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When Numbers Mean Money: Pest Precision Sampling in High-Density Mango Crops

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ABSTRACT

The development of sampling plans is essential for assertive decision-making in integrated pest management programs. The present study aimed to develop a plan for monitoring major mango pests in high-density mango crops in Brazil. For this purpose, the influence of the position of the branch to be sampled in the canopy (internal and external) and the ideal number of plants to be evaluated per area were assessed. Regarding the position, the number of insects in the plants' first and second vegetative flush was surveyed. To define the number of points per area, 12, 16, 20, 24, 28 and 32 plants/ha were evaluated. The studies were conducted in a commercial mango production area in the Submiddle São Francisco Valley, northeast Brazil. An area of 3 ha was used for the experiment, with high-density cultivation of the 'Palmer' variety. The second vegetative flush showed a higher incidence of scale insects and thrips in the first harvest, whereas no difference was observed in the second. According to the sampling plan developed, there was no variation in the population of thrips and scale insects between 12 and 32 plants/ha. Considering the cost, 12 plants/ha of high-density mango crops should be sampled based on the second vegetative flush of the plant for scale insects and thrips.

1 | Introduction

Pest monitoring is essential for initiating an Integrated Pest Management (IPM) program (Böckmann and Meyhöfer 2017). Sampling plans offer a systematic approach for monitoring pest populations, assessing infestation severity and informing intervention decisions based on established economic thresholds (Castle and Naranjo 2009). By selecting appropriate sampling units and techniques, these plans ensure precision and representativeness in pest density estimates, allowing for rapid and reliable decision-making that prevents unnecessary pesticide applications and reduces labor and costs (Liu et al. 2022; Neves et al. 2023). The sampling plans must accurately reflect the pest field population (Mota et al. 2022). Nonetheless, it is essential to be practical and low-cost to facilitate the adoption by the farmers (da Silva Lima et al. 2025). Integrating sampling plans into IPM supports the sustainable application of selective control tactics and improves pest management effectiveness by supplying actionable data to practitioners. This approach contributes to increased crop yields and minimises environmental impact (Shaw and Razaq, 2021; Pinto et al. 2023).

Research in pest monitoring has evolved in different areas, focusing on reducing labor costs and improving efficiency. In this regard, studies have been conducted on remote sensing technologies adapted to unmanned aerial vehicles (UAVs) (Abd El-Ghany et al. 2020; Rhodes et al. 2022). Automated traps are another method that, with the advantage of artificial intelligence, is evolving in identifying and counting insects (Preti et al. 2021; Popescu et al. 2023; Zhang et al. 2023). The SmartProtect Platform showcases 37 technologies from companies that are available for insect monitoring, using methods such as remote sensing and automated traps (SmartProtect Platform 2025). However, data concerning these methods are still unavailable for many pest species. Additionally, the high cost can be a barrier to adoption for many growers (Lost Filho et al. 2019; Preti et al. 2021), and traditional pest monitoring methods may still be the most cost-effective for many producers.

Optimising how to define these monitoring practices is fundamental. An effective way to improve them is to combine the analysis of collected data with statistical methods and Machine Learning (ML). This combination increases accuracy compared to isolated statistical methods (Durgabai et al. 2018; Santana et al. 2022), allowing for the precise use of large volumes of data (Choi et al. 2023) and the efficient analysis of non-normal data, identifying effects that could be missed with traditional statistical methods (Mulungu et al. 2024). Thus, ML minimises irregularities and makes the results more reliable for decision-making in pest management.

Mangoes are one of the major tropical fruits produced worldwide, and Brazil is among the top producers (FAOSTAT 2025). Fruit flies, thrips and scale insects are key pests in Brazilian mango crops (de Oliveira et al. 2011; da Costa-Lima et al. 2022; Baronio et al. 2023). Fruit flies have a well-defined monitoring system using traps (Kouloussis et al. 2022); however, other pests require direct evaluations on the plant. Several certifying standards Brazilian mango farms adopt require pest monitoring, such as GLOBALG.A.P (GLOBALGAP 2024). The last studies with recommendations for mango pest sampling plans in Brazilian conditions were completed 20 years ago (Menezes and Barbosa 2005). During this period, mango cultivation management underwent modifications, such as increasing the number of plants per hectare to 10 times (Lima et al. 2021). High-density planting in fruit crops alters the microclimate, resulting in increased humidity, lower temperature and reduced light intensity, which can favour certain pest species (Ladaniya et al. 2019) and facilitate pest movement. In Brazilian mango orchards, a gain in the importance of scale insects was observed in these conditions (da Costa-Lima et al. 2022, 2024). Thus, the present study aimed to evaluate a sampling plan for mango pests in high-density crops. The ideal number of sampling points per hectare, the influence of the vegetative flush to be sampled and the associated costs of pest monitoring were determined.

2 | Material and Methods

2.1 | Research Location and Crop Management

The research was conducted in a commercial mango orchard located in Curaçá, Bahia, Brazil (latitude 9°2′22.50″ S and longitude 39°56′16.01″ W). A 3-ha area of the 'Palmer' variety was used for the study. The spacing between plants was 2.5 m, and 6 m between rows, totaling 24 rows, each with 83 plants. The same cultural practices, weed control, irrigation and nutritional management were adopted throughout the area. The drip irrigation method was used, with two drip hoses per row. Most weeds were composed of *Momordica charantia* L. and *Commelina virginica* L. These plants were controlled using mowers, desiccant (saflufenacil) and pre-emergent (indaziflam) herbicides. The area was fertilised based on soil and leaf analyses, production estimates and soil fertility balance. Fertilisation was applied weekly via fertigation from the beginning of fruiting until the first fruit harvest. Pest control was also standardised. A 10% control level was established for scale insects and thrips, and control measures were implemented using synthetic, biological and botanical insecticides. For thrips, products with the following active ingredients were used: spinetoram (250 g/kg), bifenthrin (100 g/L), acetamiprid (186 g/L), pyriproxyfen (124 g/L) and orange peel oil (61.14 g/L). For scale insect control, the following were used: abamectin (18 g/L), neem oil (850 g/L), orange peel oil (61.14 g/L), acetamiprid (186 g/L), pyriproxyfen (124 g/L) and *Beauveria bassiana* (36 g/L).

2.2 | Number of Plants Per Area for Pest Sampling

The ideal number of plants per area for sampling thrips and scale insects was evaluated with six treatments: 12, 16, 20, 24, 28 and 32 per hectare. The experiment was conducted in blocks with 333 plants each, corresponding to 0.5 ha of the experimental area and totaling six blocks. The experiment was repeated in two harvests: (i) September 2021 to February 2022 and (ii) September 2022 to February 2023. Monitoring was conducted weekly for 6 months, covering the phases of floral induction, flowering, fruiting, fruit development and harvest. Pest sampling was conducted using a zig-zag walking pattern adapted to cover an area of 0.5 ha (Menezes and Barbosa 2005). During the experiments, two pest groups prevailed: thrips and insect scales; other species occurred sporadically and were not included in the analysis.

The last recommendation for pest monitoring in Brazilian mango orchards was to divide the plants into quadrants (Menezes and Barbosa 2005). However, with high-density crops featuring contiguous canopies, the evaluation was conducted by dividing the plant into two parts. Two random branches were sampled on each side, one from the second vegetative flush (external part of the canopy, 5602 ± 255 lx mean) and one from the first vegetative flush (internal part of the canopy, 3500 ± 168 lx mean) (Figure 1). The samples were obtained from the plant canopy at heights ranging from 1.5 to 2.0 m. Three taps were made on the vegetative structure on white trays (40 × 60 cm), following the insect count for thrips sampling. The presence of scale insects was visually assessed, and their number was recorded. Samples of thrips and scale insects were collected throughout the experiments. The thrips were identified by Dr. Élison F. B. Lima (UFPI), the Coccidae and Pseudococcidae by Dr. Ana Lúcia B. G. Peronti (UFSCAR) and the Diaspididae by Dr. Vera R. S. Wolff (FEPAGRO).

The time taken to monitor thrips and scale insects for each treatment was measured to evaluate the cost of sampling. Likewise, the time taken by the farm's monitoring program was based on Menezes and Barbosa (2005), with 10 plants per hectare and sampling in four quadrants. The worker's hourly rate was calculated based on the annual labor cost of a rural employee in the region under study. The value for each treatment monitoring

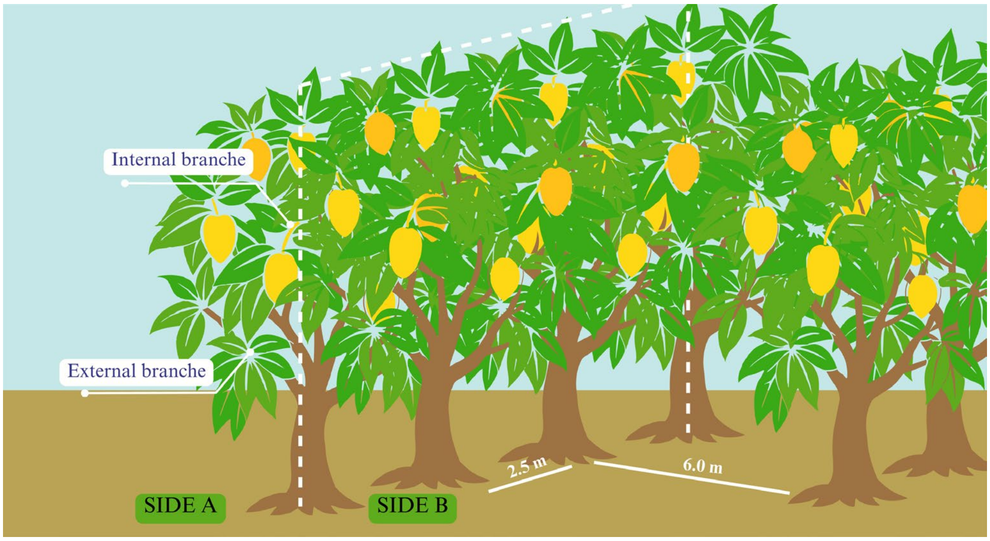

FIGURE 1 | Representation of the mango plant division in a high-density crop, in which the two branches (internal and external) were sampled from each side. [Colour figure can be viewed at wileyonlinelibrary.com]

and the farm's method was calculated using time evaluation and labor costs.

2.3 | Data Analysis

The abundance of data on thrips and scale insects in each treatment was analysed using a supervised machine learning (ML) model with a binomial distribution to categorise data as either absent or present. A confusion matrix was used to estimate the accuracy of predicting the population of thrips and scale insects based on the number of samples. The R confusionMatrix function (R Core Team 2024) computes a cross-tabulation of observed and predicted classes, along with associated statistics such as sensitivity, specificity, positive predictive value, overall accuracy and the Kappa statistic. The overall accuracy rate was calculated, along with a 95% confidence interval for this rate (using the binom.test function) and a one-tailed test to determine if the accuracy exceeded the 'no information rate', which is the most significant percentage of a class in the data. We used Accuracy and Kappa as evaluation metrics because they are traditional metrics in machine learning modelling. While accuracy tends to favour imbalanced data by inflating performance for the majority class, Kappa works against this bias. However, Kappa's bias is far weaker, making it a more balanced and reliable metric for evaluating models, especially in scenarios where class imbalance is a concern (Burkov 2019).

To count data, we used the negative binomial distribution. This distribution was adopted due to the overdispersion in the insect count data, which was detected through multiple regression analysis. Considering that the dependent variable is discrete and non-negative quantitative, a log-linear regression of the count data was adopted. To ensure the inferences of the adopted model were appropriate, a decision-making process was conducted using estimates from both a Poisson model and a Negative Binomial model. For the present data set, the detection of overdispersion in the dependent variable was conditioned on the explanatory variable, namely, the number of samples. This detection was performed using the overdisp function (Cameron and Trivedi 2020) from R (R Core Team 2024), which provides a fast and reliable solution for detecting overdispersion in count data. The overdisp function checked the generalised linear models for overdispersion by returning an approximate estimate of an overdispersion parameter. The insect occurrence data from the vegetative structures sampled from the first and second vegetative flushes were contrasted. The F-test of the deviance analysis for the generalised linear model with a negative binomial distribution and a log link function was used (Appendix S1).

3 | Results

The following species of scale insects collected in the study were identified: *Aonidiella comperei* (McKenzie), *Pseudischnaspis bowreyi* (Cockerell), *Ceroplastes stellifer* (Westwood) and *Ferrisia* sp., with the following percentages: 65%, 31%, 3% and 2%, respectively. For thrips, the species *Frankliniella brevicaulis* (Hood), *Frankliniella gardeniae* (Moulton) and *Frankliniella schultzei* (Trybom) were identified, with percentages of 94.44%, 3.03% and 2.53%, respectively. Considering the practical applicability for monitoring, the species of scale insects and thrips were grouped for statistical purposes.

A difference was observed when evaluating the occurrence of scale insects sampled from the first and second vegetative flush in the 2022 harvest ($p = 6.626e-14$). The incidence was higher in the second flush, with an average of 1.54, as opposed to the 0.74 observed in the first flush. In the 2023 harvest, no significant difference was found ($p = 0.1419$) (Table 1).

In the 2022 harvest, thrips were more prevalent in the branches from the second vegetative flush ($p = 0.04378$). However, in the following harvest, the pest's occurrence in the canopy parts of the plants did not differ ($p = 0.1413$) (Table 2).

For scale insects, there was no difference in the two monitoring seasons (2022 and 2023) in the number of samples ($X^2 = 0.5909$

TABLE 1 | Average occurrence (standard error) of the scale insect population concerning the location of the first and second mango vegetative flush.

	Vegetative flush		
Harvest	**First**	**Second**	***p***
2022	0.74 (0.06)	1.54 (0.10)	$6.626e^{-14}$
2023	2.65 (0.18)	2.29 (0.17)	0.1419

TABLE 2 | Average occurrence (standard error) of the thrips population concerning the location of the first and second mango vegetative flush.

	Vegetative flush		
Harvest	**First**	**Second**	***p***
2022	5.48 (0.44)	7.36 (0.57)	0.04378
2023	3.83 (0.44)	5.24 (0.58)	0.1413

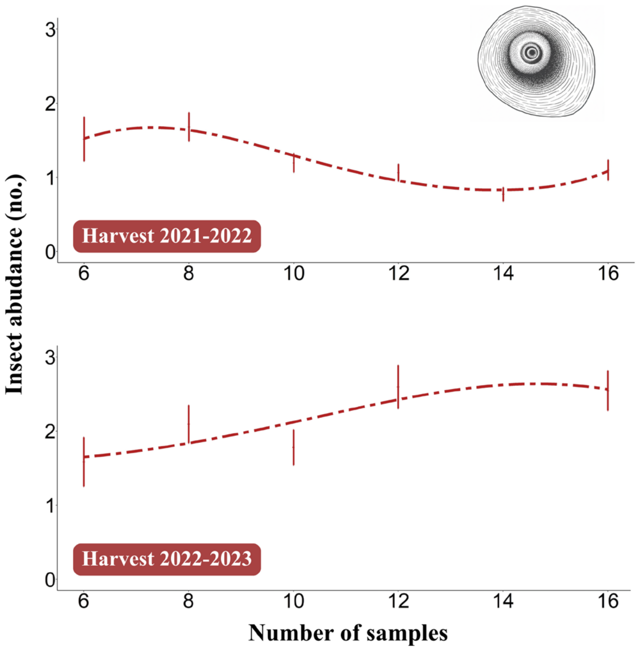

FIGURE 2 | Fluctuation in the number of scale insects as a function of the number of mango plants sampled, in two periods (September 2021–February 2022; September 2022–February 2023), Curaçá, Bahia, Brazil. [Colour figure can be viewed at wileyonlinelibrary.com]

and $X^2 = 0.4561$, respectively). Population fluctuations can be observed in Figure 2. Despite the oscillation of the curves as a function of the number of plants sampled, they present similarity according to the overlap of their confidence intervals (Figure 2).

The model's accuracy for the number of samples in predicting the population of scale insects was evaluated using accuracy metrics, including Kappa and *p*-value (Table 3). Observing accuracy values above 78%, predominantly moderate Kappa values (0.41–0.57), except the value of the plant sample (0.38) (Figure 3), classified as reasonable and highly significant *p*-values ($p < 0.0001$).

TABLE 3 | Model accuracy metrics for scale insects sampling in mango crop.

Samples *n*°/ha	Accuracy (AIC)	Kappa	*p* [Acc > NIR]
12	0.81 (0.76–0.86)	0.56	$9.986e^{-06}$
16	0.79 (0.74–0.83)	0.53	$4.342e^{-12}$
20	0.80 (0.76–0.84)	0.57	$1.989e^{-13}$
24	0.78 (0.74–0.82)	0.46	0.0004314
28	0.80 (0.77–0.83)	0.41	0.007072
32	0.81 (0.78–0.84)	0.38	$1.958e^{-05}$

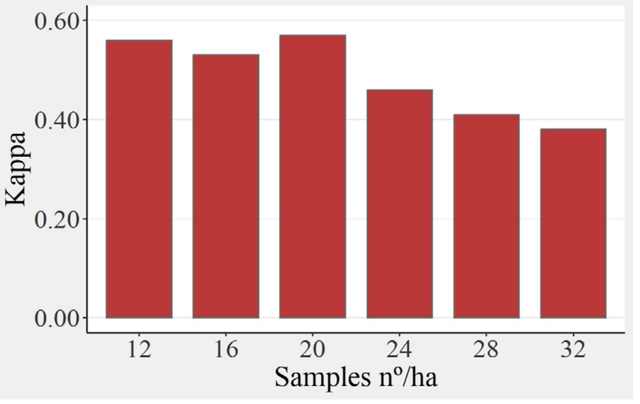

FIGURE 3 | Kappa metric versus number of samples per hectare for predicting the population of scale insects in mango crop. [Colour figure can be viewed at wileyonlinelibrary.com]

For thrips, no difference was observed between the 2022 and 2023 harvests in terms of the number of samples ($X^2 = 0.0637$ and $X^2 = 0.5614$, respectively). Despite the variation in the number of insects among the samples, these values were similar according to the overlap of their confidence intervals (Figure 4).

Accuracy metrics, Kappa and *p*-value were also used to evaluate the accuracy of the number of samples in predicting the thrips population (Table 4), with high reliability being observed according to accuracy values above 90%, almost perfect agreement according to Kappa values (above 80%) (Figure 5), and *p*-values < 0.0001 indicating high accuracy of the model.

The time and cost to perform monitoring between the minimum and maximum number of plants per hectare were 26.5 min (US$ 1.12) and 58.5 min (US$ 2.48) (Table 5).

4 | Discussion

Scale insects and thrips were prevalent in both the mango crop evaluated cycles. The increasing importance of Diaspididae

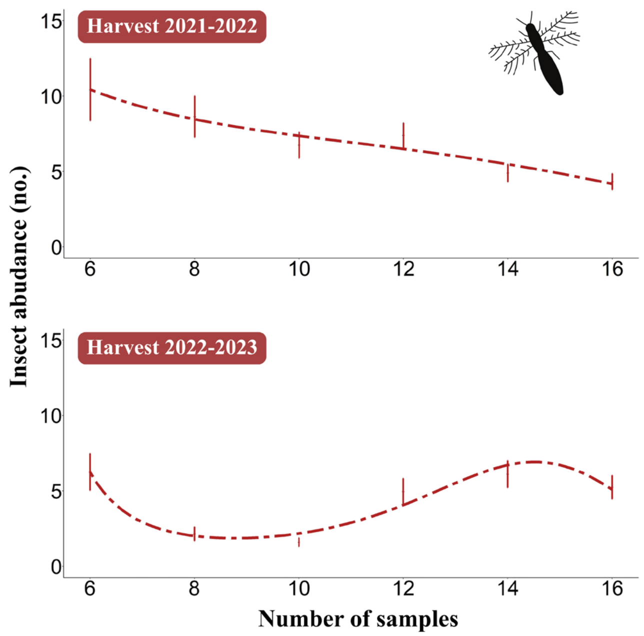

FIGURE 4 | Fluctuation in the number of thrips as a function of the number of mango plants sampled, in two periods (September 2021–February 2022; September 2022–February 2023), Curaçá, Bahia, Brazil. [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 4 | Model accuracy metrics for thrips sampling in mango crop.

Samples n°/ha	Accuracy (AIC)	Kappa	*p* [Acc > NIR]
12	0.97 (0.94–0.98)	0.92	$2e^{-16}$
16	0.96 (0.93–0.98)	0.91	$2.2e^{-16}$
20	0.95 (0.93–0.97)	0.89	$2e^{-16}$
24	0.96 (0.93–0.97)	0.89	$2e^{-16}$
28	0.95 (0.93–0.96)	0.87	$2e^{-16}$
32	0.93 (0.91–0.94)	0.78	$2e^{-16}$

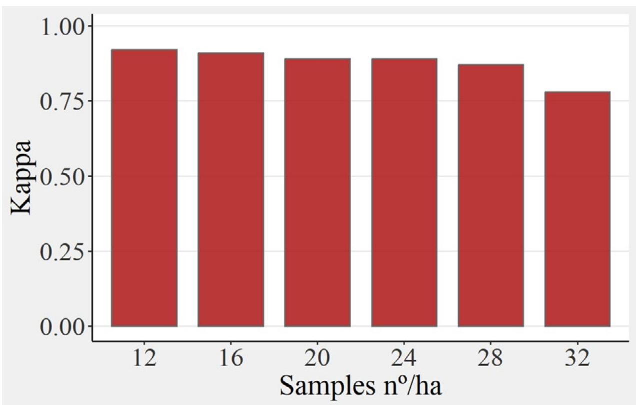

FIGURE 5 | Kappa metric versus number of samples per hectare for predicting the population of scale insects in mango crop. [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 5 | Total time for monitoring scale insects and thrips with different numbers of plants per hectare, the value related to labor for each treatment in high-density mango crops and the cost savings compared to the farm standard, Curaçá, BA, Brazil.[a]

Plants/ha	Time (min)	Labor value/ha (US$)	Cost savings/ ha (US$)
12	26.5 ± 1.70	1.12	1.13
16	39.0 ± 1.91	1.65	0.60
20	44.0 ± 2.71	1.86	0.39
24	48.0 ± 1.41	2.03	0.22
28	56.0 ± 3.56	2.37	—
32	58.5 ± 2.63	2.48	—
10* (Farm standard)	53.21 ± 3.22	2.25	—

[a]The plants were evaluated with two branches from each quadrant on the farm standard. In the other treatments, the plants were divided into two sides, sampling two branches per side.

species in mango has been recently reported, including the two predominant species sampled in the study, *A. comperei* and *P. bowreyi* (da Costa-Lima et al. 2022, 2024). For thrips, *F. brevicaulis* has already been reported in Brazilian mango crops, with a higher incidence during the flowering stage (de Oliveira et al. 2011).

The present study allowed the development of a sampling plan based on a supervised ML model for mango IPM use. This study used this model because it is considered a viable and robust alternative (Athey et al. 2019; Athey and Wager 2021) compared to other traditional statistical tools. It mainly facilitates analyses that deviate from normality, thereby avoiding irregular results obtained through analysis or algorithms (Kusrini et al. 2020; Mulungu et al. 2024). The first step in updating the pest sampling plan for high-density mango crops was to observe whether the incidence of insects varied between the interior and external parts of the plant canopy. The results showed a higher incidence of scale insects and thrips on the outer side of the canopy in the first harvest, with no difference observed in the second. The higher rainfall may have influenced this variation in the 2022 harvest, which could have resulted in more shoots and, consequently, more available resources for the pests. Thus, the need for migrations between parts of the plants could be reduced (de Toledo et al. 2006; Haviland et al. 2012). For thrips, a higher occurrence was observed for *Frankiliniella occidentalis* (Trybom) on grapevines in areas with more sunlight than in shaded areas (Allsopp 2010). In coffee crops, reduced infestations of scale insects were detected under shaded areas (Karungi et al. 2015). Possibly, the greater abundance of natural enemies in shaded areas, such as spiders, ants and predatory beetles, could, in part, explain the lower occurrence of pests (Perfecto et al. 1996; Armbrecht and Gallego 2007; Guenat et al. 2019). Generalist predators such as spiders and lacewings have already been reported in Brazilian mango crops (Barbosa et al. 2005). Microclimatic factors may also influence the observed difference in pest occurrence in the present study. Higher shaded areas can alter microclimatic conditions, affecting performance and survival of pests, as well as the effectiveness of natural enemies (Gontijo 2019; Guenat et al. 2019). Thus, light incidence may play a significant role in the higher incidence of pests observed in the second mango vegetative flush compared to the internal branches. The present results were obtained with 'Palmer' mango, the major cultivar planted in Brazil (Embrapa, 2025); however, similar findings are expected in other cultivars, such as 'Tommy Atkins', 'Kent' and 'Keit'.

The results demonstrated that a 12 to 32 plants/ha variation in high-density mango crops did not differ in the thrips and scale insect population inference. Thus, considering quick execution is important for a pest sampling plan, the treatment with a minimal number of plants can be recommended (da Silva Lima et al. 2025). Currently, the pest sampling guideline for mango producers in Brazil is 10 plants/ha, which divides the plant into quadrants totaling 40 points/ha (Menezes and Barbosa 2005). Two points per plant were sampled in the current study for high-density crops. Thus, in the most effective treatment (12 plants/ha), 24 points were evaluated, resulting in a 40% reduction from the current practice. The time spent completing the pest monitoring was decreased by 50.2%, resulting in savings of US$ 1.13/ha. All actions taken to control thrips and scale insects, including the use of products, mechanisation and labor, represent a cost of approximately US$ 875 per hectare. Therefore, 13.88% of the total value of a harvest in commercial orchards in Brazil is being directed to control these two insect groups. The cost of monitoring obtained in the current study represents 0.13% compared to the control cost. Thus, this demonstrates the importance and economic viability of monitoring, considering the high cost allocated to control. Additionally, the sampling plan is easy to learn and can be executed at all phenological stages, thereby increasing farmers' chances of adoption (Gonring et al. 2020).

The data used to develop the sampling plan were primarily based on two diaspidid and one thrips species, which are insect groups not separated during pest monitoring due to their small size. However, depending on the demand to monitor specific species, the sampling plan can also be adapted. Our findings will help mango producers implement a more accurate pest sampling plan guiding their control decisions. This study represents a significant advance in developing pest management strategies and promoting the sustainability of mango production.

5 | Conclusions

To monitor thrips and scale insects in Brazilian high-density mango crops, it is recommended that 12 plants/ha be sampled based on two branches of the plant's second vegetative flush. Further studies are stimulated, considering other variabilities that could be evaluated, such as different climatic conditions, pest species, cultivars and geographical regions.

Author Contributions

Elvis Prudêncio de Araújo Pereira was involved in conceptualisation, methodology, formal analysis, visualisation, writing – original draft, writing – review and editing and investigation. Rita de Cássia Rodrigues Gonçalves Gervásio was involved in supervision, writing – review and editing and methodology. José Bruno Malaquias was involved in conceptualization, methodology, writing – review and editing, data curation, formal analysis and software. Angélica da Silva Salustinowas involved in formal analysis and writing – review and editing. Tiago Cardoso da Costa-Lima was involved in conceptualisation, supervision, methodology, formal analysis, visualisation and writing – review and editing.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are openly available in Figshare at https://doi.org/10.6084/m9.figshare.28817195.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Appendix S1:** jen70042-sup-0001-AppendixS1.R.