SHORT, NON-REFEREED PAPER

IMPACTS OF SAMPLING EFFORT ON ESTIMATING ABUNDANCE OF THE APHID *SIPHA FLAVA* (FORBES) IN SUGARCANE IN MAZABUKA, ZAMBIA

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Abstract

The exotic aphid *Sipha flava* (Forbes) (Homoptera: Aphididae) has recently become a pest of concern for sugarcane farmers in the Mazabuka region of Zambia. The steady decline in sugarcane yields has led to the need for investigation into the spatial-temporal dynamics of *S. flava* outbreaks, its population dynamics and invasion potential. Field survey data of *S. flava*, its abundance and distribution (every 20 m by 10 lines in ±6 ha blocks), were intensely collected over a period of 6 weeks on a weekly basis in 7 separate fields. Using randomisation across subsets of these data, the authors illustrate how sampling effort might impact on estimates of abundance. These data provide much greater spatial resolution than current coarse-scale monitoring techniques are able to do. The levels of uncertainty with lower sampling effort are presented, highlighting the need for improving the current inconsistent scouting procedures. These results are discussed in the context of further development of an integrated pest management programme for aphids on sugarcane in Zambia.

Keywords: yellow sugarcane aphid, scouting methods, survey methodologies, aphid distribution

Introduction

Reliability and accuracy in monitoring methodologies are key factors in effective pest management in agroecosystems (Shea *et al*., 2002). Large-scale, precision agricultural operations rely on these methodologies to produce results that will be used as a base for management decisions, and survey methodology may therefore influence estimates of economic thresholds. Sampling or population survey methods have implications for determining not only the abundance of pest insects but also for detecting invasive or emerging pests (Winder *et al.,* 2001). Consequently, understanding the impact of survey methods on estimates of abundance becomes critical to ensure that insect invasions or novel pests are adequately detected prior to an economic impact occurring on the crop.

Farmers deal with a great amount of uncertainty when managing an outbreak or a sporadic invasion of a pest species – especially where economic thresholds are unknown, as is often the case (Schröder *et al.,* 2017). Pesticide use and its efficacy are perhaps the most critical concerns along with yield loss or economic impact (Shea *et al*., 2002; Auad *et al.,* 2012). A case in point is that of *Sipha flava*, the Yellow Sugarcane Aphid (YSA) in sugarcane in Zambia. This aphid was first considered a pest of concern at the Nakambala Sugarcane Estate in December 2014. The true extent of the problem is unfortunately unknown as much effort has been spent on various surveying methods monitoring the invasion of this pest and in many cases, this sampling effort has changed over time, without efficacy estimates of the sampling methods being assessed. This is coupled with highly dynamic population abundance, which can readily go from low to high infestation between two sampling or scouting time points. The importance of sampling consistency was not stressed early on, and this has contributed to diverse datasets that have not been able to resolve the spatial-temporal dynamics of the YSA invasion and whether a particular methodology is superior to any other to address specific management objectives. The aim of this study was therefore to collect consistent high resolution abundance data, estimate the relationship between survey effort and abundance, and thereby to better understand the dynamics of YSA for management decisions.

Methods

The study was undertaken at the Nakambala Sugar Estate, in Zambia (15°48'11.6"S; 27°44'56.6"E), in 7 separate ± 6 ha sections of larger fields, planted with N41 (4), N25 (2) and N46 (1) sugarcane varieties, that were historically highly infested with YSA. The crops were ranging from being newly replanted to their 8th ratoon and between 3 and 29 weeks of age at the beginning of the survey period (October to November 2017).

The methodology used for the surveys was a checker board design, with a sample station at 20 m intervals in a row of sugarcane. The rows sampled were 10 rows apart. A boundary edge of 5 m was taken before the first stalk in each sugarcane row was sampled. A sample station was randomly selected as the first stalk seen at a designated point. The total number of leaves on the selected stalk was counted, as was the number of leaves that were found with one or more aphids present, to give a % infestation per stalk (calculated by the division of the number of infested leaves by the number of leaves surveyed, multiplied by 100). These data could also be used to calculate the ‘presence of infestation’ (data are calculated by the presence of YSA on any of the leaves at that particular station (stalk) receiving a ‘1’, and the absence of any YSA on any of the leaves being allocated a ‘0’).

Analyses were completed on the first survey undertaken (low infestation) and on the highest YSA infestation level thereafter during the survey period. These two extremes were chosen based on the two commonly occurring scenarios taking place, those being the potential over-exaggeration of a low infestation or under-exaggeration of a high infestation of YSA. In other words, of primary concern are type I and type II statistical errors (Batterham and Hopkins, 2006) – avoiding control actions when they should have been taken, and, making a decision (e.g. to spray) when in fact it was not necessary. In order to visually understand these potential biases, the minimum effort required for monitoring on a spatial scale was determined, through the randomisation and reduction of subsets of the maximum data. This was performed in Excel with one site being chosen as an example for graphical results to be plotted in Statistica in the form of box plots to represent the range of data. This site was chosen as it shows the characteristic jump from low to high infestations. The boxes represent 25-75% of the data, the core 50%, these values are taken from the 10-90% percentage effort box for each graph in Figure 1. Sampling effort is considered significantly different if the median falls outside these two lines, and the number of the boxes that fall above or below the lines will represent significant bias in a particular direction owing to sampling effort. Piecewise regressions in R are used to identify the breakpoints or transition points in the Infestation percentage data, if they exist, using the “segmented” package (R core team, 2016; Maggeo, 2008).

Results and Discussion

The 7 sites selected had a range of between 109 and 308 stations monitored in a single survey. The unequal number of stations is due to the different step sizes of the various surveyors performing the surveys. The example site's lowest infestation % occurred on 17 October 2017 at 3.6%, with 215 stations monitored in the field. The highest infestation % occurred on 23 November 2017, at 17.7% with 181 stations monitored, an increase of 14.1% in 35 days.

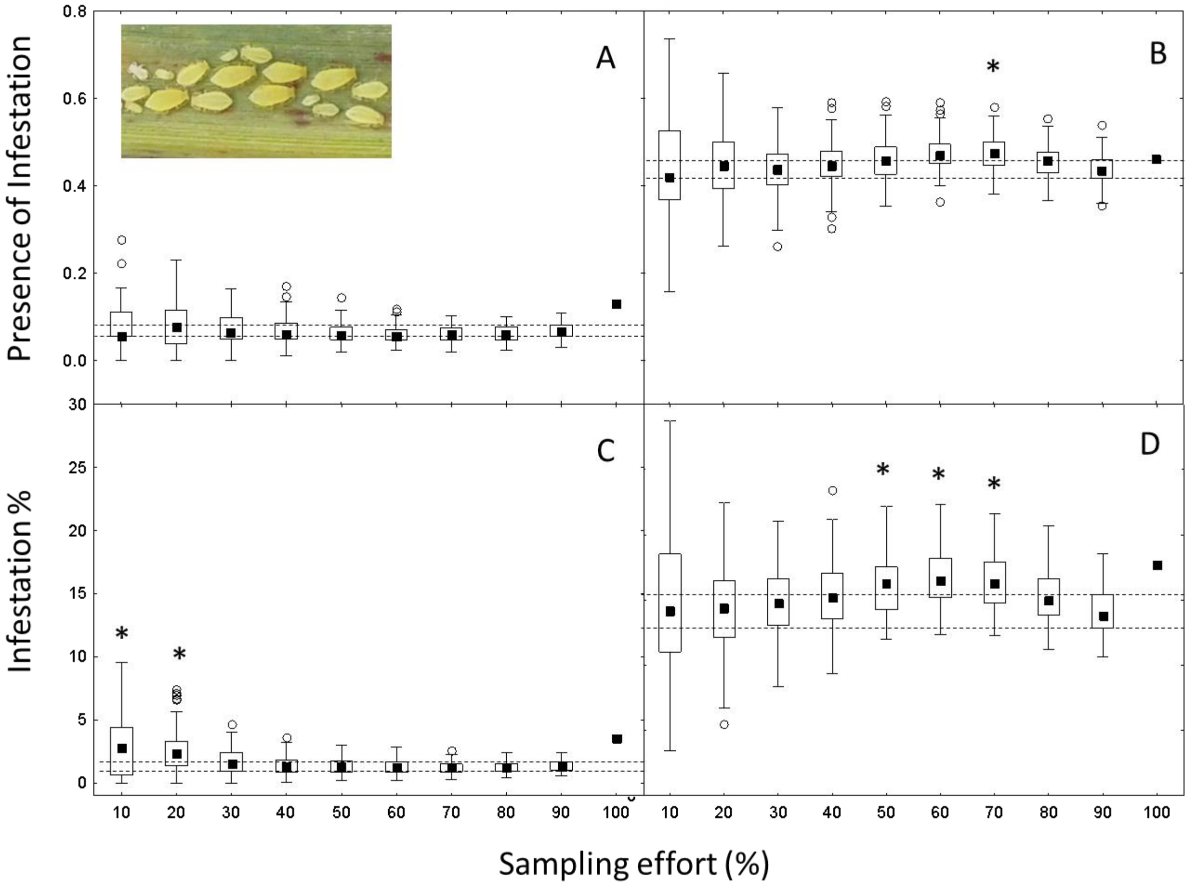

Figure 1. Box plots of the presence of infestation per stalk (A, B) and Infestation % per stalk (C, D) at different levels of sampling effort. The black squares represent the median, the boxes represent the 25-75% data range and the whiskers represent the upper and lower remaining data (minimum-maximum range) with outliers as circles. The dotted lines reflect the upper 75% and lower 25% of the '90' sampling effort. Graphs A and C are the low infestation survey and graphs B and D are the high infestation survey. Plots with an asterisk (*) show significant differences.

The data shows typical 'funnel' plots of sampling effort on estimates of pest abundance or presence. In the first case assessed (Figure 1A), at a low presence (scored on a binary scale), the 100% data point represents a 10% chance of finding a stalk in that field with one or more aphids on it. There are no medians falling outside of the dotted lines, and there are seven under-exaggerated and three over-exaggerated, although variability increases while median values remain relatively constant as sampling effort is reduced. For the same type of presence vs absence survey, Figure 1B illustrates an example of a high infestation, has one median that is significantly different, but no consistent directional bias. This set of data also has the same pattern of the median values remaining relatively constant, but with the variability increasing dramatically as the sampling effort is reduced from ~40 to 10% of the maximum.

For the infestation (%) data (Figure 1C), the 100% data point means that there is a 4% chance of finding an aphid present on a leaf in a particular field. In these data, significant overestimation of infestation occurs at low sampling effort, especially in the 10-20% sampling range.

Of critical importance, especially for effective estate-wide management of this pest, these data show that there is a large chance of overestimating 'true' infestation levels with presence/absence type data at a low infestation % at low sampling efforts. However, at higher infestation levels, there is a large chance of under- and over-estimating the true infestation level if sampling effort is reduced substantially. Most importantly, the variability (data range) increases rapidly as effort is reduced in the % infestation sampling system suggesting that an error can be made more easily in such a case. In other cases, reduced effort doesn't change the conclusions of infestation that much until data is in the 10-20% range; thus sampling effort could be reduced here without a great compromise in accuracy of conclusions.

Table 1. Summary of all site information and the corresponding breakpoints (% ± SE). The breakpoints refer to a piecewise regression automatically detecting a change in the relationship between estimates of abundance and % survey effort, and shows at what % survey effort (relative to maximum effort employed in this study) the abundance estimates likely become compromised relative to observed abundance levels.

Field ID	Sugarcane Variety	Ratoon	Irrigation Type	Cane Age (wks)	Survey Area (ha)	Survey Month	No. of stations	Presence of infestation	YSA Infestation %	Breakpoint (% ± SE)
1010	N41	6	Furrow	18	6	October	215	0.13	3.6	43.5 ± 2.8
						November	191	0.46	17.7	27.8 ± 5.4
1012	N41	0	Furrow	12	6.2	October	109	0.31	7	25.4 ± 2.7
						November	101	0.76	29.2	23.5 ± 1.4
1405	N25	5	Furrow	12	3.5	October	205	0.5	10.7	53.9 ± 6.1
						November	169	0.54	16.1	26.2 ± 2.9
1515	N25	3	Furrow	3	5.4	October	168	0.01	0.2	47.4 ± 4.4
						November	123	0.28	7.6	35.9 ± 3.1
1520	N41	6	Furrow	3	5.8	October	181	0	0	NA
						November	176	0.32	6.8	35.7 ± 3.1
1805	N46	0	Centre Pivot	22	7.4	October	308	0.01	0.2	46.3 ± 3.1
						November	288	0.01	0.1	43.3 ± 5.4
2310	N41	0	Centre Pivot	29	6.2	October	260	0	0	NA
						November	247	0	0	NA

Overall, the breakpoint estimates from piecewise regression on these data (Table 1) show that sampling effort can be reduced without compromising estimates of abundance when fields are more highly infested, but at low infestation levels more intense sampling is needed to obtain a reliable approximation of the infestation level. These data provide novel insights into how survey or scouting efforts, if they were reduced, might influence detection of YSA.

Conclusions

Clearly sampling methodology can influence decision making, as shown here for the case of YSA in Zambia. In addition, sampling efforts will affect the reliability of the field data collected, leading to a trade-off between labour and time, versus estimation of the absolute infestation level.

Despite there being a smaller chance of incorrectly detecting a low level of YSA infestation in the sampling data systems tested here, capturing the true infestation level is far more important at lower infestation levels as these can lead to rapid outbreaks in this fast-growing species. The earlier these potential outbreaks are detected, the sooner control actions can be implemented, and thereby avoid the rapid acceleration of aphid population numbers (Hentz and Nuessly, 2004). Further statistical analyses will confirm whether this is also the case spatially and temporally over broader geographical scales, and help pinpoint the minimum sampling effort required to achieve reliable management action thresholds. The temporal aspect of the YSA invasions also needs further attention to better understand the underlying conditions resulting in an outbreak or infestation and if this is related to e.g. crop health (e.g. water or other pest/ disease stresses facilitating aphid outbreaks) or other factors (e.g. sugarcane or soil type).

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