Examining the Spatial Distribution of Flower Thrips in Southern Highbush Blueberries by Utilizing Geostatistical Methods

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Environ. Entomol. 40(4): 893–903 (2011); DOI: 10.1603/EN10312

ABSTRACT Flower thrips (*Frankliniella* spp.) are one of the key pests of southern highbush blueberries (*Vaccinium corymbosum* L. x *V. darrowii* Camp), a high-value crop in Florida. Thrips' feeding and oviposition injury to flowers can result in fruit scarring that renders the fruit unmarketable. Flower thrips often form areas of high population, termed "hot spots", in blueberry plantings. The objective of this study was to model thrips spatial distribution patterns with geostatistical techniques. Semivariogram models were used to determine optimum trap spacing and two commonly used interpolation methods, inverse distance weighting (IDW) and ordinary kriging (OK), were compared for their ability to model thrips spatial patterns. The experimental design consisted of a grid of 100 white sticky traps spaced at 15.24-m and 7.61-m intervals in 2008 and 2009, respectively. Thirty additional traps were placed randomly throughout the sampling area to collect information on distances shorter than the grid spacing. The semivariogram analysis indicated that, in most cases, spacing traps at least 28.8 m apart would result in spatially independent samples. Also, the 7.61-m grid spacing captured more of the thrips spatial variability than the 15.24-m grid spacing. IDW and OK produced maps with similar accuracy in both years, which indicates that thrips spatial distribution patterns, including "hot spots," can be modeled using either interpolation method. Future studies can use this information to determine if the formation of "hot spots" can be predicted using flower density, temperature, and other environmental factors. If so, this development would allow growers to spot treat the "hot spots" rather than their entire field.

KEY WORDS *Frankliniella bispinosa*, *Vaccinium corymbosum* x *V. darrowi*, semivariogram, inverse distance weighting, kriging

Southern highbush blueberries (SHB) (*Vaccinium darrowii* Camp) are an important high-value crop in Florida. During 2009, 6.4 million kg of fresh market blueberries were harvested from 1,295 ha in Florida at an average of $11.89 per kg (USDA 2010). Flower thrips are one of the key pests of SHB blueberries and *Frankliniella bispinosa* (Morgan), the Florida flower thrips, is the dominant species found (England et al. 2007). Flower thrips feed on and reproduce in all flower tissues. They injure the flower tissues while feeding and laying their eggs. When the ovaries of the flowers develop into fruit, this injury can become magnified and appear as scars on fruit tissue that renders the fruit unmarketable (Liburd and Arévalo 2005).

In SHB blueberries thrips are monitored using sticky traps or by directly sampling the flowers (Liburd and Arévalo 2005, Liburd et al. 2009). Arévalo and Liburd (2007) found a strong correlation (r = 0.76) between thrips per flower and thrips per trap in rabbiteye blueberries (*Vaccinium vergatum* Aiton). Rodriguez-Saona et al. (2010) found that sticky trap data were useful for predicting the flight activity of thrips and monitoring for the timing of insecticide applications. Although there is no significant difference in numbers of flower thrips caught on white and blue traps in Florida blueberries (Chu et al. 2006, Liburd et al. 2009), white traps are the best to employ because the dark coloring of the blue traps can make it difficult to see the thrips that are present on them (England et al. 2007).

Flower thrips have a highly clumped distribution and tend to form small areas of high population termed "hot spots" (Arévalo and Liburd 2007). If these "hot spots" can be modeled and predicted, insecticide applications could specifically target these spots instead of the entire field.

With the advent of geostatistics into the world of insect ecology, the spatial relationships of insect populations now can be studied in much greater depth than was possible with previous techniques (Liebhold et al. 1993). The cornerstone of geostatistics is called the variogram or semivariogram (Webster and Oliver 2001). A semivariogram plots the semivariance, one-half of the average squared difference between data values at the same separation distance, on the y-axis and the specified distance between sample pairs, the

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0046-225X/11/0893–0903$04.00/0

lag, on the x-axis (Wright et al. 2002). Because it is very difficult to fit a model to a semivariogram where each individual semivariance is plotted, the semivariance is averaged for each of several lags (Webster and Oliver 2001). The important features of semivariograms are the sill, range, and nugget. The sill is the value of the semivariance when it stops increasing, which indicates the variability in the data. The higher the sill value is, the greater the variability in the data. The range is the distance at which spatial independence is reached. The nugget value is the semivariance value at lag 0 and is a combination of measurement error and variation over distances less than the shortest lag distance sampled for all continuous variables (Webster and Oliver 2001).

Semivariograms have been used to examine and describe the spatial relationship of several corn pests, including western corn rootworm (*Diabrotica virgifera virgifera* LeConte) adults on yellow sticky traps in corn (*Zea mays* L.) (Midgarden et al. 1993), corn rootworm injury to corn (Park and Tollefson 2005), and European corn borer [*Ostrinia nubilalis* (Hübner)] larvae and their damage in whorl stage corn (Wright et al. 2002). Semivariograms also have been used to examine and describe the spatial relationships of three species of *Xylella fastidiosa* (Wells) sharpshooter vectors on citrus (Farias et al. 2003) and of *Lygus hesperus* (Knight) in lentils (*Lens culinaris* Medikus) (Schotzko and O'Keeffe 1990). Florez and Corredor (2000) also used semivariogram analysis, along with other geostatistical analyses, to examine the spatial dependence of *F. occidentalis* in a covered strawberry (*Fragaria* spp.) crop at Bogota plateau. Spatial dependence was found in three of 12 sampling weeks. They found that although thrips colonies were aggregated at first, over time the pattern changed toward a random pattern. This change was caused by thrips movement to neighboring quadrants.

Kriging is a method that allows researchers to estimate the continuous properties of abiotic or biotic factors in the environment from a finite number of sampled points (Webster and Oliver 2001). Ordinary kriging (OK) is the most common kriging method used in most applications (Webster and Oliver 2001). In OK, the overall mean of the population is assumed to be unknown. OK uses a weighted average to estimate unknown values based upon the semivariogram model. Using the semivariogram model, the weights are allocated to the sample points so that the kriging variance is minimized (Webster and Oliver 2001). Hao et al. (2006) created kriged maps of *Apocheima cineraius* Erschoff egg, larval, and adult distribution that agreed well with measured distribution patterns.

Another commonly used interpolation technique is inverse distance weighting (IDW). In IDW, a set of samples that are a given distance away from the unknown point are used to interpolate the value at that point. IDW is, in effect, a weighted average that weights sample points closer to the unknown point higher than those points farther away (Ess and Morgan 2003). Reay-Jones et al. (2010) used IDW to create distribution maps of several stink bug populations, including the green stink bug [*Nezara viridula* (L.)], the brown stink bug [*Euschistis servus* (Say)], and the southern green stink bug [*Acrosternum hilare* (Say)], in cotton. Cross-validation indicated that the maps gave an accurate representation of stink bug distribution.

The objectives of this study were two-fold: 1) determine the best performing spatial interpolation method to model thrips population distributions, including "hot spots". For this objective, two common methods, IDW and OK, were compared. Our hypothesis was that if thrips variation can be modeled with semivariograms, OK will be the most accurate method in predicting thrips distribution patterns. However, if the thrips variation cannot be modeled well with semivariograms, IDW will be as accurate as, if not more accurate than, OK, and 2) optimum trap spacing was determined by calculating the range of the semivariogram, which is the distance where spatial independence is reached.

Materials and Methods

The experimental site consisted of 4- to 7-yr-old SHB blueberry plants spaced 1.5 m apart within the rows, with 2 m separating each row. Each row was planted with the same variety of SHB. However, multiple varieties are grown on the farm including 'Emerald', 'Jewel', 'Millennia', and 'Premadonna'. Vegetation adjacent to the farm, on the other side of the fences (Fig. 1), included a mixture of grasses and low growing herbaceous plants.

A 2-yr study was conducted to determine the best spatial interpolation method to model thrips "hot spots" in a commercial blueberry planting. In 2008, 100 white sticky traps (Great Lakes integrated pest management [IPM], Vestaburg, MI) were distributed throughout a 1.13-ha SHB blueberry planting in Inverness, FL. Traps were placed in a regular grid at 15.24-m increments (Fig. 1) and hung within the canopy, just below the upper-most branch (Liburd et al. 2009) An additional 30 traps were placed randomly throughout the plot to collect information on distances shorter than 15.24 m. Traps were collected and replaced weekly over a 3-wk period from 7 February 2008, when the first set of traps were placed in the field, to 28 February 2008, when the final set of traps were collected. Traps were transported to the Small Fruit and Vegetable Integrated Pest Management Laboratory at the University of Florida in Gainesville, FL, where the number of thrips per trap was counted and recorded with the aid of a dissecting microscope.

Trap locations were mapped using a Trimble GeoXT GPS receiver (Trimble, Sunnyvale, CA) in the World Geodetic System 1984 (WGS84) datum. The data then were imported into ArcMap 9.1 (ESRI 2005), a geographic information system (GIS), and projected into Albers Equal Area Conic projection with North American Datum 1983 (NAD 83). Local Moran's I analysis (Bolstad 2006) was done for the thrips per trap data from each week in ArcMap.

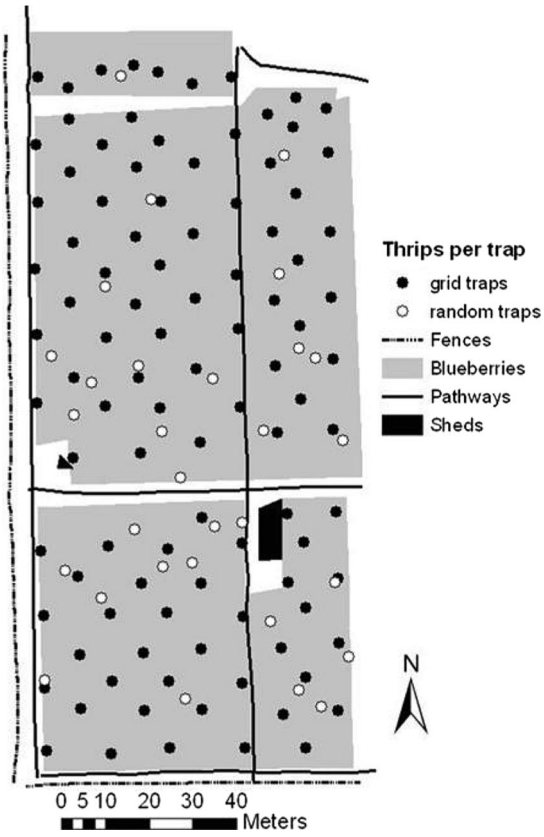

Fig. 1. GIS map of the study area in 2008.

IDW was computed in ArcMap 9.1. In IDW, the estimated value for the unknown point at location j, x_j, is calculated using the equation $\Sigma_i(x_i/d_{ij}^p)/\Sigma_i(1/d_{ij}^p)$, where d_{ij} is the distance between known point i and unknown point j, x_i is the value at known point i, and p is an exponent defined by the user that is commonly set equal to two (Bolstad 2006). In our IDW calculations, p was set at the default two and the search area was divided into four quadrants from which at least five data points per quadrant were included.

The semivariograms for the OK were constructed in the Space Time Information System (STIS) (Terraseer Inc. 2007), which uses the least squares method to fit semivariogram models. The semivariance is calculated using the equation

$$\hat{\gamma}(h) = \frac{1}{2m(h)} \sum_{i=1}^{m(h)} \{z(x_i) - z(x_i + h)\}^2,$$

where $\hat{\gamma}(h)$ is the semivariance at lag h, $m(h)$ is the number of data point pairs separated by lag h, and $z(x_i)$ and $z(x_i + h)$ are the data values separated by h (Webster and Oliver 2001). The lag spacing for each semivariogram was 5 m, which produced 23 lags in total. The semivariograms were then input into ArcMap for use in OK. In OK, the search area, with a radius equal to the range of the semivariogram, was divided into four quadrants from which at least one point per quadrant, up to five points in total, was used in the interpolation.

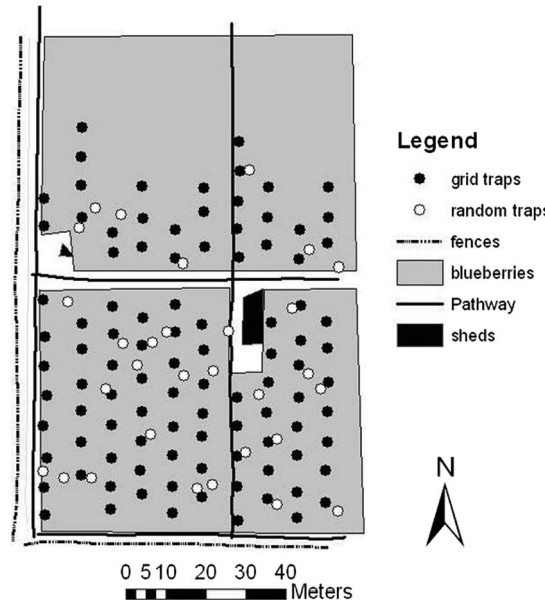

Fig. 2. GIS map of the study area in 2009.

Our 2009 experimental protocol was similar to the one used in 2008. One hundred white sticky traps were distributed throughout a 1-ha block of the same blueberry planting used in the previous year. However, traps were spaced closer together in a regular grid at 7.61-m increments (Fig. 2). A smaller area was used to identify finer scale spatial variability. An additional 30 traps were again placed randomly throughout the plot to collect information on distances shorter than 7.61-m. Traps were collected and replaced weekly over a 5-wk period on 30 January, and 5, 13, 20, and 26 February 2009. The number of thrips per trap was counted and recorded as discussed for 2008. The collected data were imported into ArcGIS in the same manner as described above.

The semivariograms for the OK were constructed in SGeMS (Remy 2007) by using the same lag spacing as in 2008 and then input into ArcMap for kriging. SGeMS was used because it is an open source software that is freely available, whereas STIS is a commercial software and our student license ran out after a year. Both SGeMS and STIS allow the same fitting of semivariograms for OK. It was necessary to normalize the data for semivariogram analysis by using a natural logarithmic transformation for all sample dates except 13 February 2009. The same interpolation settings as adopted for data collected in 2008 were used for data collected in 2009. ArcGIS was used to perform the kriging and automatically back-transforms the predicted data and provides cross-validation results.

Cross-validation, in ArcMap, was used to assess the accuracy of the predictions from both interpolation

Table 1. Summary data of thrips per trap for each sample date in 2008 and 2009

Year	Date	Mean	Min	Median	Max	Std. Dev.	SEM	Skewness coefficient	Kurtosis
2008	Feb. 14	277	8	195	1331	236	21	1.36	5.23
	Feb. 21	351	40	268	1895	303	27	2.3	10.01
	Feb. 28	179	10	158	1081	147	13	2.75	14.90
2009	Jan. 30	213	14	164	724	160	14	1.35	4.29
	Feb. 5	11	1	8	51	9	1	1.53	5.61
	Feb. 13	490	35	499	1173	225	20	0.22	2.97
	Feb. 20	571	37	512	2212	361	32	1.33	5.92
	Feb. 26	660	59	506	2184	469	41	1.27	4.11

SEM: Standard error of the mean.

methods in both years. In cross-validation, a sample point is excluded from the data set and the interpolation method is used to predict the value at this sampled point. This method is done for each sample point in the data set. Several error metrics were used to compare the measured and predicted values (Webster and Oliver 2001). ArcMap calculates the mean prediction error (ME) and root mean square error (RMSE) by using the equations $ME = [\sum_{i=1}^{n} (\hat{x}_i - x_i)/n]$, where $\hat{x}_i$ is the predicted value, x_i is the measured value, and n is the sample size (Johnston et al. 2004), and $RMSE = \sqrt{\sum_{i=1}^{n} (\hat{x}_i - x_i)^2/n}$, where x_i, $\hat{x}_i$, and n are as defined above (Bolstad 2006). The ideal model would have a ME of 0 and a RMSE equal to the square root of the interpolation variance (Webster and Oliver 2001). The residual prediction deviation (RPD) was calculated using the equation $\sigma_{val}/[RMSE\sqrt{n/(n-1)}]$, where σ_{val} is the standard deviation of the validation set, RMSE is the root mean square error of the validation as calculated above, and n is the sample size (Vasques et al. 2010). Higher RPDs indicate better accuracy. R^2 values were calculated using the equation

$$R^2 = \frac{\sum_{i=1}^{n} (\hat{x}_i - \bar{x})^2}{\sum_{i=1}^{n} (x_i - \bar{x})^2},$$

where x_i, $\hat{x}_i$, and n are as defined above and $\bar{x}$ is the mean of the measured values (Vasques et al. 2010).

Results

There were averages of 277 ± 21, 351 ± 27, and 179 ± 13 thrips per trap recorded on 14, 21, and 28 February, respectively (Table 1). On 14 February, local Moran's I analysis at $P \leq 0.05$ indicated three clusters of high values or "hotspots" and one outlier (Fig. 3). Two clusters of high values were found on 21 February along with one outlier that was in a different location than the outlier found the previous week. On 28 February, one cluster of high values was found. Local Moran's I did not detect any outliers on 28 February.

The semivariograms varied greatly among the weeks. The 14 February semivariogram was modeled with two Gaussian functions and had a very large nugget (29,444.49) and a large range (≈ 80 m). The nugget to sill ratio was also large at 0.59. The sill value was 66,873.71. The 21 February semivariogram was modeled with a cubic function and showed a distinct spatial trend with a small nugget (0.14), a sill value of 95,681.77, a very small nugget to sill ratio (0.0000015) and a range of 11.04 m. The 28 February semivariogram was modeled with an exponential function, had a small nugget of 0.002, a sill value of 25,354.82, a very small nugget to sill ratio (0.000000071), and a very short range of 2.51 m.

Locations of areas of high thrips population, "hot spots," are similar in the IDW and OK interpolations (Figs. 4 and 5) and generally are located where local Moran's I analysis indicated clusters of high values. On 14 February, one "hot spot" was distinguishable in the IDW map. It also was present in the OK map, but the estimated number of thrips was much smaller. On 21 February, three major "hot spots" had formed. The one present on 14 February still was present along with several other smaller "hot spots". However, the area of the "hot spots" was smaller in the IDW map. On 28 February, the remnants of the "hot spots" in the southern half of the field could be seen. The kriging map showed fewer thrips in these "hot spot" remnants compared with the IDW method. Inverse distance weighting and OK had very similar RMSEs, RPDs, and R^2 values on all three dates (Table 2), indicating that their accuracies were similar. However, IDW had a ME much closer to 0 than OK on 21 February indicating that IDW was more accurate on this date.

On 30 January, there was an average of 213 ± 14 thrips per trap (Table 1). The thrips population dropped to an average of 11 ± 1 on 5 February. The thrips population increased throughout the remaining weeks with an average of 490 ± 20, 571 ± 32, and 660 ± 41 recorded on 13, 20, and 26 February, respectively. The 30 January summary data were similar to the data found for all three weeks in 2008. Two clusters of high values, as indicated by local Moran's I analysis at $P \leq 0.05$, were found on 30 January (Fig. 6). Local Moran's I also showed a cluster of low values and four outliers on 30 January. All values on 5 February were low because very few thrips were caught on the traps during the preceding week. Local Moran's I showed three clusters of high values and three outliers on 5 February. The skewness coefficient and kurtosis were much smaller on 13 February. Three clusters of high

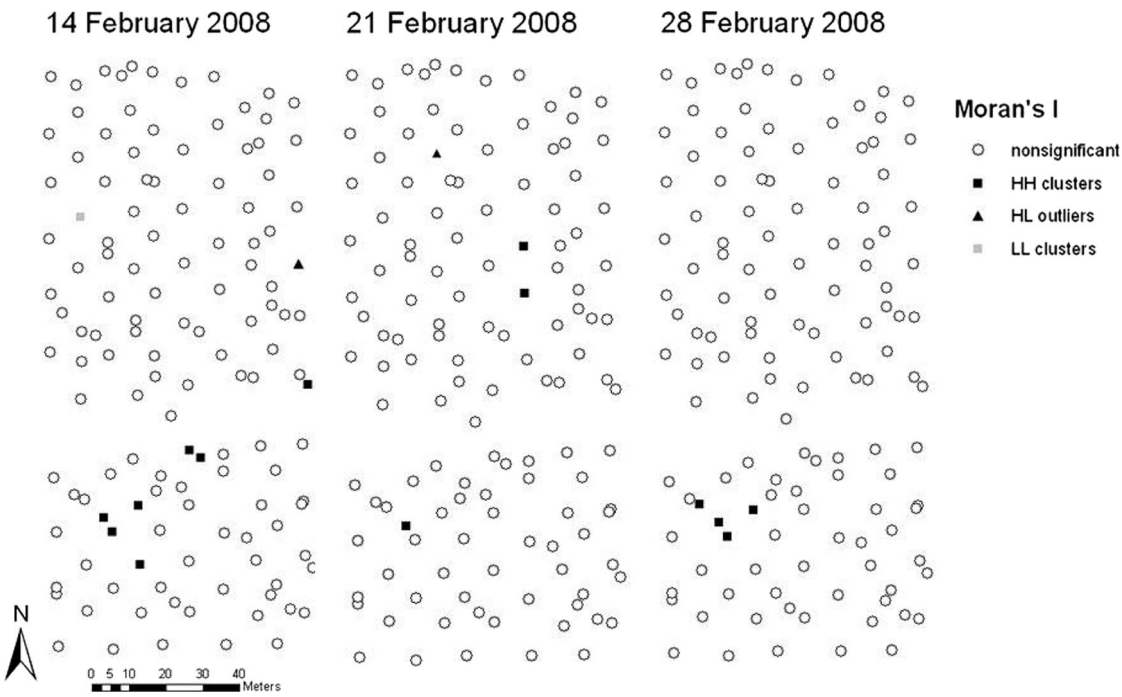

Fig. 3. Clusters and outliers indicated by local Moran's I analysis at $P \leq 0.05$ for 14 February 2008, 21 February 2008, and 28 February 2008. (HH = high value surrounded by high values, HL = high value surrounded by low values, LL = low value surrounded by low values).

values and one large cluster of low values were found on13 February. On 20 February, three clusters of high values were located close together and a cluster of low values and an outlier also were found. On 26 February, five clusters of high values, a cluster of low values, and an outlier were found.

The semivariograms varied among the weeks, but not as much as in 2008. The 30 January semivariogram

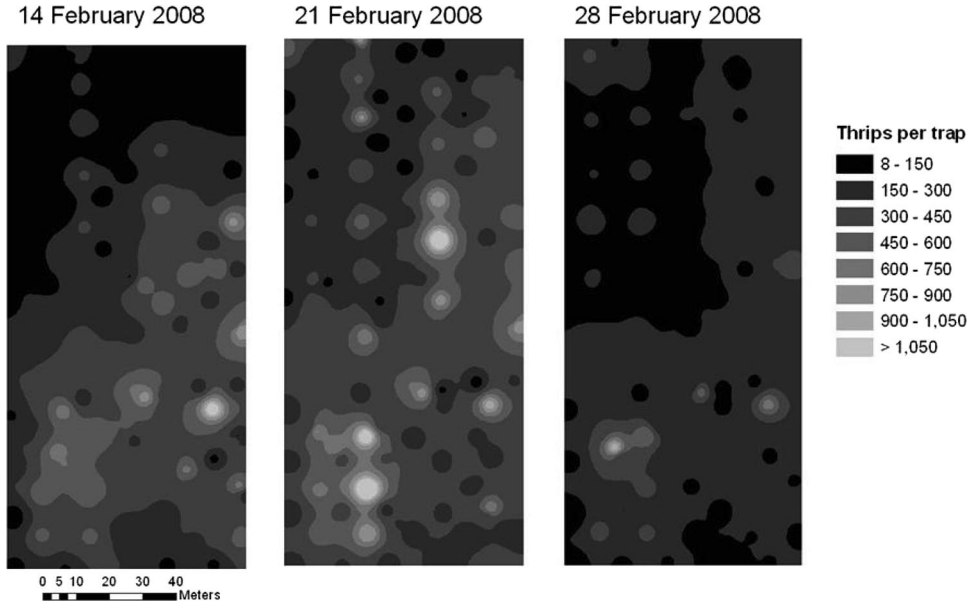

Fig. 4. Inverse distance weighting interpolation ($P = 2$, no. points = 20) of thrips per trap from 14 February 2008, 21 February 2008, and 28 February 2008.

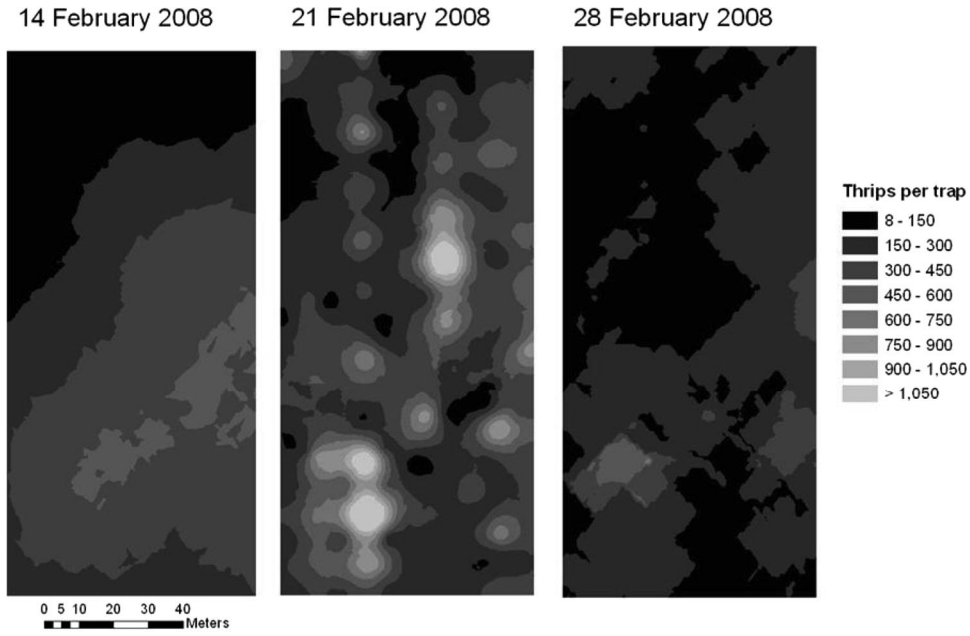

Fig. 5. Ordinary kriging interpolation of thrips per trap from 14 February 2008, 21 February 2008, and 28 February 2008.

was modeled with an exponential function, whereas the remaining four were modeled with spherical functions. The 30 January semivariogram had a fairly large nugget (0.25), a sill value of 0.90, a nugget to sill ratio of 0.28, and a range of 28.75 m. The 5 February semivariogram was mostly nugget with a nugget to sill ratio of 0.42 and a range of 22.50 m. Its nugget and sill values were 0.50 and 1.20, respectively. The 13 February semivariogram, the only data set that could be modeled without transformation, had a small nugget (9,000); a sill value of 53000; a nugget to sill ratio of 0.17; and a range of 17.50 m. The 20 February semivariogram was mostly nugget with a nugget to sill ratio of 0.42 and a range of 27.50 m. Its nugget and sill values were 0.30 and 0.71, respectively. The 26 February semivariogram had a very large nugget (0.30), with a sill value of 0.75, a nugget to sill ratio of 0.40, and a range of 23.75 m.

As in 2008, locations of "hot spots" are similar in both interpolation (Figs. 7 and 8) methods and are generally located where local Moran's I analysis indicated clusters of high values. On 30 January, several "hot spots" appeared to be developing. They are visible in both maps, but are less distinct and contain a smaller number of thrips in the OK map. On 5 February, the thrips population in the field had all but disappeared. The areas

Table 2. Several error metrics for thrips count predictions derived from inverse distance weighting (IDW) and ordinary kriging (OK) for each sample date in 2008

Year	Date	Interpolation method	Mean prediction error	Root mean square error	Residual prediction deviation	R^2
2008	Feb. 14	IDW	4.78	208.80	1.13	0.34
		OK	1.61	202.90	1.16	0.29
	Feb. 21	IDW	0.10	307.80	0.98	0.11
		OK	−7.11	331.80	0.91	0.37
	Feb. 28	IDW	5.13	147.20	0.99	0.20
		OK	4.49	151.60	0.97	0.26
2009	Jan. 30	IDW	1.17	164.70	0.97	0.13
		OK	3.28	157.90	1.01	0.18
	Feb. 5	IDW	−0.02	9.93	0.96	0.20
		OK	0.41	9.43	1.01	0.20
	Feb. 13	IDW	1.15	184.00	1.29	0.22
		OK	0.54	180.90	1.31	0.45
	Feb. 20	IDW	−2.69	367.50	1.00	0.30
		OK	20.16	342.10	1.08	0.28
	Feb. 26	IDW	0.30	476.40	1.01	0.24
		OK	16.61	442.80	1.08	0.26

The error metrics for all dates in 2009 except Feb. 13 were calculated using the back transformed data.

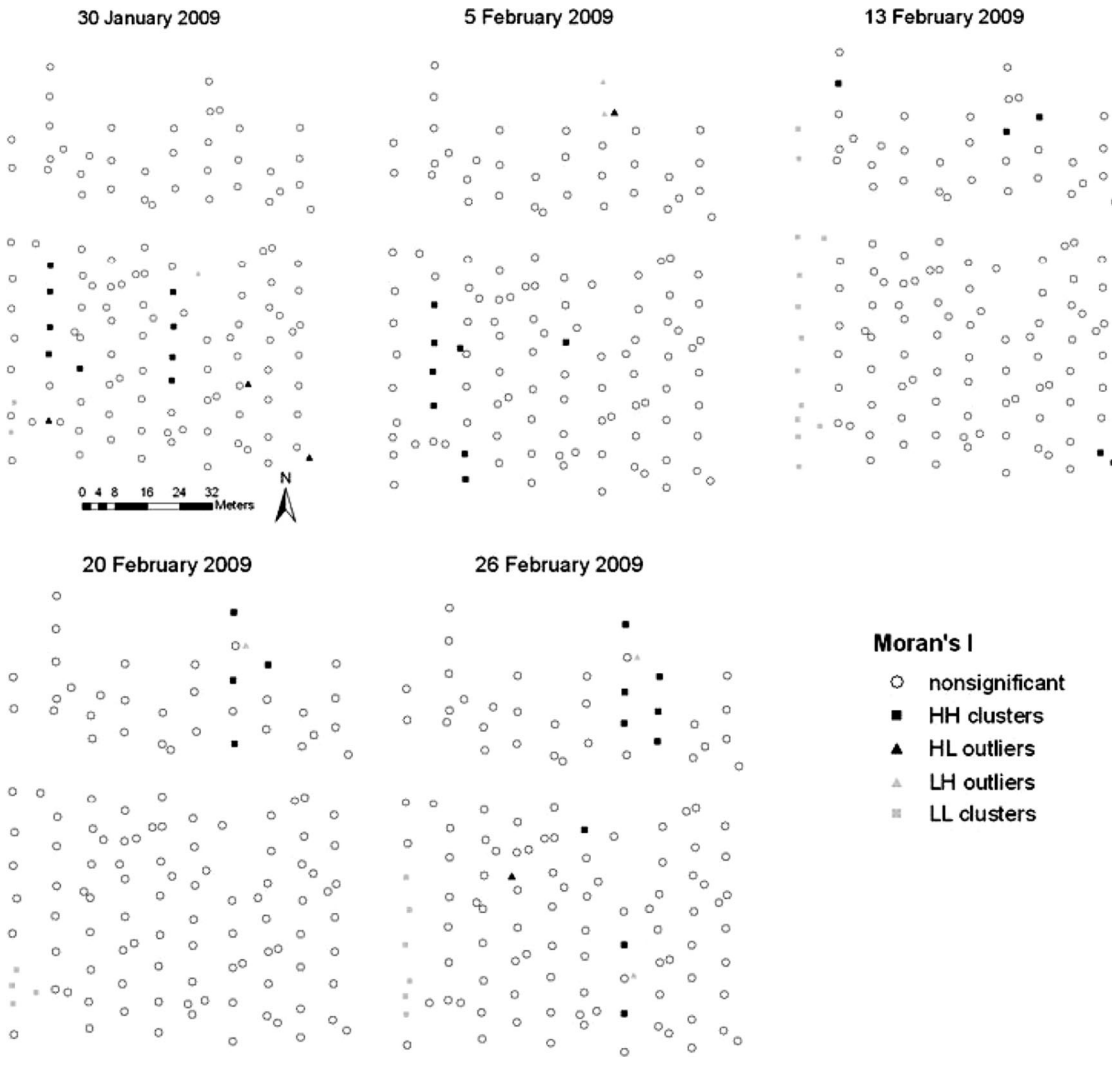

Fig. 6. Clusters and outliers indicated by local Moran's I analysis at $P \leq 0.05$ for 30 January 2009, 5 February 2009, 13 February 2009, 20 February 2009, and 26 February 2009. (HH = high value surrounded by high values, HL = high value surrounded by low values, LH = low value surrounded by high values, LL = low value surrounded by low values).

where the developing "hot spots" had been the previous week had <50 thrips per trap. The rest of the field had <15 thrips per trap. On 13 February, "hot spots" reappeared in the same areas where they had been developing on 30 January along with a new "hot spot" in the northeast area of the field. The "hot spots" were smaller in the IDW map compared with the OK map and contained fewer thrips. On 20 February, the "hot spot" in the northeast corner of the field had expanded in both maps and had continued to expand on 26 February. The expansion was much less pronounced in the IDW map for both weeks. On both sampling dates, many other, smaller "hot spots" were present in the IDW map, but not in the OK map because they were smoothed out. As in 2008, IDW and OK had very similar accuracies (Table 2). On 30 January, 5 February, 20 February, and 26 February, IDW was more accurate than OK. On 13 February, the reverse was true.

Discussion

To our knowledge, this is first study modeling thrips "hot spots" in a commercial blueberry planting by using geostatistical methods. Our findings indicate that the thrips distribution pattern is clumped, which is consistent with the findings of other researchers (Navas et al. 1994, Florez and Corredor 2000, Arévalo and Liburd 2007). Our results also indicate that both IDW and OK can be used to model thrips "hot spots" in a blueberry planting because both interpolation methods produced maps with equal accuracy during both years of our study.

The range of the semivariograms varied greatly in 2008 from 2.51 to 79.8 m. In 2009, the ranges of the semivariograms were much more consistent and varied from 17.5 to 28.8 m. These ranges fall within those commonly found for various species of adult insects

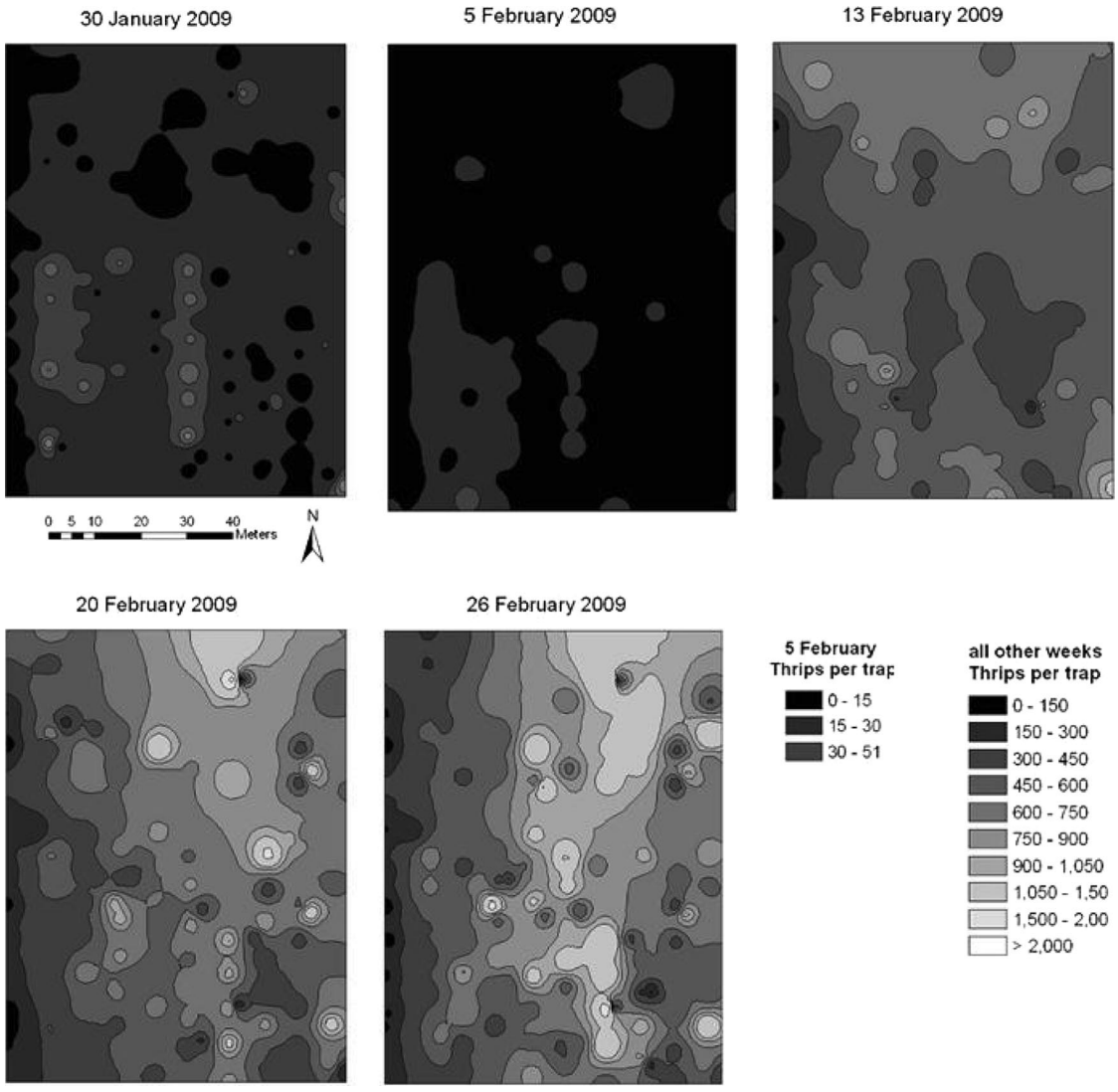

Fig. 7. Inverse distance weighting interpolation ($P = 2$, no. points = 20) of thrips per trap from 30 January 2009, 5 February 2009, 13 February 2009, 20 February 2009, and 26 February 2009.

(Qiang et al. 2003, Alves et al. 2006, Hao et al. 2006). The semivariogram with the range of 79.8 m (14 February 2008) had a high degree of error as indicated by the nugget to sill ratio of 0.59. In contrast, all of the other semivariograms had nugget to sill ratios ≤ 0.42. Therefore, it appears that spacing white sticky traps at least 28.8 m apart should result in independent sampling of flower thrips populations in most cases. This information is important for researchers because the independence of samples is an assumption for most statistical tests.

In 2008, the differences in thrips populations among the three weeks could be explained by the flowering stage of the blueberry plants. Arévalo and Liburd (2007) documented the close relationship between thrips numbers and blueberry flowering stage. Plants were approaching peak flowering during the week of 7–14 February. The thrips population also was increasing and "hot spots" were beginning to form. The plants were at peak flowering during the week of 14–21 February. The thrips population also reached its peak during this week. By 21 February, petal fall had begun and fruits were forming on some of the varieties. One week later, on 28 February, most of the plants contained developing fruit along with few remaining flowers and the thrips population had greatly diminished as well.

In 2009, both stage of flowering and temperature appeared to play major roles in explaining the difference in the thrips population among the weeks. The blueberry plants had reached ≈80% open flowers on 30 January. The thrips population was increasing and "hot spots" were beginning to form. Plants had reached peak flowering between 5 February and 13

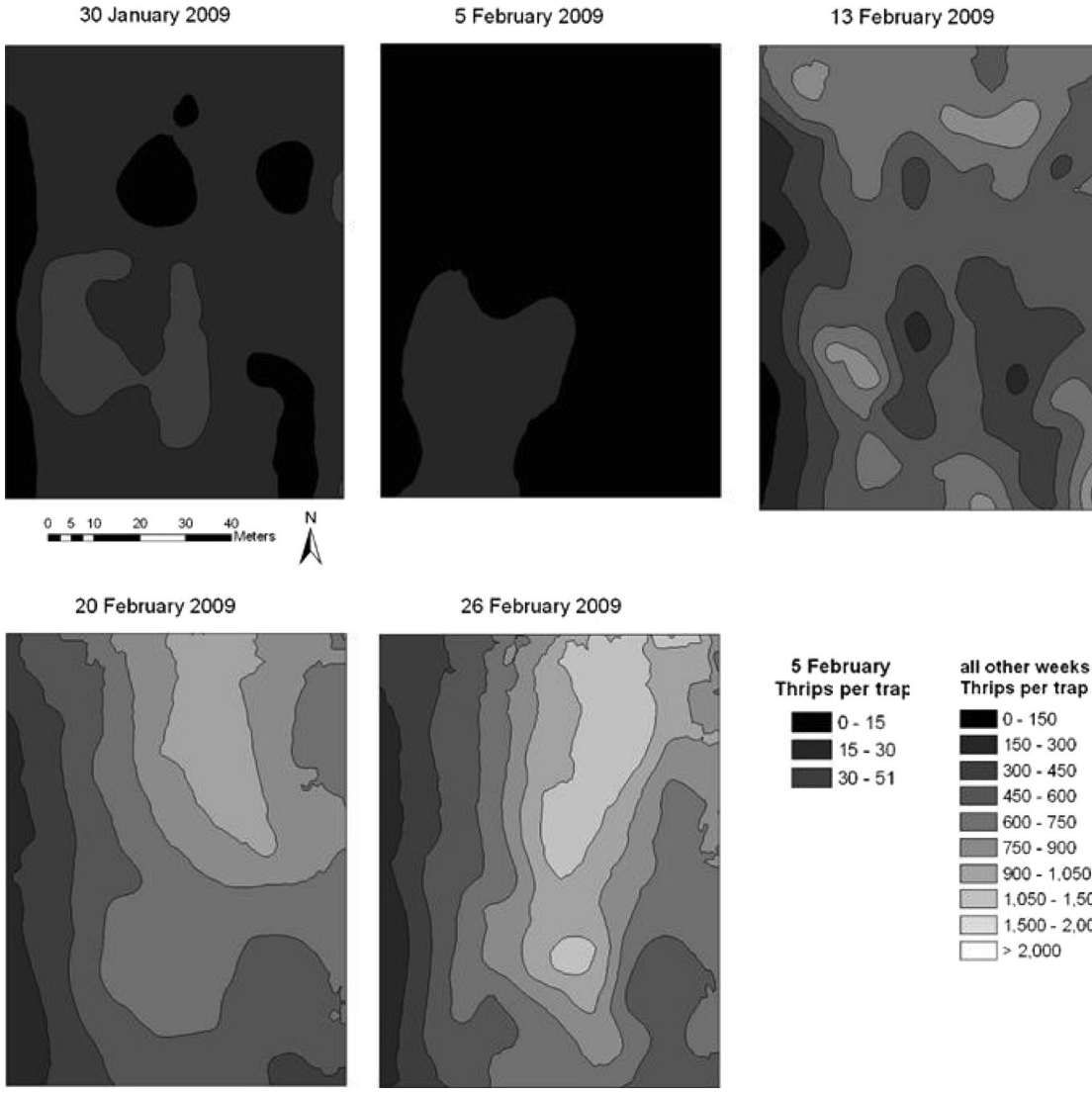

Fig. 8. Ordinary kriging interpolation of thrips per trap from 30 January 2009, 5 February 2009, 13 February 2009, 20 February 2009, and 26 February 2009.

February. In contrast, the thrips population had crashed to very low levels on 5 February. This crash was most likely caused by an extreme cold front that blew through Florida during that week. Average temperatures recorded from Citra, FL were below 10°C on 31 January, 1 February, and 3–7 February, and the low temperature was below 0°C on all of these dates except 3 February (FAWN 2009). Inverness, FL, where this study was conducted, is ≈64.4 km (40 miles) southwest of Citra. During the following week the thrips population rebounded and was increasing rapidly by 13 February. Thrips numbers remained high throughout the next two weeks. In contrast, the blueberry bushes had declined to 31% open flowers on 20 February and then to 10% open flowers on 26 February. The extreme temperature event seemed to cause the thrips population to rise well after peak flowering.

Both interpolation methods showed "hot spots" in the same areas of the blueberry field during both years. On 14 and 28 February 2008 and on all dates in 2009 except 5 February, the OK maps showed a much lower number of thrips in these "hot spots" than the IDW maps. This difference is because there were only a few traps with very high numbers of thrips on these dates. The "hot spot" was centered where the one trap with >1,000 thrips on it was located. This point on the map is set equal to this value in IDW interpolation, but not in OK. This setting causes the kriged map to be much smoother. The combination of setting the points at data locations to the value of the data point and using a weighted average causes the 'bulls-eye' effect that IDW maps are known to exhibit (Bolstad 2006). On 21 February 2008, the maps were very similar. The area of the three major "hot spots" is smaller in the

IDW map. This is because the nature of the semivariogram for this week (see below) causes the OK map to display the same property as if it were calculated using a local average.

The OK interpolation varied among the weeks during both years because the data varied greatly and was not always modeled well using semivariograms. Wright et al. (2002) found that the spatial distribution of European corn borer larvae was modeled well by semivariograms in only four out of seven data sets. Farias et al. (2003) calculated 36 semivariograms for sharpshooters on citrus, but could fit only nine of them with mathematical models. The semivariograms from 14 February 2008, 5 February 2009, 20 February 2009, and 26 February 2009 had large nuggets. This data resulted in excessive smoothing. The range of the 28 February 2008 semivariogram was so short that no traps were at a distance shorter than the range. This caused most of the points to be weighted the same in the interpolation resulting in a map similar to one constructed of thiessen polygons. In contrast, the semivariogram from 21 February 2008 had a very small nugget, but leveled off very rapidly. Because of this, only points very close to the unknown point were given a high weight in the interpolation and the interpolation, therefore, closely resembled a local average. The semivariograms from 30 January 2009 and 13 February 2009 had a moderate and small nugget, respectively, and had ranges that encompassed many data points. The resulting maps are, therefore, the best examples of OK. Our findings demonstrate the constraints imposed by OK modeling of temporal thrips populations, which are dependent on the quality of the semivariograms describing spatial dependence structures.

In terms of accuracy, the OK and IDW interpolations were similar. Ordinary kriging is only as powerful as the semivariograms used to perform it and semivariograms, in turn, are dependent on the spatial structure of the thrips population that changes throughout the season. In 2008, the spatial trend in flower thrips populations in blueberries was localized. Because of this localization, the semivariograms either had a very short range (21 and 28 February) or a large nugget because of a lack of sample point pairs below the actual range (14 February). The result was that, in 2008, OK interpolation was no more accurate than IDW interpolation. The reduced grid spacing in 2009 resulted in better semivariograms, suggesting that the spatial variability of thrips is high and could be better captured with the finer grid spacing used in the 2009 sampling. In both years, the shortest distance sampled was 2 m. However, in 2008, there were only two data pairs at this distance although in 2009, there were approximately ten. The data from the weeks of 30 January and 13 February was modeled very well by semivariograms resulting in kriged maps with a slightly higher accuracy than the IDW maps from these weeks. Therefore, both IDW and kriging are reasonable interpolation methods to model flower thrips distribution in blueberry fields. This conclusion is in agreement with results presented by Roberts et al. (1993) and others. The accuracy of kriging is dependent upon the accuracy of the semivariogram. Semivariogram models are sensitive to many factors, including non-normality; outliers; directional differences in spatial trends; nonstationarity in variances and means; and the density, placement, and spacing of the sample points.

Our results show that both IDW and OK can be used to model flower thrips distribution in blueberry plantings. The choice of which one to use will depend on the study. Inverse distance weighting requires fewer sample points and is easier to compute than OK. However, the construction of semivariograms for OK provides more information than does IDW. In the case of this study, the semivariograms indicated that white sticky traps should be spaced at least 28.8 m apart to ensure spatial independence and that the 7.61-m grid spacing was better able to capture thrips spatial variability.

The ability to model the distribution of flower thrips in blueberry plantings has the potential to provide valuable information for pest management. Thrips populations in blueberry plantings tend to form one to several "hot spots", or areas of high population density, during the course of a flowering season (Arévalo and Liburd 2007). Our results show that both IDW and OK can be used to model these "hot spots" and that a grid spacing of 7.61 m is adequate for creating these models. This information can be used in future research. One important next step is to determine if environmental factors, such as flower density and temperature, can be used to predict where the "hot spots" will develop. The intensive trapping necessary to create the geostatistical models presented in this paper would be highly impractical for growers to implement because of the cost of purchasing large numbers of traps and the labor involved. However, if "hot spots" can be predicted with environmental factors that growers can easily monitor, then insecticide applications and other pest management tactics can target developing "hot spots" rather than encompassing entire fields.

Acknowledgments

We thank Drs. Robert McSorley and Joe Funderburk for their initial review of this manuscript. We also thank the Florida Blueberry Grower's Association for allowing us to do this study on one of their farms. Many thanks also go to all of the current and previous staff and students of the Small Fruit and Vegetable IPM laboratory for their help in collecting samples.

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Received 21 December 2010; accepted 14 May 2011.