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# SPATIAL ANALYSIS OF BROWN SPIDER MITE (*Oligonychus punicae* Hirst) DAMAGE IN AVOCADO USING SPATIAL ANALYSIS BY DISTANCE INDICES (SADIE)

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## ABSTRACT

Avocado (*Persea americana* Mill.) is a perennial crop that belongs to the Lauraceae family. This crop is affected by various pests, the most important of which is the spider mite *Oligonychus punicae* Hirst (Acari: Tetranychidae), also known as the brown avocado spider. The damage begins with reddish spots that spread throughout the leaf, eventually tanning the foliage and staining the fruit, resulting in its rejection in the market. As a result, understanding its spatial distribution is critical for growers to plan and implement integrated pest management programs effectively, reducing their economic and environmental impacts. This study used spatial analysis by distance indices (SADIE) to determine the spatial distribution of damage to the Hass avocado crop caused by brown spider mite populations in Coatepec Harinas and Donato Guerra, two municipalities in the State of Mexico, Mexico. Spatial behavior allows for the development of preventive or corrective control measures for the use of precision farming techniques. Spatial distribution maps were created using the geostatistical technique of ordinary Krigeing, and the mean and variance of damage caused by the brown spider mite in avocado were examined. The findings revealed a clustered spatial distribution with several aggregation centers that shift over time and correlate with the plots' terrain and climate. No homogeneous pattern was found in any plot, indicating the need to continue this type of research to better understand concentration conditions and implement specific actions in the field.

**Keywords:** mites, density maps, SADIE, infested area.

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## INTRODUCTION

Avocado (*Persea americana* Mill.) is the fourth most important tropical fruit in the world. Mexico is the leading producer of "green gold," with its export success being based on its quality and safety. Michoacán is the state with the highest production volume, with a value of 1 826 416 Mg, followed by Jalisco with 256 021 Mg (SIAP, 2022). This crop is susceptible to several pests and diseases. The mite *Oligonychus punicae* Hirst (Acari: Tetranychidae), known as avocado brown spider mite, is one of the most important pests in this crop. It feeds on its foliage, inserting its stylet into plant tissue and causing reddish spots.

The biotic potential of the pest depends on extrinsic and intrinsic factors, host plant characteristics (morphological and chemical), environmental conditions (temperature and humidity), population density and age, fertility, and behavioral parameters. Defoliation and production loss occur when damage is severe, causing the mesophyll to collapse. When necrotic tissue caused by the mite exceeds 8 % of the leaf surface, there is a high probability that accelerated defoliation will occur, leading to significant losses in productivity (Lemus-Soriano and Pérez-Aguilar, 2016; Ferraz *et al.*, 2020).

The growing demand for chemical-free products has led to the use of new technologies. To monitor *O. punicae* populations, it is necessary to know the distribution of this mite in the plots. Spatial analysis by distance indices (SADIE) is a tool for the analysis of spatially explicit data in one or two dimensions (e.g., transects and surfaces) based on distance indices. From a methodological point of view, it is a tool that allows us to explore whether a variable follows a homogeneous, heterogeneous, or random spatial distribution pattern. Although it has been specifically designed for the analysis of counts (e.g., the number of insects per plant), it can also be used with binary data and pre-categorized ordinal and continuous variables.

SADIE is specifically designed to analyze counts of individuals in known locations. The system was developed to deal with ecological data that can be considered "patchy" (Winder *et al*., 2019), allowing the detection of aggregations and gaps in spatially referenced count data and is often used for the characterization of spatial patterns of pests (Knight *et al*., 2017). This tool identifies the spatial model for two-dimensional data with an associated aggregation index and a test for randomness deviation based on an attraction algorithm, which incorporates a biological model for the dispersion of individuals from an origin in which every individual is assigned a dynamic territory (Rivera-Martínez *et al*., 2022).

The implementation of a successful integrated pest management (MIP) program relies on the determination of population thresholds through the use of reliable pest monitoring tools. Mean and variance-based models can be used to create sampling plans for a variety of arthropod pests, but they only consider frequency distributions of pest counts and do not take into account the spatial locations of pest population samples. Therefore, these models are not suitable for characterizing the distribution of populations within the field (Gireesh *et al*., 2021). Using spatial distribution, a visual representation of pest infestations in the field can be developed by creating prediction maps and Krigeing maps for specific site-pest management (Leyton-Flor *et al*., 2018). Knowing the infestation rates and applying control measures to precise areas of the crop can generate savings for the producer.

The use of spatial statistics (SADIE and geostatistics) allows for accurate and real-time knowledge of the spatial distribution of the pest within the crop. For this reason, the aim of this work was to determine the spatial distribution of damage caused by brown spider mite (*O. punicae*) populations in Hass avocado crops in plots in the municipalities of Coatepec Harinas and Donato Guerra in the State of Mexico, Mexico, using SADIE indices to understand their spatial dynamics with the physical factors of the environment at different time intervals.

## MATERIALS AND METHODS

### Sampling points

The study was carried out in the municipalities of Coatepec Harinas (18° 54′ N and 99° 43′ W) and Donato Guerra (19° 18′ N and 100° 08′ W), with average altitudes of 2260 and 2200 m, respectively. Eight plots (four per municipality) of 2 ha each were selected based on the avocado variety present (Hass), with an average age of eight years and similar agronomic management. Each plot was divided into 50 subplots of 10 x 10 m, and 25 subplots per plot were taken at random, where two trees were selected. Each tree was marked and geo-referenced using a GPS map60 (Garmin, USA). One sampling was carried out per month, from October 2021 to May 2022, selecting 60 leaves from each tree and taking 15 per cardinal point (north, east, west, and south). Their corresponding tree stratum was registered, considering three strata (lower, middle, and upper). Only leaves showing damage were counted. The obtained data were analyzed with the Kurtosis test to determine their normality (Barrantes-Aguilar, 2019).

### Climatic factors measurement

Temperature and precipitation were measured using a portable Datta Loger HOBO Pro V2 sensor (Onset Computer Corporation, USA), which was placed in the middle part of an avocado tree located at the central part of the plot to identify variations that could explain the behavior of the damage distribution of *O. punicae*.

### Spatial analysis by distance indices (SADIE)

The distance-based index for regularity (Ia) and the distance-based index for clustering (*Ja*) (Rivera-Martínez *et al*., 2017) were calculated for brown spider populations at the sampling points. The sample is aggregated if $Ia > 1$, random if $Ia = 1$, and regular if $Ia < 1$; on the other hand, the sample is aggregated if $Ja > 1$, spatially random if $Ja = 1$, and regular if $Ja < 1$. The values of the *Ja* index are used to confirm the results obtained with the *Ia* index. The index is used to discriminate between spatial patterns where there is a single relevant cluster, for which its values are significantly greater than the unit, and when there are two or more clusters, for which its value is not significantly different from or even less than the unit. To determine significance in relation to the unit, the respective probability (*Qa*) is used (Perry, 1998). The program used to determine the values and probabilities of both indices was SADIE 1.22 (Winder *et al*., 2019).

### Krigeing

Krigeing is a local estimation technique that provides the best linear unbiased estimator at the unsampled locations of the variable under study. Ordinary Krigeing was used to obtain values at the unsampled points of the plot. With these, it was possible to graphically display the variable over the entire plot using the Surfer 16.0 program (SurfaceMappingSystem, Golden Software, USA) to determine the infested area and the presence of damage within the study plots. Ordinary Krigeing was used as the mean, and variance of the brown spider damage populations were known.

### Infested area

The infested area of the estimates, represented in the form of maps for each plot on the different sampling dates, was established using the Surfer 16.0 program and the ordinary Krigeing technique, in order to establish the areas to be targeted for control measures.

## RESULTS AND DISCUSSION

### Climatic factors

According to the data recorded in the climate sensors, in Coatepec Harinas (Figure 1A), October 2021 and May 2022 were the months with the highest precipitation (94.55 and 103.42 mm, respectively), and registering very low values in the remaining months. The hottest months were April and May, with 25.43 and 26.98 °C, respectively. In contrast, February was the month with the lowest temperature (19.37 °C). In the municipality of Donato Guerra (Figure 1B), October 2021 was the month with the highest precipitation (115.19 mm), and the hottest months were also April and May with 32.8 and 33.4 °C, respectively.

With the data obtained, it was possible to generate spatial modeling and mapping of the avocado leaf damage caused by *O. punicae*. The application of the SADIE indices (Table 1) provided the values of *Ia* and *Ja*. The Ia index had its lowest value (1.26) in plot one, located in the municipality of Coatepec Harinas, in April, and in plot eight (1.29), located in Donato Guerra, in January. Its highest value (1.78) was in plot three, located in Coatepec Harinas, in April. In all cases, their value was significantly greater than one, indicating that the spatial distribution of leaf damage by the mite is aggregated (Perry, 1998).

This behavior was also observed by Rivera-Martínez *et al*. (2022) when studying the branch borer (*Copturus aguacatae* Kissinger) in avocado, obtaining Ia index values between 1.3 and 1.77; and by Maldonado-Zamora *et al*. (2017), who state that the population of thrips (Thysanoptera) in the avocado crop is distributed in an aggregate form, given that the Ia index values in all their samplings were higher than one. In their work with stem borer (*Diatraea* spp.) in sugar cane, Leyton-Flor *et al*. (2018) point out that the spatial distribution, when aggregated, is concentrated in attack foci that

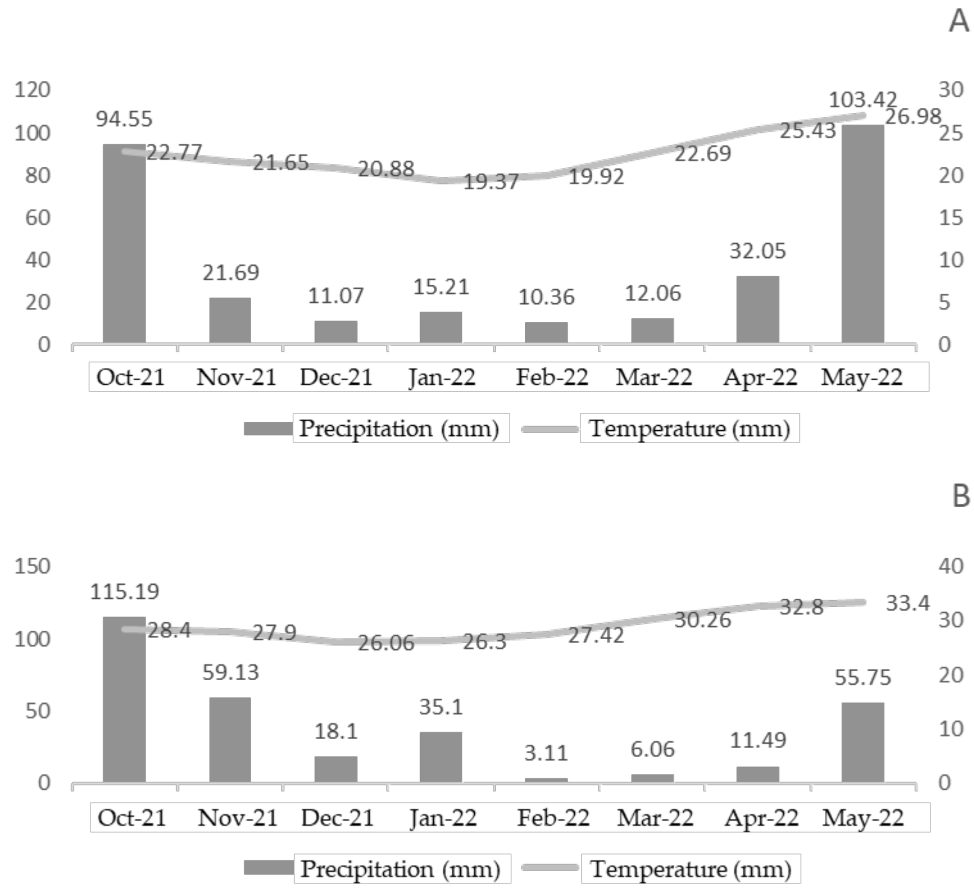


**Figure 1.** Precipitation and temperature records of the plots during the study period. A: municipality of Coatepec Harinas, State of Mexico, Mexico; B: municipality of Donato Guerra, State of Mexico, Mexico.

become larger and easier to observe. Once the damaged area has been identified, management methods can be developed and control measures can be applied to the centers of aggregation where the pest is found, thus avoiding widespread applications or total coverage. This represents a saving in inputs by visualizing the infestation hotspots through the maps generated.

In the case of the *Ja* index, the lowest value was recorded in the municipality of Coatepec Harinas, corresponding to plot one, in the month of December (1.06); the highest value was recorded in plot three, in February (1.24). For the municipality of Donato Guerra, the lowest value was recorded in plot seven, in December (1.05), and the highest value in plot five, in October (1.24) (Table 1). For the present study, the *Ja* index also recorded values above the unit, which corroborates that the spatial distribution is aggregated (Perry, 1998). Rivera-Martínez *et al.* (2022), in their study, indicate that the values of the *Ja* index are between 1.07 and 1.25, with values significantly greater than one in all

**Table 1.** Value of the indices Ia and Ja and their respective probabilities Pa and Qa, of the damage caused by the mite Oligonychus punicae in the municipalities of Coatepec Harinas (plots 1, 2, 3, and 4) and Donato Guerra (plots 5, 6, 7, and 8) in State of Mexico, Mexico.

| Plot | Date | Variance | Density average | Min | Max | $I_a$ | $P_a$ | $J_a$ | $Q_a$ |
|---|---|---|---|---|---|---|---|---|---|
| 1 | October 2021 | 0.015 | 1.37 | 1.10 | 1.56 | 1.27 | 0.017s | 1.11 | 0.137ns |
| | November 2021 | 0.027 | 1.60 | 1.20 | 1.95 | 1.45 | 0.009s | 1.20 | 0.211ns |
| | December 2021 | 0.021 | 1.38 | 1.00 | 1.72 | 1.36 | 0.014s | 1.06 | 0.238ns |
| | January 2022 | 0.044 | 1.02 | 0.50 | 1.58 | 1.58 | 0.006s | 1.15 | 0.267ns |
| | February 2022 | 0.047 | 1.26 | 0.68 | 1.80 | 1.42 | 0.015s | 1.18 | 0.149ns |
| | March 2022 | 0.064 | 1.67 | 0.97 | 2.13 | 1.66 | 0.008s | 1.23 | 0.249ns |
| | Abril 2022 | 0.063 | 2.14 | 1.53 | 2.67 | 1.26 | 0.002s | 1.20 | 0.195ns |
| | May 2022 | 0.062 | 2.44 | 1.77 | 2.96 | 1.53 | 0.004s | 1.09 | 0.230ns |
| 2 | October 2021 | 0.037 | 1.11 | 0.80 | 1.42 | 1.64 | 0.005s | 1.16 | 0.161ns |
| | November 2021 | 0.042 | 1.30 | 0.94 | 1.60 | 1.32 | 0.012s | 1.17 | 0.280ns |
| | December 2021 | 0.045 | 1.45 | 1.09 | 1.80 | 1.57 | 0.003s | 1.13 | 0.257ns |
| | January 2022 | 0.054 | 1.18 | 1.92 | 0.79 | 1.48 | 0.010s | 1.22 | 0.182ns |
| | February 2022 | 0.063 | 1.53 | 1.17 | 2.33 | 1.71 | 0.013s | 1.08 | 0.296ns |
| | March 2022 | 0.065 | 1.86 | 2.33 | 1.47 | 1.69 | 0.011s | 1.11 | 0.289ns |
| | Abril 2022 | 0.085 | 2.21 | 1.68 | 2.97 | 1.28 | 0.016s | 1.15 | 0.223ns |
| | May 2022 | 0.082 | 2.40 | 1.93 | 2.97 | 1.39 | 0.006s | 1.19 | 0.139ns |
| 3 | October 2022 | 0.010 | 1.63 | 1.42 | 1.85 | 1.73 | 0.003s | 1.07 | 0.185ns |
| | November 2022 | 0.016 | 1.75 | 1.47 | 2.03 | 1.31 | 0.012s | 1.12 | 0.290ns |
| | December 2022 | 0.022 | 1.22 | 0.97 | 1.80 | 1.75 | 0.013s | 1.21 | 0.201ns |
| | January 2022 | 0.056 | 0.88 | 0.50 | 1.45 | 1.51 | 0.015s | 1.15 | 0.172ns |
| | February 2022 | 0.064 | 1.14 | 0.65 | 1.73 | 1.62 | 0.010s | 1.24 | 0.150ns |
| | March 2022 | 0.073 | 1.62 | 1.12 | 2.21 | 1.70 | 0.009s | 1.11 | 0.273ns |
| | Abril 2022 | 0.090 | 2.17 | 1.63 | 2.85 | 1.78 | 0.007s | 1.21 | 0.179ns |
| | May 2022 | 0.103 | 2.50 | 1.73 | 2.97 | 1.68 | 0.011s | 1.09 | 0.244ns |
| 4 | October 2022 | 0.024 | 1.08 | 0.80 | 1.32 | 1.47 | 0.004s | 1.16 | 0.144ns |
| | November 2022 | 0.013 | 1.73 | 1.47 | 2.00 | 1.35 | 0.014s | 1.10 | 0.293ns |
| | December 2022 | 0.043 | 1.31 | 1.03 | 1.80 | 1.40 | 0.004s | 1.13 | 0.188ns |
| | January 2022 | 0.054 | 1.12 | 0.75 | 1.72 | 1.55 | 0.011s | 1.22 | 0.252ns |
| | February 2022 | 0.073 | 1.43 | 1.00 | 2.22 | 1.29 | 0.011s | 1.07 | 0.262ns |
| | March 2022 | 0.080 | 1.85 | 1.33 | 2.57 | 1.49 | 0.007s | 1.14 | 0.283ns |
| | April 2022 | 0.087 | 2.18 | 1.50 | 2.63 | 1.44 | 0.005s | 1.17 | 0.225ns |
| | May 2022 | 0.097 | 2.35 | 1.73 | 2.98 | 1.38 | 0.008s | 1.10 | 0.153ns |
| 5 | October 2021 | 0.029 | 0.96 | 0.64 | 1.29 | 1.51 | 0.004s | 1.24 | 0.216ns |
| | November 2021 | 0.088 | 1.17 | 0.70 | 1.84 | 1.30 | 0.008s | 1.14 | 0.292ns |
| | December 2021 | 0.064 | 0.72 | 0.41 | 1.30 | 1.64 | 0.011s | 1.10 | 0.183ns |
| | January 2022 | 0.080 | 0.78 | 0.49 | 1.58 | 1.59 | 0.014s | 1.16 | 0.248ns |
| | February 2022 | 0.100 | 1.21 | 0.73 | 2.12 | 1.32 | 0.003s | 1.07 | 0.233ns |
| | March 2022 | 0.097 | 1.59 | 0.90 | 2.39 | 1.71 | 0.007s | 1.13 | 0.173ns |
| | April 2022 | 0.084 | 2.07 | 1.13 | 2.66 | 1.78 | 0.012s | 1.20 | 0.259ns |
| | May 2022 | 0.078 | 2.29 | 1.52 | 2.87 | 1.62 | 0.010s | 1.12 | 0.196ns |

**Table 1.** Continue

| Plot | Date | Variance | Density average | Min | Max | $I_a$ | $P_a$ | $J_a$ | $Q_a$ |
|---|---|---|---|---|---|---|---|---|---|
| 6 | October 2021 | 0.050 | 1.30 | 0.92 | 1.77 | 1.40 | 0.002s | 1.18 | 0.273ns |
| | November 2021 | 0.075 | 1.45 | 0.93 | 1.97 | 1.37 | 0.017s | 1.11 | 0.180ns |
| | December 2021 | 0.150 | 1.29 | 0.52 | 1.85 | 1.68 | 0.016s | 1.13 | 0.284ns |
| | January 2022 | 0.090 | 1.01 | 0.54 | 1.55 | 1.46 | 0.015s | 1.09 | 0.266ns |
| | February 2022 | 0.108 | 1.29 | 0.73 | 1.97 | 1.74 | 0.013s | 1.19 | 0.208ns |
| | March 2022 | 0.099 | 1.61 | 0.89 | 2.28 | 1.35 | 0.012s | 1.17 | 0.290ns |
| | April 2022 | 0.130 | 1.91 | 1.19 | 2.68 | 1.49 | 0.007s | 1.11 | 0.281ns |
| | May 2022 | 0.128 | 2.27 | 1.40 | 2.94 | 1.43 | 0.009s | 1.15 | 0.190ns |
| 7 | October 2021 | 0.045 | 1.20 | 0.98 | 1.62 | 1.51 | 0.010s | 1.19 | 0.295ns |
| | November 2021 | 0.051 | 1.40 | 1.05 | 1.80 | 1.70 | 0.004s | 1.20 | 0.270ns |
| | December 2021 | 0.048 | 1.20 | 0.85 | 1.60 | 1.56 | 0.015s | 1.05 | 0.211ns |
| | January 2022 | 0.050 | 0.81 | 0.40 | 1.20 | 1.50 | 0.013s | 1.08 | 0.175ns |
| | February 2022 | 0.080 | 1.25 | 0.65 | 1.83 | 1.75 | 0.016s | 1.21 | 0.204ns |
| | March 2022 | 0.103 | 2.06 | 1.39 | 2.86 | 1.67 | 0.010s | 1.14 | 0.225ns |
| | April 2022 | 0.120 | 2.38 | 1.69 | 3.18 | 1.34 | 0.005s | 1.11 | 0.292ns |
| | May 2022 | 0.086 | 2.68 | 1.97 | 3.07 | 1.73 | 0.015s | 1.18 | 0.240ns |
| 8 | October 2021 | 0.012 | 1.47 | 1.22 | 1.65 | 1.61 | 0.011s | 1.10 | 0.200ns |
| | November 2021 | 0.024 | 1.67 | 1.36 | 2.16 | 1.41 | 0.003s | 1.07 | 0.286ns |
| | December 2021 | 0.016 | 1.38 | 1.07 | 1.87 | 1.55 | 0.009s | 1.16 | 0.251ns |
| | January 2022 | 0.030 | 1.58 | 1.18 | 2.04 | 1.29 | 0.014s | 1.06 | 0.185ns |
| | February 2022 | 0.031 | 1.35 | 1.01 | 1.78 | 1.69 | 0.008s | 1.17 | 0.277ns |
| | March 2022 | 0.035 | 1.66 | 1.22 | 2.14 | 1.31 | 0.012s | 1.09 | 0.227ns |
| | April 2022 | 0.045 | 2.11 | 1.60 | 2.63 | 1.44 | 0.006s | 1.12 | 0.177ns |
| | May 2022 | 0.043 | 2.20 | 1.69 | 2.71 | 1.38 | 0.010s | 1.07 | 0.262ns |

ns: not significant ($p < 0.05$); s: significant ($p < 0.05$).

samples. Similarly, Maldonado-Zamora *et al*. (2017) found Ja index values significantly greater than one.

Using the SADIE methodology, it is possible to determine the spatial behavior of other organisms, as shown by Klick *et al.* (2016) in their study of the spatial distribution and activity of *Drosophila suzukii* Matsumura on raspberry grown in Oregon, USA. On the other hand, the spatial distribution of leaf damage caused by *O. punicae* in avocado orchards in the studied municipalities indicates that this mite is spatially distributed in the form of aggregation centers at specific geographical points within the plots. These results are in agreement with Baek and Lee (2021), who found that populations of *Ricania shantungensis* Chou & Lu at each stage of development have a spatial distribution in aggregates, except in the nymphal stage.

This technique has also been used in other work with phytosanitary problems. Such is the case of the study by Nita *et al.* (2012) with the spatial pattern of *Phomopsis* leaf and cane spot symptoms in vineyards in Ohio, USA, in which spatial patterns of incidence were established, determining that the aggregation index was significantly less than one in 78 and 98 % of the cases of diseased leaves and internodes, respectively. Results based on SADIE indicated an aggregate of disease on an individual scale for most vineyards.

## Map preparation

The spatial distribution maps of leaf damage caused by *O. punicae* show the behavior in aggregates, as it can be clearly distinguished visually how the damage is spatially distributed in the avocado plots at the time of sampling (Figures 2 and 3). The maps were made with different colors in order to see the spatial behavior of the damage. Red indicates the highest percentage of damage caused by *O. punicae* in each case, and white indicates the absence of damage. It should be noted that the colors orange and yellow were also used, indicating the gradual transition from white to red.

In the case of plot one, from the maps of the area with damage by *O. punicae* in Coatepec Harinas (Figure 2), it can be seen that there is a similar tendency in the months of October, November, and December, since the distribution of the centers of aggregation or foci of damage are distributed in the central part, with a tendency towards the edges (left and right). For the months of January, February, March, and April, the centers of aggregation are concentrated in the central part, with a tendency towards the borders in the four cardinal points. Finally, for May, the trend in spatial distribution is more homogeneous.

This type of behavior was also observed with the cotton boll weevil (*Anthonomus grandis* Boheman), where the spatial distribution is according to the prevailing climatic variables, with adult densities increasing at the end of the dry season and decreasing at the end of the rainy season in cotton fields (Oliveira *et al*., 2022). Likewise, Rijal *et al.* (2016) indicate that the spatial distribution of *Tetranychus urticae* C.L. Koch on mint was concentrated in certain areas during most of the growing season, as the aggregation distribution pattern becomes more or less stable.

Analysis of spatial variation using the ordinary Krigeing method has used in other works on phytosanitary problems. Such is the case of the study of the intensity and distribution of grapevine wood diseases using geostatistical techniques and spatial analysis, where a map was obtained with the pattern of evolution of the syndrome, as well as its intensity, showing that there were areas with more than 8 % of affected vines (Casadomet-Cercas *et al*., 2015).

On the other hand, with the use of infestation maps, it is possible to visualize the spatial behavior of the damage caused by *O. punicae* in comparison to the physical space in the plot, allowing producers to carry out targeted management of the pest, including both corrective and preventive actions based on the level of infestation in deferred times. Crop characteristics vary in space and time, so these types of maps help to optimize the use of agricultural inputs, depending on the potential and requirements of each area.

Density maps generated through the Krigeing technique are used in precision agriculture, as they determine areas in need of management. It is therefore important

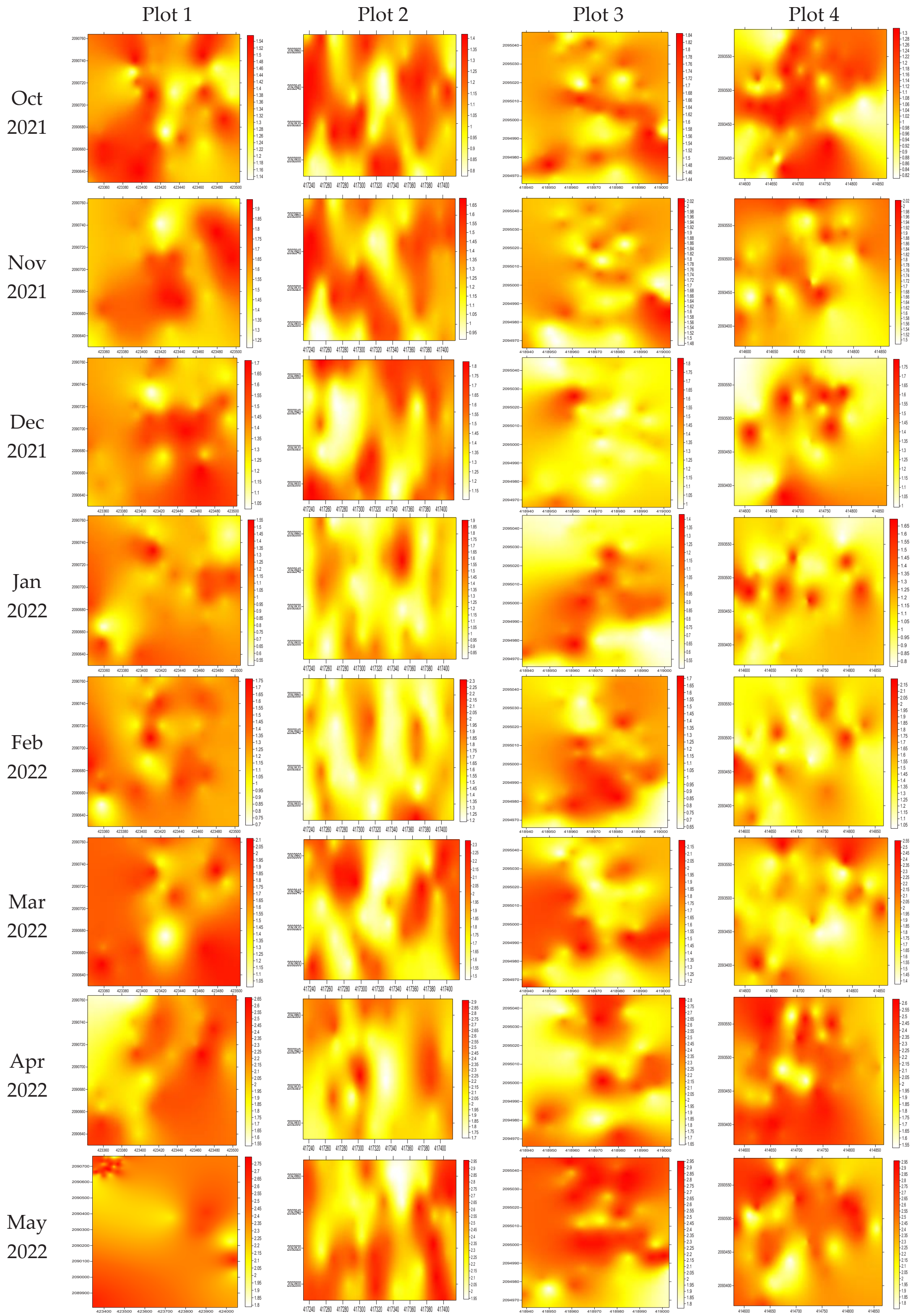


**Figure 2.** Damage maps caused by *Oligonychus punicae* in the avocado crop (*Persea americana* Mill.), from October 2021 to May 2022, in plots in the municipality of Coatepec Harinas. Red tones indicate a higher percentage of damage, white tones indicate no damage.

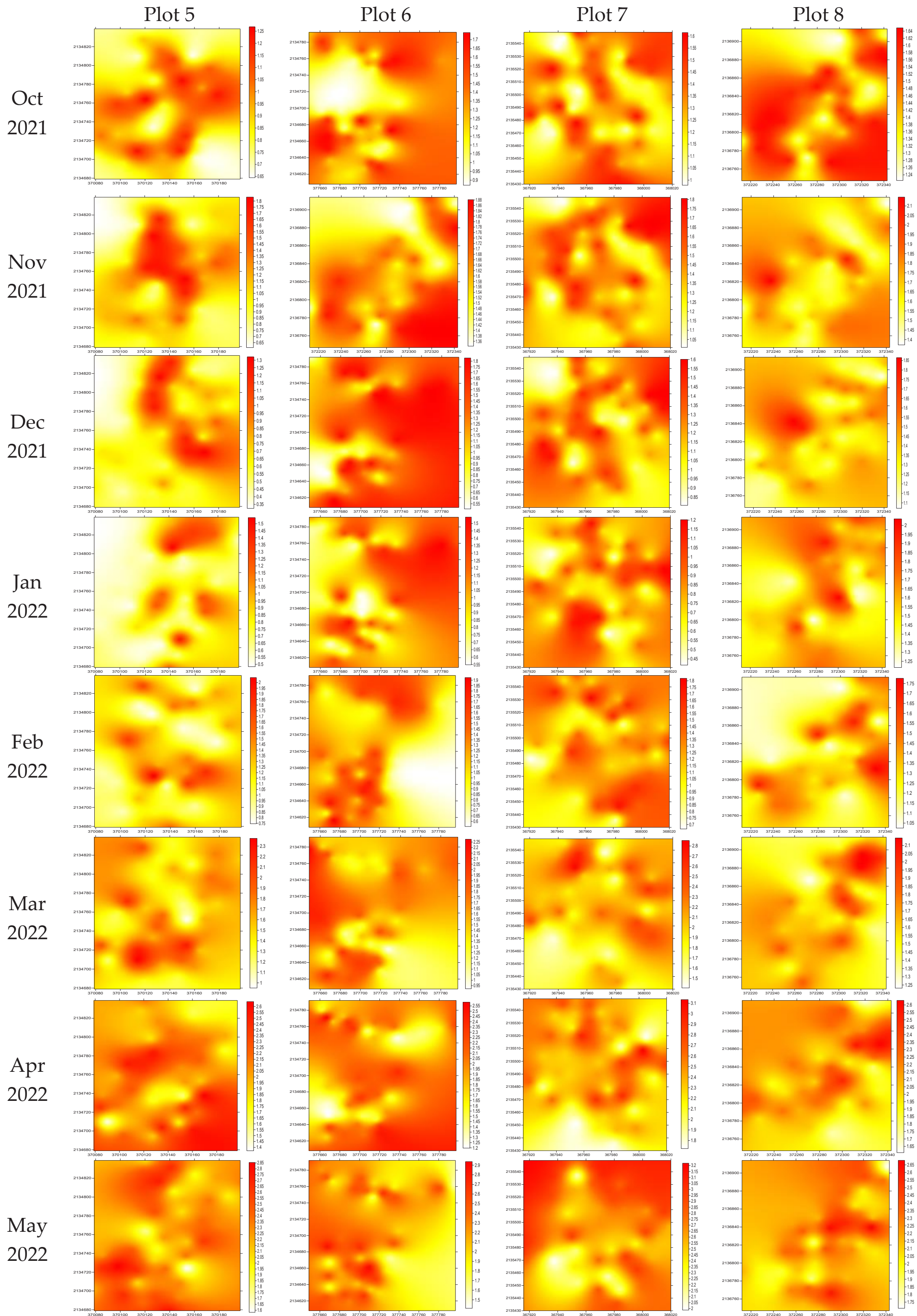


**Figure 3.** Damage maps caused by *Oligonychus punicae* in the avocado crop (*Persea americana* Mill.), from October 2021 to May 2022, in plots in the municipality of Donato Guerra. Red tones indicate a higher percentage of damage, white tones indicate no damage.

that sampling is random and that a determined percentage of the total area is considered. To elucidate stocking density, it is important to sample well before choosing and implementing a feasible management practice. Knowledge of the spatial distribution, ecology, and genetics of any pest population can increase our understanding of species dynamics and accelerate population management in the field (Kabir *et al*., 2018).
The maps obtained in the present study show that leaf damage caused by *O. punicae* was not 100 % distributed in the study plots, i.e., the distribution is not uniform, as each plot varies according to abiotic and biotic conditions. In the case of the municipality of Coatepec Harinas, the sampling that had the highest percentage of damage was when data was taken from plot three in April (96 %), while the plot with the least damage was plot two in February (67 %) (Table 2). This aggregate type of damage behavior suggests that infestation reduction can be achieved by focusing management strategies on specific points or infestation foci where the aggregation points are located, given that the spatial distribution does not behave homogeneously within plots.

**Table 2.** Area with damage (%) caused by *Oligonychus punicae* in the study plots in the municipalities Coatepec Harinas (Plots 1, 2, 3, and 4) and Donato Guerra (Plots 5, 6, 7, and 8) in State of Mexico, Mexico.

| Date | Coatepec Harinas | | | | Donato Guerrero | | | |
|---|---|---|---|---|---|---|---|---|
| | P1 | P2 | P3 | P4 | P5 | P6 | P7 | P8 |
| October 2021 | 80 | 81 | 79 | 88 | 77 | 77 | 87 | 86 |
| November 2021 | 94 | 77 | 90 | 92 | 81 | 81 | 88 | 91 |
| December 2021 | 92 | 72 | 82 | 81 | 88 | 88 | 86 | 92 |
| January 2022 | 87 | 78 | 76 | 90 | 86 | 82 | 89 | 90 |
| February 2022 | 95 | 67 | 89 | 88 | 75 | 74 | 90 | 84 |
| March 2022 | 91 | 70 | 92 | 86 | 95 | 95 | 87 | 93 |
| April 2022 | 90 | 80 | 96 | 91 | 79 | 86 | 81 | 96 |
| May 2022 | 89 | 82 | 91 | 89 | 94 | 94 | 88 | 97 |

These results are in agreement with Gireesh *et al.* (2021) in their study of the spatial distribution of hunting weevils (Coleoptera: Curculionidae) on grass farms, where larvae feed within the grass stem and roots. This insect is controlled with insecticides; however, their application to entire grass fields is not an economical and practically feasible option, and a sampling plan is justified to improve management decisions. On the other hand, Duarte *et al.* (2015) indicate that insect populations, like mite populations, are distributed heterogeneously in space and time, occurring in pockets of high and low populations. Studying the spatial variability of arthropod populations and their fluctuations provides information, improving their efficiency and reducing the impact of unnecessary control measures in problem areas.

It is necessary to analyze the climatic factors based on their importance for the presence of *O. punicae.* In the epidemiological triangle, according to Mora-Aguilera *et al.* (2021), three factors must coexist: the susceptible host (in this case, the avocado plant), the aggressive pest (the mite), and favorable conditions, which are all the abiotic factors that favor the development of the pest (soil, management, variety, climate). Oliveira *et al.* (2021) indicate that *O. punicae* feeds on avocado leaves, causing an imbalance in the plant's water transpiration system resulting in water stress, affecting the photosynthetic process, and reducing carbohydrate accumulation, especially during certain seasons of the year. In this regard, Huanes-Carranza and Wilson-Krugg (2016) indicate that it is critical to seek alternative methods to reduce the use of agrochemicals because they are highly toxic, have long-term environmental effects, induce resistance, and eliminate native controllers.

## CONCLUSIONS

With the use of spatial analysis by distance indices (SADIE), it can be inferred that the spatial pattern of damage generated by *Oligonychus punicae* on avocado (*Persea americana* Mill.) leaves is distributed in several aggregation centers by visualizing the density maps generated through the Krigeing technique. By knowing the spatial distribution of the damage, it is possible to plan targeted control measures of the mite, which can generate economic savings and mitigate the environmental impact of chemical use.

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