIMZADEH and S. IRANIPOUR, 2023. Spatio-temporal distribution of aphids and ladybirds in alfalfa fields. *Journal of Entomological Society of Iran*, 43(4): 393–404. <https://doi.org/10.61186/JESI.43.4.7>

GOOVAERTS, P., 1998. Geostatistical tools for characterizing the spatial variability of microbiological and physico-chemical soil properties. *Biology and Fertility of Soils*, 27(4): 315–334. <https://doi.org/10.1007/s003740050439>

HASANI PAK, A., 1998. *Geostatistics*. Tehran University Press, Tehran. 314 pp.

ISAACS, E.H. and R.M. SRIVASTAVA, 1989. *An Introduction to Applied Geostatistics*. Oxford University Press, New York. 561 pp.

KARIMZADEH, R., M.J. HEJAZI, H. HELALI, S. IRANIPOUR and S.A. MOHAMMADI, 2011. Spatio-temporal distribution of *Eurygaster integriceps* using geostatistics. *Environmental Entomology*, 40: 1253–1265. <https://doi.org/10.1603/EN10188>

KARIMZADEH, R., M. ZAKERI and S. IRANIPOUR, 2015. Spatial distribution of *Hypera postica* and *Sitona* spp. in alfalfa using geostatistics. *Applied Entomology and Phytopathology*, 83: 223–236. <http://dx.doi.org/10.22092/JAEP.2016.106119>

KHRISTI, V. and V.H. PATEL, 2016. Therapeutic potential of *Hibiscus rosa-sinensis*: A review. *International Journal of Nutrition and Dietetics*, 4(2): 105–123. <http://dx.doi.org/10.17654/ND004020105>

LIEBHOLD, A.M., R.E. ROSSI and P. KEMP, 1993. *Geostatistics and GIS in applied insect ecology*. *Annual Review of Entomology*, 38: 303–327.



MOHISENI, A.A., A. PIRHADI and A. NABATI, 2007. Geostatistical analysis of major wheat aphids in Borujerd. Proceedings of the 18th Iranian Plant Protection Congress.

NAGRARE, V.S., S. KRANTHI, R. KUMAR, B. DHARA, M. AMUTHA, A.J. DESHMUKH, K.D. SONE and R. KRANTHI, 2011. Compendium of Cotton Mealybugs. CICR Publication.

PARK, Y.L. and J.J. OBRYCKI, 2004. Spatio-temporal distribution of corn leaf aphids and lady beetles. Biological Control, 31: 210–217. <https://doi.org/10.1016/j.biocontrol.2004.06.008>

PARK, Y.L. and J.J. TOLFSON, 2005. Spatial prediction of corn rootworm emergence. Journal of Economic Entomology, 98: 121–128. <https://doi.org/10.1111/j.1570-7458.2006.00428.x>Digital

REAY-JONES, F.P.F., 2012. Spatial analysis of cereal leaf beetle (*Oulema melanopus*) in wheat. Environmental Entomology, 41: 1516–1526. <https://doi.org/10.1093/ee/nvx034>

RENDU, J.M., 1981. An Introduction to Geostatistical Methods of Mineral Evaluation. South African

Institute of Mining and Metallurgy, Johannesburg. 84 pp.

RIJAL, J.P., C.C. BREWSTER and J.C. BERGH, 2014. Spatial distribution of grape root borer infestations in Virginia vineyards. Environmental Entomology, 43: 716–728. <https://doi.org/10.1603/EN13285>

SCHOTZKO, D.J.O. and L.E. KEEFFE, 1989. Spatial distribution of *Lygus hesperus* in lentils. Journal of Economic Entomology, 82: 1277–1288. <https://doi.org/10.1093/jee/82.5.1277>

SOARES, J.R.S., et al., 2020. Spatiotemporal dynamics and natural mortality factors of *Myzus persicae* (Sulzer) (Hemiptera: Aphididae) in bell pepper crops. Neotropical Entomology, 49: 445–455. <https://doi.org/10.1007/s13744-020-00761-2>

UTSET, A., M.E. RUIZ, J. HERRERA and P. DE LEON, 1998. Geostatistical method for salinity sample spacing. Geoderma, 86: 143–151. [https://doi.org/10.1016/S0016-7061\(98\)00037-8](https://doi.org/10.1016/S0016-7061(98)00037-8)

WRIGHT, R.J., T.A. YOUNG, K.J. JARVI and R.C. SEYMOUR, 2002. Small-scale distribution of European corn borer larvae and damage.



Environmental Entomology, 31(1): 160–167.

<https://doi.org/10.1603/0046-225X-31.1.160>