# Feasibility of the application of electronic nose technology to detect insect infestation in wheat

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Wu, J., D.S. Jayas, Q. Zhang, N.D.G. White and R.K. York. 2013. **Feasibility of the application of electronic nose technology to detect insect infestation in wheat**. Canadian Biosystems Engineering/Le génie des biosystèmes au Canada **55**: 3.1-3.9. An Alpha MOS FOX-3000 electronic nose (e-nose) equipped with 12 metal oxide semiconductor (MOS) sensors was used to evaluate the presence of insects in wheat. Samples of Canada western red spring (CWRS) wheat (cv. AC Barrie) infested with rusty grain beetle (RGB), *Cryptolestes ferrugineus* (Stephens), and red flour beetle (RFB), *Tribolium castaneum* (Herbst), were placed in glass jars fitted for the collection of headspace volatiles. Different insect densities (0, 1, 2, 10 and 20 insects/kg) were tested for each insect species in combination with three moisture content levels for wheat (14%, 16%, and 18% wet mass basis). The headspace volatiles from insect-infested or non-infested wheat were sampled and injected into the e-nose. The response of e-nose sensors, in the form of a multi-dimensional matrix, was extracted and interpreted using AlphaSoft V8.0 software. The automated pattern recognition algorithms in the software (Principal Component Analysis, Discriminant Factorial Analysis, and Partial Least Square) were used to evaluate the samples.

The e-nose could only detect the presence of RFB in wheat with the high infestation level (20 insects/kg) at 14% and 16% moisture content. However, the e-nose did not detect the presence of RFB in wheat at 18% moisture content. The e-nose also failed to detect the presence of RGB in wheat. **Keywords**: Electronic nose, Gas sensors, Insect infestation, Grain storage.

Un nez électronique (e-nez) Alpha MOS FOX-3000 équipé de 12 capteurs semi-conducteur à métal-oxyde a été utilisé pour déterminer la présence d'insectes dans le blé. Des échantillons de blé roux de printemps de l'Ouest canadien (CWRS - AC Barrie) infestés de cucujides roux (RGB), Cryptolestes ferrugineus (Stephens), et de tribolium rouge de la farine (RFB), Tribolium castaneum (Herbst), ont été placés dans des bocaux de verre équipés d'un mécanisme pour la collecte de vapeurs dans l'espace libre au-dessus des grains. Différentes densités d'insectes (0, 1, 2, 10 et 20 insectes/kg) ont été testées pour chaque espèce d'insectes et pour trois différentes teneurs en eau du blé (14%, 16% et18% base humide). Les vapeurs dans l'espace libre provenant de blé infesté ou de blé non-infesté ont été échantillonnées et injectées dans le e-nez. Les mesures obtenues par les capteurs du e-nez, sous forme d'une matrice multidimensionnelle, ont été extraites et interprétées en utilisant le logiciel AlphaSoft V8.0. Les algorithmes automatisés de reconnaissance du logiciel (analyse des composantes principales, analyse factorielle discriminante et moindres carrés partiels) étaient utilisés pour évaluer les échantillons.

Le e-nez a pu seulement détecter la présence de RFB dans le blé à une infestation élevée (20 insectes/kg) et à des teneurs en eau de 14% et 16%. Cependant le e-nez n'a pas détecté la présence de RFB dans le blé à une teneur en eau de 18%. De plus, le e-nez n'a pu détecter la présence de RGB dans le blé. **Mots clés**: nez électronique, capteurs de gaz, infestation d'insectes, entreposage du grain.

## INTRODUCTION

Under most climatic conditions and in most countries, farmers store grains in grain bins with the capacity for at least one year's production. However, long-term storage in these structures could provide an ideal environment for population development of common stored-product insects. Furthermore, the presence of insects in the stored-grain facilities can contribute to substantial losses during storage. Sinha and Watters (1985) have discussed that the most common insect pests of stored grain in western Canada are the rusty grain beetle (RGB), *Cryptolestes ferrugineus* (Stephens), and the red flour beetle (RFB), *Tribolium castaneum* (Herbst), which can survive even in severe environments for long periods. These insects not only consume the grain, but also contaminate it with their excreta, reducing both the quality and quantity of the commodity.

An important part of insect control in stored grain is the early detection of insects in the bin. Although several methods have been developed to monitor the quality of grain in storage, they lack the sensitivity for early detection of insets. New technologies that can accurately and quickly detect the early insect infestation of grains are needed. Sensor technologies, such as electronic nose (e-nose), might offer numerous advantages over traditional stored-product insect detection techniques. The e-nose technology might be used to analyze interstitial gas in stored grain for specific insect-produced volatiles. However, little information about the effects of insects on changes in grain odour during storage is available (Pederson 1992; Pomeranz 1992). Volatiles produced by a few insects in a

relatively large grain bulk are not easy to detect with the human nose. According to Seitz and Sauer (1996), the red flour beetle causes some off-odour while the rusty grain beetle causes little objectionable smell even when the number of the insects is large. Smith et al. (1971) indicated that chemical compounds from red flour beetle infested bread are benzoquinones. Olsson et al. (2000) found that wheat produces different volatiles with changing storage time, and the medium-polarity volatiles increase gradually while the small-polarity volatiles reduce gradually.

Several e-noses have been commercialized to the market. For example Fox from Alpha M.O.S. (DeMotte, IN), AromaScanner from AromaScan (Hollis, NH) and The Nose from Neotronics (Gainesville, GA). E-nose has been introduced to research and industry applications. Salim et al. (2005) studied using e-nose as a non-destructive tool to determine fruit ripeness. Trihaas et al. (2006) used e-nose for the quality assessment of Danish Blue Cheese during ripening. Hosseini et al. (2007) with his research group employed Cyranose 320 e-nose to evaluate the freshness of fish. In principle, such instruments consist of an array of non-selective electronic gas sensors, which have a range of sensitivities to different volatile compounds, so that the electronic nose has great sensitivity to a particular class of volatiles associated with different insect species. However, there are also some limitations to the sensor, it requires a long-term training process (Gardner and Bartlett 1999) to build a database for one sample, which means you have to train the e-nose to find certain volatile compounds. Normally each sensor has to be replaced yearly due to oxidation of the coating material. By calibration and data processing, it might possibly be used for rapid and automated detection of insects in stored grain.

The output from the e-nose measurements is usually multi-dimensional matrices from the multi-sensor array, and therefore, it is more difficult to process the data compared to other measurement methods. Furthermore, the e-nose sensors are generally sensitive to a wide range of organic vapours (Gardner and Bardner 1999), while the chemical compounds of grain in a large grain bulk may change depending on storage conditions (Abramson et al. 2005). The research questions that need to be investigated are how to extract interpretable information from the output of the e-nose and whether the grain moisture would affect the ability of the e-nose in measuring insect-produced volatiles.

The aim of this research was to investigate the technical feasibility of using e-nose technology for early detection of insect infestation in stored grain. The specific objectives were to: (1) detect the presence of insects in wheat at 14%, 16% and 18% (wb) moisture content having low or high infestation levels; (2) differentiate the insect species in wheat; and (3) identify and predict insect density for each insect species.

## MATERIALS AND METHODS

The purpose of the study was to test the effectiveness of e-nose in detecting the presence of a few adult insects in a large volume of grain.

### E-nose feature and setup

Alpha MOS FOX-3000 e-nose device was available for this research at Richardson Centre for Functional Foods and Nutraceuticals, University of Manitoba. It has two sensor chambers, each is equipped with 6 metal oxide semiconductor (MOS) sensors, and each sensor with distinct coating may be sensitive to various volatile compounds. These sensors are either n-type coating (mainly tin-dioxide) or p-type coating (mainly nickel-oxide). A transient sensor response is expressed by the value of relative change in the sensor resistance, i.e., (R0-R)/R0, where R0 is the resistance of sensor at t = 0 s (baseline resistance) and R is the resistance at the selected time. Based on the coating material, all LY sensors (LY2/G, LY2/AA, LY2/Gh, LY2/gCT1, LY2/gCT, and LY2/LG) were p-type semiconductors, while P and T sensors (T30/1, P10/1, P10/2, P40/1, T70/2, and PA2) were n-type semiconductors. During the signal acquisition period, the responses of 12 sensors were automatically recorded by the data acquisition system in the AlphaSoft V8.0 software.

To simulate real storage conditions, a small grain storage system, consisting of a 4-L capacity glass jar with a hand-tight plastic lid, was designed and constructed for collection of insect-produced volatiles. Canada western red spring (CWRS) wheat samples infested with different insect infestation levels (0 insect/kg, 1 insect/kg, 2 insects/kg, 10 insects/kg, and 20 insects/kg) were prepared. Adult rusty grain beetle (RGB) and adult red flour beetle (RFB) were reared in the lab at the Cereal Research Centre, Agriculture and Agri-Food Canada, Winnipeg. Only one species of insect was mixed with the wheat for individual samples. Headspace volatiles of the sample collected in Tedlar bags were transferred to the Alpha MOS FOX-3000 sensor array by the flowcell sampling method (Alpha MOS SA 2002).

### Grain storage jars and wheat

Glass jars (4-L capacity, 24 cm high, 13 cm exterior diameter with a hand-tight plastic lid) were used (Fig. 1) to simulate grain storage conditions. Four different infestation levels were selected for each insect species in combination with three moisture content levels (14%, 16%, and 18%). Two kilograms of wheat were placed into each jar with the designated number of insects to simulate different insect infestation levels. The wheat occupied 2/3 of the total space in the jar. Two holes (6.35 mm interior diameter) were drilled along a diameter of the lid, approximately 1.5 cm from the edge of the lid, through which two glass tubes were inserted into the jar as air inlet and outlet, respectively. The ends of two tubes were extended approximately 0.06 m in height above the jar. The inlet tube was inserted into the grain mass, ending near the

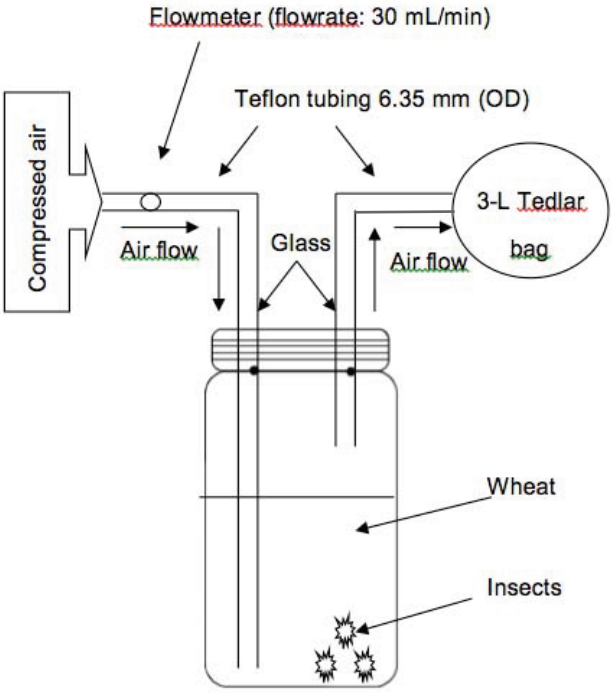


**Fig. 1. Schematic of the sample jar used to collect headspace volatiles from infested or non-infested wheat into a gas-tight Tedlar bag.**

bottom of the jar, whereas the end of outlet tube was in the headspace. Compressed air could be flushed through the inter-granular space of the wheat from the bottom to the top through the inlet and outlet tubes. Between flushing, the inlet and outlet tubes were both capped with rubber septa to allow volatiles to accumulate in the headspace. To collect headspace gas, Teflon tubing was used to direct clean compressed air to the inlet tube through a flow meter to control the airflow rate. Another Teflon tubing was used to connect a 3-L Tedlar bag (St. Croix Sensory, Inc., Stillwater, MN, USA) to the outlet tube (Fig. 1).

Compressed air at room conditions was circulated through the grain mass at a rate of 30 mL/min for 10 min to collect the headspace volatiles above the wheat samples in the glass jars. The time and volume of collection were manually controlled using a Teflon valve. The total volume of gas (30 mL/min ×10 min = 0.3 L) flushed into the container was much smaller than the total air volume in the jar (4 L×1/3 + 40% × 4 L×2/3 L = 2.4 L, assuming a grain porosity of 40%). Thus flushing air resulted in about 10% dilution to the headspace volatiles, which should not cause any noticeable effect on the detection of volatiles by the e-nose.

To investigate whether the wheat moisture would affect the ability of the e-nose in measuring insect-produced volatiles, wheat samples of three different moisture contents were prepared (approximately 14, 16, and 18%). The calculated amount of distilled water was added and then mixed with wheat in a rotating mixer for 2 h. The conditioned wheat was held in a sealed plastic bag

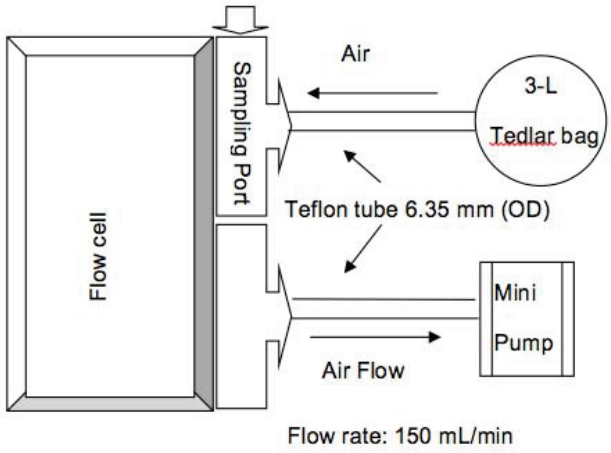


**Fig. 2. Schematic of the flowcell design used to insufflate volatiles into the e-nose.**

for 48 h at 2.5°C for moisture equilibration (Abramson et al. 2005). All samples were stored at 4°C in a walk-in refrigerator before experiments and equilibrated to room temperature for the experiments.

Gas samples collected in Tedlar bags were transferred to the e-nose directly. Two Teflon tubes (6.35 mm exterior diameter, 0.5 m long) were connected to the inlet and outlet of the flow cell of the e-nose (Fig. 2). Gas was drawn through the e-nose by a portable air sampler pump (Gilair 5, Gilian Instrument Corp., Clearwater, FL, USA) located downstream in order to avoid any contamination of the headspace sample by the pump.

**Electronic nose data pre-processing**

The responses of the e-nose to volatiles were the relative changes in resistance of the 12 sensors during 120 s of signal acquisition period. The acquisition files were first loaded in the pre-processing window of Alphasoft V8.0 (Alpha M.O.S., Toulouse, France). Then the sensor responses were visualized and compared. To further process multivariate statistics, the libraries or databases were built by selecting all the data. Within the software, automated pattern recognition algorithms (e.g., Principal Component Analysis, Discriminant Factorial Analysis and Partial Least Square) could be selected to do quick comparison and identification of samples.

**Multivariate approaches of insect monitoring results**

All data analyses were performed using Alpha Soft V8.0 (Alpha M.O.S., Toulouse, France). For differentiation and classification, sensor responses were evaluated by multivariate statistics available in the AlphaSoft V8.0 software (Alpha M.O.S., Toulouse, France). Unsupervised learning techniques, such as Principal Component Analysis (PCA) were used to reduce the multi-dimensional data of sensor responses to a 2-dimensional matrix that made it easy to explore the data and to assess discrimination performances in a 2-dimensional plot. The discrimination performance could be shown through separation or overlap between groups and expressed by the

discrimination index. Outliers could also be detected by visual inspection in the PCA plot. If a sample was not grouped with the other samples of the same treatment group, or it was located evidently far away from the other samples of the same group, it was possible to be regarded as an outlier. By visual inspection, any sample whose sensor responses were in different plot area from others was thought to be an outlier and was removed.

Once the PCA (discrimination) was completed, supervised pattern recognition techniques, Discriminant Factorial Analysis (DFA) and Partial Least Squares (PLS) were performed. Based on the computation of the distance to gravity center of each group, a DFA model was built and used to separate different groups. To validate the DFA model, cross-validation by the full leave-one-out method over all samples was used (Duda et al. 2001). By applying this validation, each sample was removed from the data set and considered as an unknown sample; the total score of all samples was computed. Generally, the model would be valid if a score of 90% was obtained in the validation process (Alpha MOS SA 2002). To predict unknown samples, the recognition scores were calculated based on the distance to the gravity center of each group from unknown sample. An unknown sample was grouped into a certain group if its distance was less than the model Mahalanobis distance and its residual error was lower than the model residual error (Mahalanobis 1948).

The Partial Least Square (PLS) algorithm in the Alpha Soft V8.0 software based on the linear regression technique was used to predict the value of the quantitative information on the unknown sample (i.e., insect infestation level or moisture content).

## RESULTS AND DISCUSSION

### Sensor array responses to wheat samples

The raw data for 12 sensors for non-infested, low insect-infested and high insect-infested wheat at 14%, 16%, and 18% moisture are given in Wu (2008). A typical response curve is shown in. 3. Each curve in the plot represents a sensor response to a gas sample in a certain amount of time. To compare different sensor responses between two gas samples, two plots of sensor signals are plotted in the same diagram.

It can be seen that the response of a sensor increased during the initial phase of exposure to the gas samples, and then the response gradually returned to the baseline after peaking. The peak values were significantly different, whereas, the differences in peaking time were relatively small. The average values of peak response for each of 12 sensors to the samples are shown in the Table 1.

It was noticed that the peak values of all sensors increased with the wheat moisture content for the non-infested wheat samples. Usually the sensor sensitivity is visualized by the peak value of sensor (Alpha MOS 2002). García-González and Aparicio (2002) stated that sensor sensitivity is affected by humidity and poisoning material, so that this observation was consistent with the point

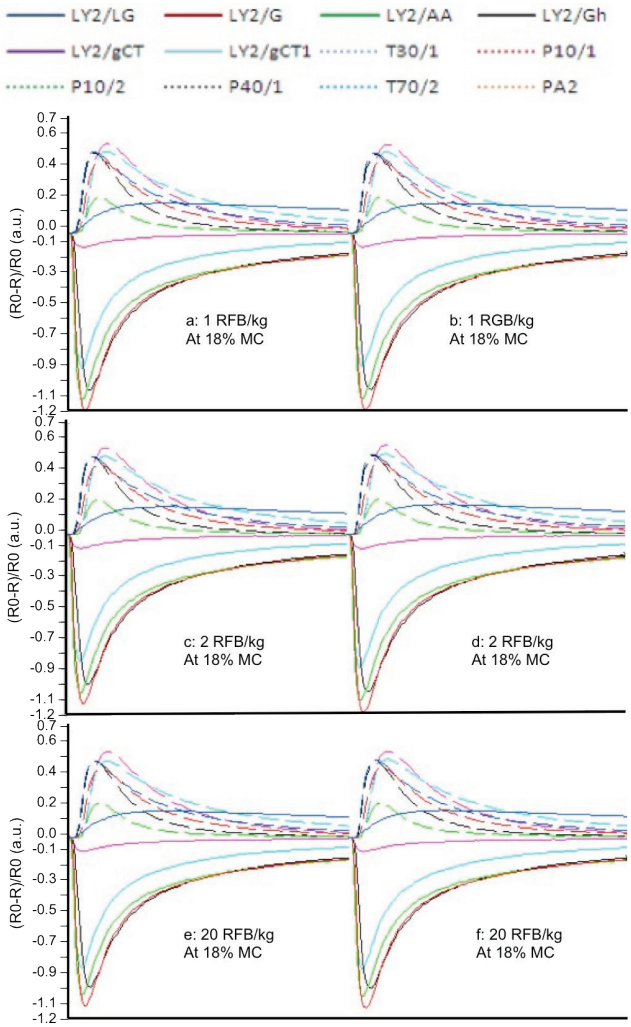


**Fig. 3. Comparison of sensor response curves to RFB and RGB infested-wheat at three densities and 18% moisture content wheat.**

presented by Shiers (1995) that MOS sensors were sensitive to humidity due to low operation temperature (<50°C). All LY sensors were more sensitive to the 16% moisture content wheat than 14%. For example, the sensor LY2/gCT increased its peak response from -0.008 to -0.038, or 5 times; the sensor LY2/G increased its peak response from -0.058 to -0.460, or 7 times; sensor LY2/AA 7 times; sensor LY2/Gh 7 times, sensor LY2/gCT1 9 times, and sensor LY2/LG 9 times when the moisture changed from 14% to 16%. While most P and T sensors with n-type semiconductors increased its peak value less than 3 times. Comparing the sensor responses between 14% to 16% and 16% to 18% in moisture content indicated that each sensor response increased in the peak response when moisture was higher. However, each sensor response changes, when moisture content increasing from 16% to 18%, was less than that from 14% to 16%. In other words, the LY sensors with p-type semiconductors were more sensitive to the changes in grain moisture in the lower moisture range.

**Table 1. The average values of the peak response for each of 12 sensors to the headspace volatiles.**

| sample \ sensor | LY2/LG | LY2/G | LY2/AA | LY2/Gh | LY2/gCTl | LY2/gCT | T30/1 | P10/1 | P10/2 | P40/1 | T70/2 | PA2 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| P40 | 0.008 | -0.058 | -0.055 | -0.047 | -0.032 | -0.008 | 0.103 | 0.091 | 0.077 | 0.116 | 0.079 | 0.142 |
| P60 | 0.076 | -0.46 | -0.438 | -0.393 | -0.316 | -0.038 | 0.282 | 0.266 | 0.213 | 0.335 | 0.26 | 0.33 |
| P80 | 0.21 | -1.357 | -1.322 | -1.189 | -1.017 | -0.102 | 0.623 | 0.541 | 0.238 | 0.561 | 0.621 | 0.679 |
| F42 | 0.014 | -0.1 | -0.086 | -0.081 | -0.056 | -0.01 | 0.125 | 0.102 | 0.081 | 0.125 | 0.098 | 0.166 |
| F4T | 0.023 | -0.158 | -0.125 | -0.127 | -0.088 | -0.012 | 0.151 | 0.113 | 0.083 | 0.135 | 0.117 | 0.192 |
| F4M | 0.035 | -0.236 | -0.19 | -0.193 | -0.135 | -0.017 | 0.202 | 0.137 | 0.089 | 0.156 | 0.159 | 0.241 |
| G42 | 0.009 | -0.061 | -0.058 | -0.049 | -0.033 | -0.008 | 0.104 | 0.092 | 0.078 | 0.117 | 0.08 | 0.145 |
| G4T | 0.009 | -0.067 | -0.063 | -0.054 | -0.037 | -0.008 | 0.106 | 0.093 | 0.079 | 0.118 | 0.082 | 0.149 |
| G4M | 0.009 | -0.074 | -0.071 | -0.06 | -0.04 | -0.009 | 0.112 | 0.096 | 0.08 | 0.121 | 0.086 | 0.157 |
| F62 | 0.022 | -0.162 | -0.143 | -0.128 | -0.088 | -0.014 | 0.125 | 0.128 | 0.115 | 0.172 | 0.106 | 0.163 |
| F64 | 0.021 | -0.159 | -0.141 | -0.126 | -0.087 | -0.014 | 0.124 | 0.127 | 0.114 | 0.171 | 0.105 | 0.162 |
| F6M | 0.037 | -0.198 | -0.152 | -0.161 | -0.118 | -0.018 | 0.127 | 0.124 | 0.118 | 0.171 | 0.107 | 0.157 |
| G62 | 0.034 | -0.18 | -0.164 | -0.143 | -0.098 | -0.018 | 0.176 | 0.181 | 0.204 | 0.262 | 0.148 | 0.221 |
| G64 | 0.034 | -0.177 | -0.162 | -0.141 | -0.096 | -0.018 | 0.174 | 0.179 | 0.203 | 0.26 | 0.146 | 0.219 |
| G6M | 0.033 | -0.172 | -0.157 | -0.137 | -0.094 | -0.018 | 0.174 | 0.179 | 0.202 | 0.259 | 0.147 | 0.217 |
| F82 | 0.22 | -1.436 | -1.401 | -1.258 | -1.081 | -0.108 | 0.652 | 0.567 | 0.247 | 0.588 | 0.652 | 0.709 |
| F84 | 0.214 | -1.42 | -1.386 | -1.244 | -1.069 | -0.106 | 0.646 | 0.563 | 0.245 | 0.584 | 0.645 | 0.704 |
| F8M | 0.209 | -1.414 | -1.376 | -1.24 | -1.088 | -0.105 | 0.637 | 0.556 | 0.247 | 0.58 | 0.635 | 0.697 |
| G82 | 0.182 | -1.197 | -1.16 | -1.048 | -0.892 | -0.091 | 0.558 | 0.488 | 0.22 | 0.514 | 0.553 | 0.615 |
| G84 | 0.187 | -1.248 | -1.213 | -1.091 | -0.93 | -0.094 | 0.582 | 0.508 | 0.226 | 0.531 | 0.578 | 0.639 |
| G8M | 0.179 | -1.226 | -1.191 | -1.073 | -0.925 | -0.092 | 0.579 | 0.504 | 0.225 | 0.528 | 0.573 | 0.638 |
| M44 | 0.008 | -0.062 | -0.058 | -0.05 | -0.034 | -0.008 | 0.105 | 0.093 | 0.078 | 0.118 | 0.081 | 0.147 |
| M64 | 0.021 | -0.158 | -0.141 | -0.125 | -0.087 | -0.014 | 0.124 | 0.127 | 0.114 | 0.171 | 0.105 | 0.163 |
| M84 | 0.201 | -1.348 | -1.314 | -1.178 | -1.008 | -0.1 | 0.619 | 0.538 | 0.237 | 0.56 | 0.616 | 0.676 |

Nomenclature: for the first letter of the sample name: P= Control, F= RFB, G=RGB, M= RFB&RGB; for the second number: 4=14% MC, 6=16% MC, 8=18% MC, for the third number or letter: 0=0 insect, 2=2 insects, 4= 4 insects, T=10 insects, M= 20 insects.

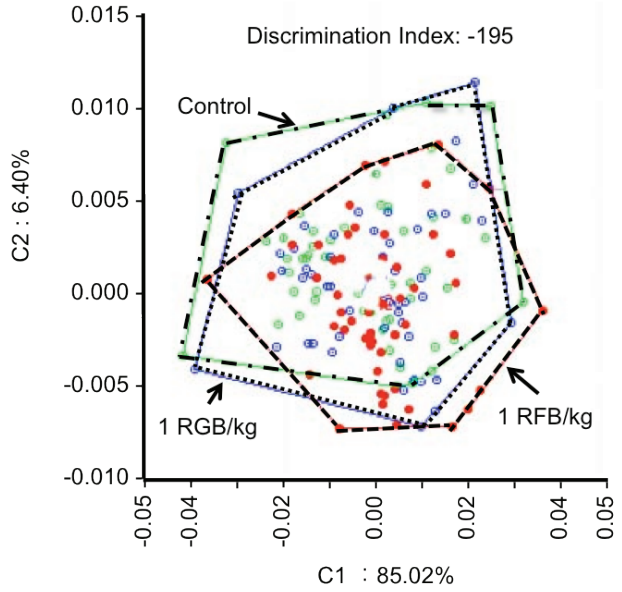


**Fig. 4. PCA plot of control and low infested-wheat by RFB and RGB at 14% moisture content. Note: Three groups are overlapped with each other showing no differentiation among the groups.**

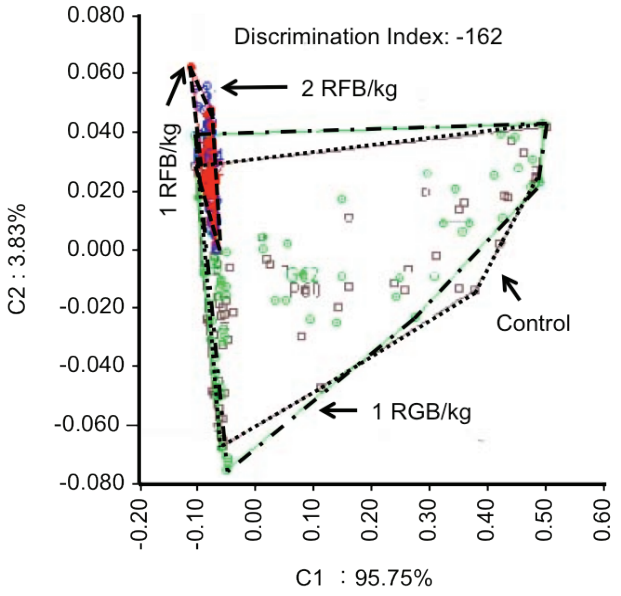


**Fig. 5. PCA plot of control and low infested-wheat by RFB and RGB at 16% moisture content. Note: Four groups are overlapped with each other showing no differentiation among the groups.**

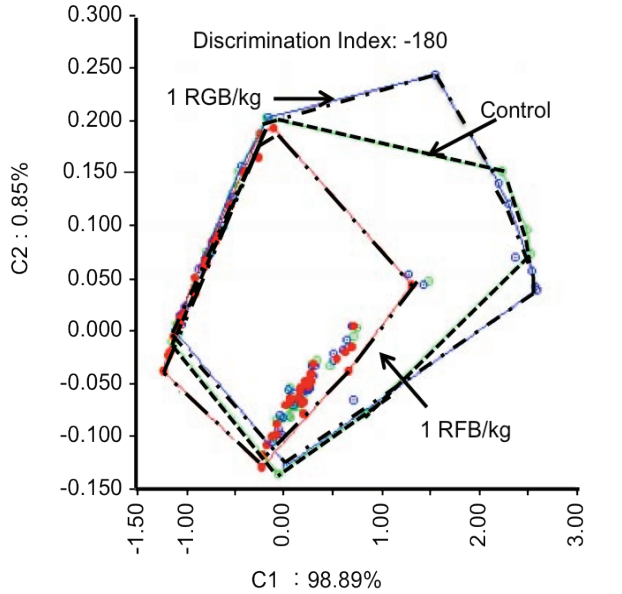


**Fig. 6. PCA plot of control and low infested-wheat by RFB and RGB at 18% moisture content. Note: Three groups are overlapped with each other showing no differentiation among the groups.**

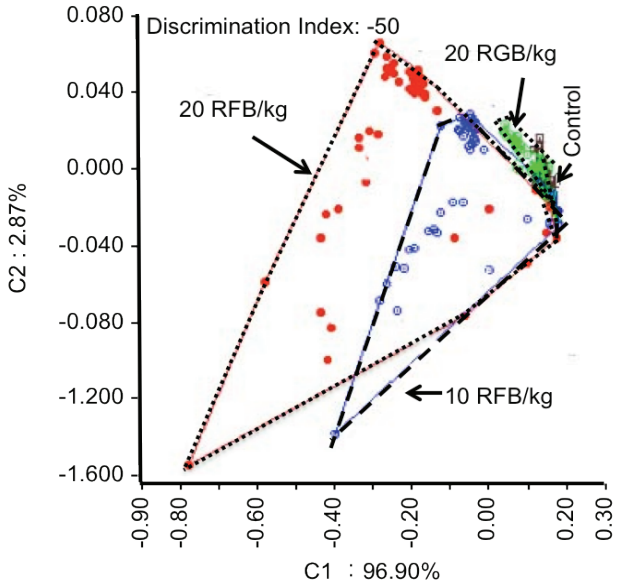


**Fig. 7. PCA plot of control and high infested-wheat by RFB and RGB at 14% moisture content. Note: 20 RFBs/kg is separated from Control.**

At 14% moisture content, the average values of peak response to RFB infested-wheat were greater than the corresponding values for RGB infested-wheat. The sensor responses to RFB infested-wheat were 75%, 188%, and 338% at 1, 10, and 20 insects/kg, respectively. In comparison with the RGB-infested wheat, the peak sensor response increased only 13%, 16%, and 29% at 1, 10, and 20 insects/kg levels, respectively.

At 16% moisture content, the average values of peak responses in relative resistance were compared for low and high insect infestation levels between the control, RFB- and RGB-infested wheat samples. The maximum difference in sensor responses between RFB-infested wheat and RGB-infested wheat at 16% moisture content at the low insect density was 4% and 7%. However, sensor responses to RFB-infested wheat became greater than that to RGB-infested wheat at the high insect density (95% vs. 7%).

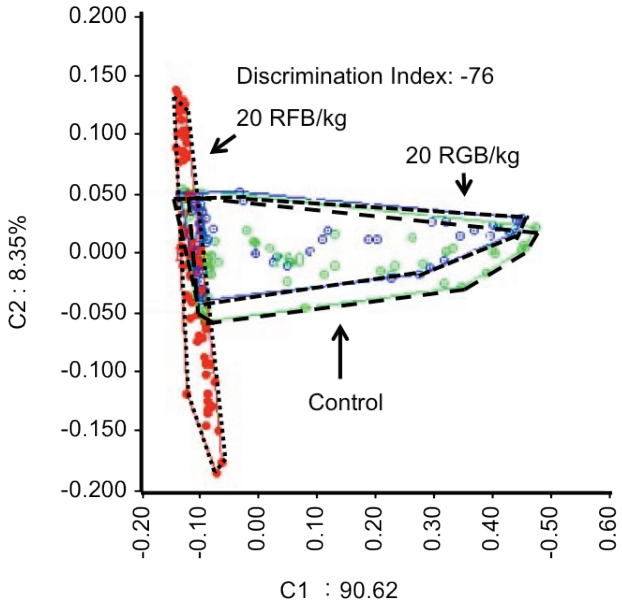


**Fig. 8. PCA plot of control and high infested-wheat by RFB and RGB at 16% moisture content. Note: 20 RGBs/kg and Control group are overlapped with each other.**

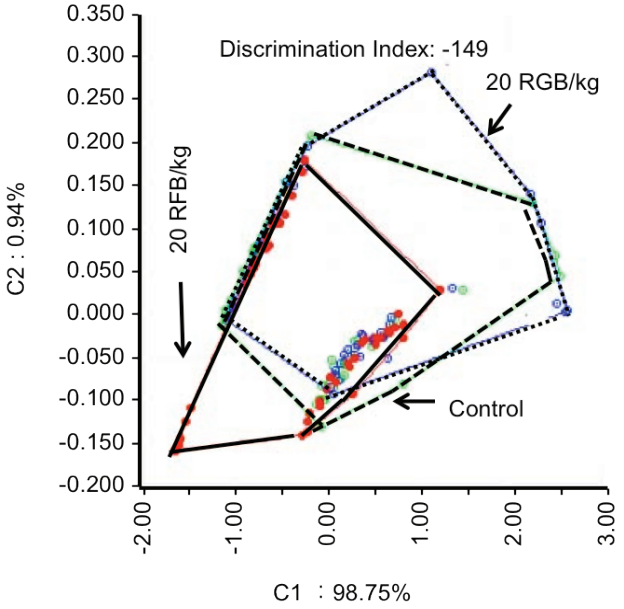


**Fig. 9. PCA plot of control and high infested-wheat by RFB and RGB at 18% moisture content. Note: Three groups are overlapped with each other showing no differentiation among the groups.**

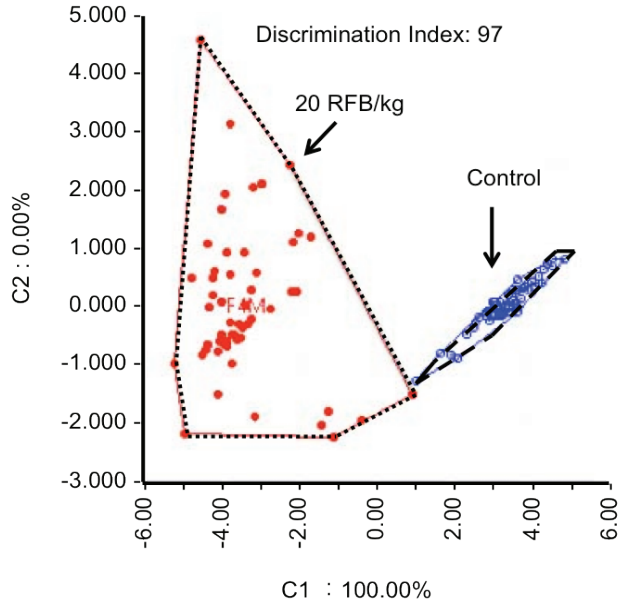


**Fig. 10. DFA plot of control and infested-wheat by RFB at 14% moisture content. Note: Two groups are separated showing the difference between the two groups.**

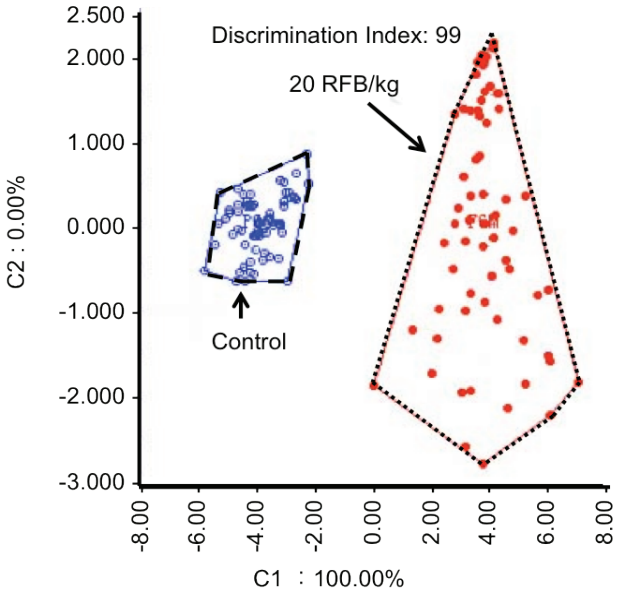


**Fig. 11. DFA plot of control and infested-wheat by RFB at 16% moisture content. Note: Two groups are separated showing the difference between the two groups.**

At 18% moisture content, the differences in sensor responses to different infestation levels were relatively small (<12%). It seems that the moisture itself overwhelmed the sensor responses. Therefore, for the 18% moisture content wheat, sensor signals changed little (<4%) when the insect infestation level changed.

In summary, the e-nose sensors were more sensitive to the moisture content of wheat than to the insect density changes. The sensors were more sensitive to the volatiles and metabolites by RFB at low moisture content wheat (14% and 16% moisture) than by RGB.

**Detection of the presence of insects and insect species differentiation**

For 14%, 16% and 18% moisture content wheat, samples were analyzed by selecting the sensor responses to low insect infestation levels from the training set. It is suggested by the equipment standard operational procedure (SOP) that the first sample was run for "warm up" and its sensor signals were not used for further analysis (Alpha M.O.S., Toulouse, France). The PCA was performed in the multivariate statistic window from AlphaSoft V8.0 software (Alpha MOS, Toulouse, France). The responses of the sensor array to low density insect infested and non-infested wheat samples at 14%, 16% and 18% moisture content were interpreted and demonstrated in the PCA plots (Figs. 4-11).

It was observed that the plots for RFB and RGB infested-wheat at low density of insects and clean wheat were overlapped with each other for all three different moisture contents tested (Figs. 4-6). In other words, the e-nose could not detect the presence of either RFB or RGB in wheat at low infestation levels (1 and 2 insects/kg) and it also failed to differentiate the RFB from RGB when insect density was low.

Maps of RGB infested-wheat were overlapped with clean wheat at 14%, 16% and 18% moisture content, while RFB infested-wheat was totally separated from clean wheat at 14% moisture content (Figs. 7-9). Furthermore, both RFB and RGB infested-wheat with the high insect density were overlapped with clean wheat at 18% moisture content. Therefore, the e-nose could not detect the presence of RGB in wheat at both low and high infestation levels for all three moisture contents. This observation was consistent with the conclusion by Seitz and Sauer (1996) that there was little objectionable odour present in RGB infested-grain sorghum. Since there was no superimposition between the high density of RFB infested-wheat and clean wheat at 14% moisture content and partial superimposition between the high density of RFB infested-wheat and clean wheat at 16% moisture content, DFA was performed to classify the two groups (Figs. 10-11).

In Figs. 10 and 11, two territories were defined for two groups for 20 RFBs/kg at 14% and 16% moisture levels, respectively. The percentage of recognition was 97% for 20 RFBs/kg at 14% M/C (Fig. 10), which meant that 97% of the samples could be classified as two categories (clean and infested) correctly during the cross validation for 14% moisture content wheat, and, 99% of the samples were classified during cross validation for 16% moisture content wheat (Fig. 11).

## CONCLUSIONS

The following conclusions were drawn from the study:

1. The Alpha MOS FOX-3000 electronic nose sensors were shown to be sensitive to the volatile compound, especially moisture. When wheat moisture was low (14% and 16%), sensors were sensitive to the volatiles and metabolites from red flour beetle (RFB), whereas, when wheat moisture was high (18%), the sensor could not differentiate insect volatiles from other volatiles. Discriminant Factorial Analysis and Partial Least Squares algorithms were effective in the application of e-nose to predict wheat moisture content.
2. The e-nose used in this research could detect the presence of red flour beetle (RFB) in wheat with a high infestation level of 20 insects/kg at 14% and 16% moisture content. However, it did not detect the presence of RFB in wheat at 18% moisture content.
3. The e-nose did not detect the presence of rusty grain beetle (RGB) in wheat.
4. The e-nose was able to differentiate 1 RFB/kg infestation level from 20 RFBs/kg infestation level in wheat at 14% and 16% moisture content.

**Closing Remarks**

Using e-noses for the detection of insects in the grain storage system is a quick, objective, less poisoning high technology. However, it requires a large amount of experimental data for training the e-nose. The cost may not be economical for using in small-scale (on-farm) grain storage systems. It should be noted that the focus of this study was to evaluate the feasibility of using e-noses for insect detection; therefore only two common insect species were tested. We recommend that other species, such as larger grain borer (LGB) and rice weevil (RW) also be tested.

Furthermore, to use an e-nose in a grain storage bin in the real world, a gas sampling system has to be developed to draw interstitial gas from the bin and deliver it to the e-nose. The sampling systems may consist of a series of ports (tubings) buried in the grain and a vacuum pump could be used to draw and deliver the gas.

## LIST OF SYMBOLS

RFB = Red Flour Beetle

RGB = Rusty Grain Beetle

CWRS = Canada Western Red Spring

PCA = Principal Component Analysis

DFA = Discriminant Factorial Analysis

PLS = Partial Least Square

SSC = Sensory Panel Score Correlation (linear regression algorithms). This is a term specific to the AlphaMOS AlphaSoft V8.0 software.

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