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DETECTION OF SPROUTED AND MIDGE-DAMAGED WHEAT KERNELS USING NEAR-INFRARED HYPERSPECTRAL IMAGING

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Abstract

Sprout damage which results in poor bread making quality due to enzymatic activity of alpha-amylase is one of the important grading factors of wheat in Canada. The potential of near-infrared (NIR) hyperspectral imaging was investigated to detect sprouting of wheat kernels. Artificially sprouted, midge-damaged and healthy wheat kernels were scanned using NIR hyperspectral imaging system in the range of 1000 nm to 1600 nm at 60 evenly distributed wavelengths. Multivariate image analysis (MVI) technique based on principal components analysis (PCA) was applied to reduce the dimensionality of the hyperspectral data. Three wavelengths 1101.7, 1132.2, and 1305.1 nm were identified as the significant wavelengths and used in analysis. Statistical discriminant classifiers (linear, quadratic and Mahalanobis) were used to classify sprouted, midge-damaged and healthy wheat kernels. The discriminant classifiers gave maximum accuracy of 98.3 and 100% for classifying healthy and damaged kernels, respectively.

Keywords: Hyperspectral imaging, Near-infrared, Sprout damage, Midge-damage, Grain quality.

INTRODUCTION

Canada is the sixth largest producer of wheat and ranks among the top exporters in the world with 27 Mt average annual production and 15 Mt annual export (FAOSTAT, 2007). Canada has a reputation of producing and supplying very high quality wheat in the world grain market. Sprouting is considered one of the important grading factors of wheat in Canada and all classes of Western Canadian wheat are tested for sprout damage. Sprouting occurs as a result of germination of wheat kernels by absorbing water mostly due to rain before the harvest. Enzymatic activity in the germinated kernels results in decrease in starch, increase in sugar, increase in total protein, change in amino acid composition, and dry matter loss (Lorenz and Valvano, 1981). Alpha-amylase, a common enzyme produced in sprouted wheat kernels affects the baking quality of bread, and thus lowers the premium paid for wheat. Alpha-amylase is present in very high concentration in sprouted kernels (Kruger, 1999). The quality of wheat flour for bread making is defined by several parameters such as water absorption capacity, dough mixing, loaf volume, crumb strength, and slicing characteristics of baked bread. These parameters are adversely affected due to starch damage in sprouted kernels (Fenney et al., 1988). Sprouted kernels are at a high risk of being contaminated with pathogens and ideal for the growth of bacteria (Health Canada, 2006). These pathogens are trapped in cracks and crevices that develop due to sprouting and cause cross-contamination when the grain is mixed in elevators, shipped and processed. Stored grain with a significant number of sprouted kernels is more vulnerable to infestation by insects as they can easily feed on the damaged kernels. Sprout damaged kernels also have lower mean density (1190 kg/m^3) than the healthy kernels (1280kg/m^3) (Martin et al., 1998).

Midge-damage occurs when the orange wheat blossom midge (*Sitodiplosis mosellana* Gehin) larva feeds on the developing wheat kernels by exuding an alpha-amylase enzyme to release sugars from grain (Oakley et al., 1998). Midge-damage in wheat causes the kernels to shrivel, crack and become deformed and mishapen. Lunn et al. (1995) concluded that sprouting of grain results due to the interaction between midge-damaged kernels and weather conditions. Oakley (1994) also hypothesized that midge-damage splits the kernel’s pericarp, facilitating the water uptake and hence sprouting in poor weather. Midge-damaged wheat kernels have high protein content, reduced flour yield, dark flour color, high flour ash, weak sticky dough properties, and poor bread quality (Dexter and Edwards, 1997). Pre-harvest sprouting occurs mostly due to rain when the wheat is left in the swath after cutting. Midge infestation is a serious cause of sprouting, and yield and economic losses.

The Canadian Grain Commission has set a tolerance for sprouted kernels in the grading of wheat. Grain inspectors assess the sprouted kernels in wheat by visual inspection using a magnifying lens. In many kernels (characteristics of variety) the germ emerges to a significant extent which breaks the bran overlaying the germ and gives a false impression of sprouting (ICC Standard, 1972). These grains are likely to be misclassified as sprouted kernels by the visual inspection method. A traditional method in which falling number is related to alpha-amylase is used for evaluation of sprouted bulk kernels. Rapid visco-analyzer (RVA) is also used for the screening of sprouted kernels. These methods are destructive and time consuming, so they can not be used for online inspection and some methods are either subjective or inconsistent. Neethirajan et al. (2007) used X-rays to classify sprouted and healthy wheat kernels and indentified 95% sprouted and 90% healthy kernels. However, X-rays pose health risks to humans due to exposure to ionizing radiation and the technique may not be implemented due to safety regulation issues. Some of the millers and bakers demand wheat with a very low level of sprout damage. Therefore, an accurate and timely detection technique for sprout-damaged wheat kernels is needed. Near-infrared spectroscopy (NIR) has been applied for quality evaluation of many cereal grains (Singh et al., 2006). Shashikumar et al. (1993) used a NIR reflectance analyzer to predict sprout damage in wheat. Instead of using the whole wavelength range to develop the calibration model, they used only three different combinations of wavelength filters in the range of 1445 to 2345 nm. This lack of robustness in the calibration model did not give very good prediction accuracy (r = 0.75-0.87) but demonstrated the potential for sprout damage detection using NIR spectra.

Hyperspectral imaging provides the spectral information in a spatially resolved manner to analyze a sample. This technique has shown potential for quality inspection of many agricultural and food products (Polder et al., 2002; Park et al., 2002; Lu, 2003; Liu et al., 2006). In grain quality evaluation, hyperspectral imaging has been experimented with for detection of insect damage (Ridgway and Chambers, 1998), moisture and oil content prediction (Cogdil et al., 2004), and detection of fungi (Singh et al., 2007). Studies detecting artificially sprouted wheat kernels have also been reported (Koc et al., 2007; Smail et al., 2006). Most of these studies have used only PCA score images for detection of damaged kernels by unsupervised classification and did not develop any algorithm for future prediction by training the classifier. Therefore, the objective of this study is to develop a supervised discriminant algorithm for classification of damaged wheat using the features of NIR hyperspectral images of the artificially sprouted, field damaged (midge-damaged), and healthy wheat kernels.

MATERIAL AND METHODS

Samples and Preparation of Damaged Kernels

Healthy, artificially created sprouted, and naturally midge-damaged wheat samples were used in this study. Sprouted wheat kernels were created for Canada Western Red Spring (CWRS) wheat (cv. AC Barrie). A 4 kg sample was first surface sterilized by soaking into 2.5% sodium hypochlorite aqueous solution for approximately 10 min. The wheat sample was thoroughly rinsed with distilled water and soaked in excess distilled water overnight. The sample was then spread on paper towel for about 48 h to germinate. The germinated sample was stored in a freezer at -40^{o}C and freeze-dried to 14% moisture content (wet basis) prior to imaging. The falling number of the sprouted and healthy samples was determined at the Cereal Research Centre (CRC), Agriculture and Agri-Food Canada, Winnipeg, Canada. The falling number test is used to determine the levels of alpha-amylase enzyme. A high falling number value indicates low alpha-amylase level. The falling number of sprouted samples was 61 which indicated very high level of sprouting and the falling number of the healthy samples was 343. Three hundred healthy and 300 artificially sprouted kernels were randomly picked for imaging.

Midge-damaged composite samples from five different growing regions namely Camrose East, AB (4.3% midge), Vegreville, AB (5.2% midge), North Battleford, SK (5.5% midge), Cutknife, SK (4.1% midge), and Yorkton, SK, (6.2% midge) across western Canada were procured from Cargill Foods. The falling number of these samples were 334, 271, 387, 325, and 190, respectively. Interestingly, one of the midge-damaged samples showed higher falling number value (387) than the healthy kernels (343). These falling numbers represent bulk samples from which obvious midge-damaged kernels were selected. Three hundred midge-damaged kernels from each of the five locations were manually selected by using a microscope and were verified by an expert on midge-damage at CRC. These 300 kernels from each sample were divided into independent training (80%) and test set (20%) and used in classification.

Hyperspectral Imaging System

The details of the hyperspectral imaging system used in this study are given in Singh et al. (2007). The system consisted of an InGaAs camera (Sensors Unlimited Inc., Princeton, NJ) of 640×480 pixels detector size and a VariSpec liquid crystal tunable filter (LCTF) (Cambridge Research and Instrumentation Inc., Woburn, MA), which had a tuning range of 900 nm - 1700 nm. Two 300 W halogen-tungsten lamps were used as illumination sources and fixed at 45° angles and 0.5 m away from the imaging area. System controls developed under LabVIEW (National Instruments, Austin, TX) were used to acquire images, align the imaging system, and store hyperspectral data in a binary file. The program stores the imaging system setup, spectral range and number of wavelength bands along with the hyperspectral imaging data in a file.

Image Acquisition

Healthy kernels, artificially sprouted, and midge-damaged wheat samples from five locations (300 kernels for each sample) were randomly selected, scanned and used in the analysis. Three hundred healthy kernels were also imaged and images were stored for further analysis. For every image, five non-touching kernels with the same orientation (crease-down for artificially sprouted kernels, and crease-up and crease-down for midge-damaged kernels) were placed in the imaging area of the hyperspectral imaging system and scanned at 60 evenly spaced wavelengths in the range of 1000 to 1600 nm. The imaging system was aligned at the central wavelength of the full spectral range. A dark-current image was acquired by blocking the entrance of the camera at the beginning of in each imaging session. The control program automatically subtracted the dark-current image from subsequent acquired images.

Data Analysis

A MATLAB (Mathworks Inc., Natick, MA) program was written to import the image files from the control program, and to display and analyze the hyperspectral data. The dead pixels in the images were removed by applying a 3×3 median filter. The signal-to-noise ratio was improved by automatically co-adding an image 10 times at each of the 60 wavelengths during image acquisition. Single-kernel images from five non-touching kernels in the original images were obtained and labeled by implementing a code developed in MATLAB. The image data were transformed into reflectance using a 99% standard reflectance panel (Labshpere Inc, North Sutton, NH). A Multivariate Image Analysis (MVI) program written in MATLAB was used to analyze each of the five labeled kernels in an image. The MVI was performed using principal components analysis (PCA) (Geladi and Grahn, 1996). A simple multivariate image had two pixel coordinates (width and height) and a variables index (wavelength value) making a three-way array (hypercube). The hypercube data were reshaped into a two-way array by rearranging all the pixel intensities (reflectance) of a kernel into a row at each of the 60 wavelengths. This resulted into k×60 size two-dimensional array, where k is the total number of pixels in a labeled kernel. Principal components analysis was applied to the reshaped data set of each kernel. The most significant wavelengths corresponding to the highest factor loadings of the first principal component (PC) were selected and used for feature extraction. A total of six image features namely mean, maximum, minimum, median, standasrd deviation, and variance from the images corresponding to the selected wavelengths were extracted and used in classification. The classification algorithms were developed by applying various statistical discriminant analyses (linear, quadratic, and Mahalanobis). Linear discriminant classifier (LDA) uses pooled co-variance in Bayes' criteria to assign an unknown sample to one of the predefined groups. In many biological applications, data do not follow normal distribution, so using pooled co-variance may not give appropriate classification. Quadratic discriminant classifier (QDA) uses covariance of each class instead of pooling them in Bayes' criteria for grouping of unknown samples. If the covariance of the classes is equal, both LDA and QDA give the same results. The Mahalanobis discriminant classifier is a simplified form of the LDA with assumptions that all the known groups have equal posterior probabilities. This method gives good classification when the data distribution is elliptically concentrated and an unknown sample is assigned to the group with minimum Mahalanobis distance.

RESULTS AND DISCUSSION

Two wavelength regions with dominating peaks near 1100 and 1300 nm had the highest first PC factor loadings. The first PC accounted for 95-98% variability of data in healthy, artificially sprouted, and midge-damaged kernels. The first PC score images (pseudo color image) showed the obvious differences in compositional distribution between the damaged and healthy kernels (Fig. 1). The kernels shown in Figure 1 were imaged with germ facing right side and crease-down position. The healthy kernels have solid contours and the germ area is clearly visible with relatively higher and concentrated intensity. However, in sprouted and midge-damaged kernels the germ portion does not show that pattern. This could be due to the starch decomposition or embryo development in the germ area of the sprouted and midge- damaged kernels.

In the discrimination of artificially sprouted and healthy kernels two wavelengths (1101.7 and 1305.1 nm) corresponding to the highest factor loadings of the first PC were selected as the significant wavelengths. In the classification of midge-damaged samples, three wavelengths (1101.7, 1132.20, and 1305.1 nm) were selected as significant wavelengths. In midge-damaged samples two wavelengths (1101.7, 1132.20 nm) in the 1100 nm peak region were selected due to the small shift in highest factor loadings with respect to the wavelengths for different location samples (Fig. 2). The significance of the selected wavelengths can also be observed from the reflectance spectra as these three wavelengths correspond to the main dominating peaks (Fig. 3). The wavelengths 1101.7 and 1132.2 nm correspond to the second overtone of C-H and 1305.1 nm corresponds to the first overtone of C-H combination bands. The significance of these wavelengths can be associated with absorption by starch molecules. The wavelength region examined in our study was also found significant by other researchers. Delwiche (1998) found the spectral region from 1100 to 1400 nm as the most significant region for protein content analysis of wheat and interpreted 1138 nm as the wavelength attributable to the protein absorption band. In another study, Delwiche and Hareland (2004) found spectral region from 1130 to 1190 nm as very stable for classifying normal and scab-damaged wheat kernels. Xie et al. (2004) related 1155 nm wavelength to the starch structure changes which correspond to the second overtone of the $C\text{-}H_3$ bond. Barton and Burdick (1979) related the peak around the 1330 nm C-H bond to the fiber and starch content.

A binary classification model was developed to classify artificially sprouted wheat kernels and healthy wheat kernels (Table 1). Both LDA and QDA classifiers correctly classified healthy and sprouted kernels. Mahalanobis classifiers also classified all the sprouted kernels and more than 98% healthy kernels. This high accuracy is expected as very low falling number value (high alpha amylase level) in the sprouted kernels was determined. In actual field conditions, the degree of sprout damage varies depending on weather conditions and level of midge-damage. Though, the midge-damage usually occurs on the pericarp side, it does not happen all the time. The distribution of alpha-amylase within individual wheat kernels is heterogeneous. So the artificial sprout damage does not always simulate the actual sprout damage wheat in the field.
To develop a robust classification model, we used the midge-damaged samples from five different locations across western Canada. Due to the non-uniform nature of midge-damage, the damaged samples were scanned both in crease-up and crease-down orientation. Two-way discriminant classification models were developed by using independent training set (80%) and test set (20%) from each of the five location samples and healthy samples for both crease-up and crease-down orientations separately. The classification results of the crease-down orientation samples are given in Table 2. More than 95% of healthy kernels were correctly classified by LDA and QDA classifiers whereas Mahalanobis classifier correctly classified 85% of the healthy kernels. The LDA and QDA classifiers gave moderate to high classification accuracy (83.33 to 100%) in classification of midge-damaged samples from various locations and Mahalanobis classifier gave the highest classification accuracy in classifying the midge-damaged samples (91-100%).

The classification results of samples with crease-up orientation are given in Table 3. The LDA, QDA, and Mahalanobis classifiers correctly classified 93.3%, 100%, and 65% healthy kernels, respectively. The classification accuracy of LDA and QDA for classifying midge-damaged kernels varied from low (55%) to very high (100%) and Mahalanobis classifier correctly classified 95 to 100% midge-damaged kernels. Smail et al. (2006) measured the Mahalanobis distance between spectra of sprouted and the mean spectra of healthy kernels by manually selecting 20 pixels in the germ area. The measured Mahalanobis distance also showed promise for use in discriminanat analysis. In the discussed classification models, Mahalanobis discriminant classifier gave consistent and highest classification for damaged samples. Both LDA and QDA gave better accuracy in the classification of healthy samples. The overall classification accuracy of midge-damaged samples by NIR hyperspectral imaging was very high compared to manual inspection (approximately 60%) (Personal communication, Ian Wise, Cereal Research Centre, Winnipeg). The classification accuracy of the crease-down sample was slightly lower (91.67-100%) than crease-up samples (95-100%), however, these results clearly indicate that kernel orientation has a limited effect on the identification of midge-damaged samples compared to visual inspection.

CONCLUSION

Sprouted and midge-damaged wheat kernels can be easily detected from healthy kernels by NIR hyperspectral imaging in the wavelength region of 1000-1600 nm. Three wavelengths, i.e. 1101.7, 1132.20, and 1305.1 nm, corresponding to the highest factor loadings of first principal component were selected as significant and used in feature extraction. All the artificially sprouted kernels were detected by linear (LDA), quadratic (QDA), and Mahalanobis discriminant classifiers. Midge-damaged samples from various locations were also discriminated from healthy kernels by discriminant analyses. Mahalanobis classifier gave the highest and most consistent classification accuracy in classifying damaged samples whereas the LDA and QDA gave better results in classifying healthy kernels. The classification accuracy of crease-up orientation samples (95-100%) was slightly higher than the crease-down orientation samples (91.7-100%). The results of this study indicate that NIR hyperpsectral imaging holds promise for detection of sprouted and midge-damaged wheat samples.

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Table 1: Classification of sprout damaged wheat kernels

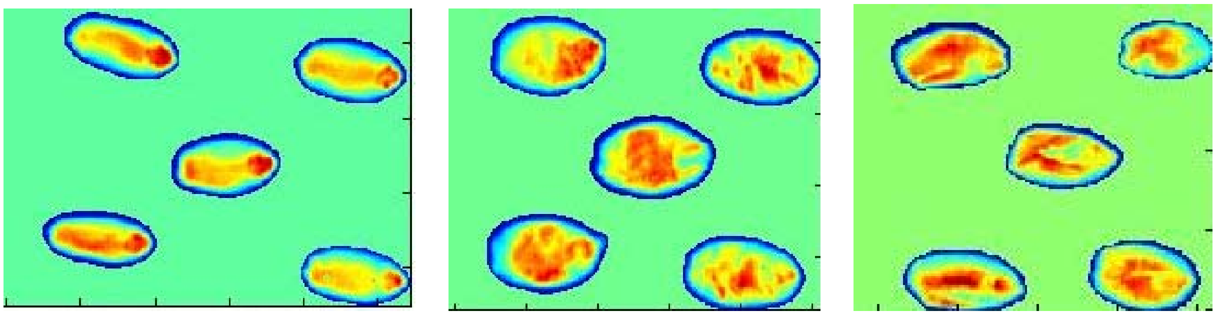
Discriminant Classifier	Classification Accuracy (%)	
	Healthy	Sprouted
Linear	100.0	100.0
Quadratic	100.0	100.0
Mahalanobis	98.3	100.0

Table 2: Classification of midge-damaged wheat kernels (Crease-down)

Grain Type	Classification accuracy (%) of various discriminant classifiers		
(location)	Linear	Quadratic	Mahalanobis
Healthy	96.7	95.0	85.0
Yorkton	86.7	93.3	96.7
Camrose East	100.0	100.0	100.0
Cutknife	96.7	100.0	100.0
Vegreville	83.3	86.7	91.7
North Battleford	100	100.0	100.0

Table 3: Classification of midge-damaged wheat kernels (Crease-up)

Grain Type	Classification accuracy (%) of various discriminant classifiers		
(location)	Linear	Quadratic	Mahalanobis
Healthy	93.3	100.0	65.5
Yorkton	91.7	81.7	98.3
Camrose East	100.0	100.0	100.0
Cutknife	100.0	100.0	100.0
Vegreville	68.3	55.0	95.0
North Battleford	100.0	100.0	100.0



Healthy Sprouted Midge damaged

Fig.1. First principal component (PC) scores images of healthy, sprouted, and midge-damaged kernels.

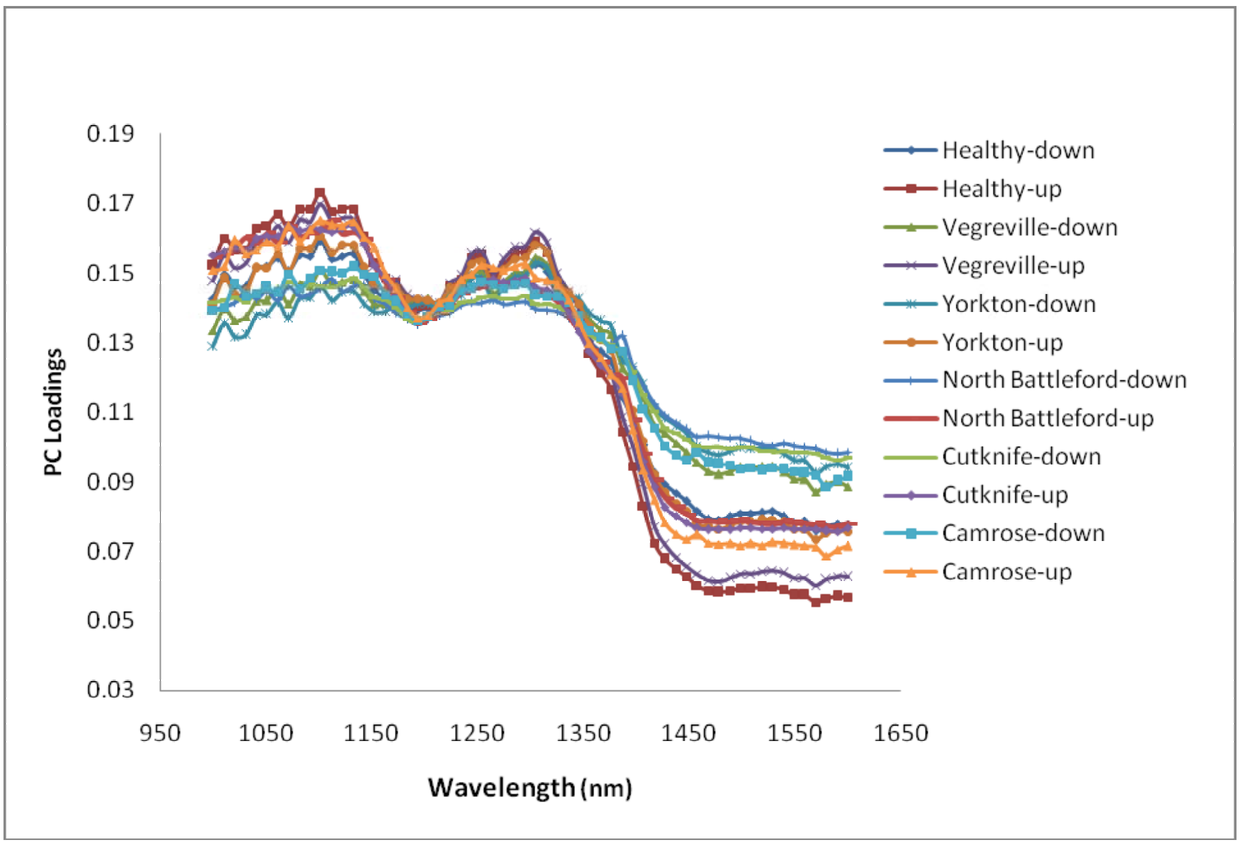


Fig. 2. PC loadings of first principal component (PC) of healthy and midge-damaged kernels.

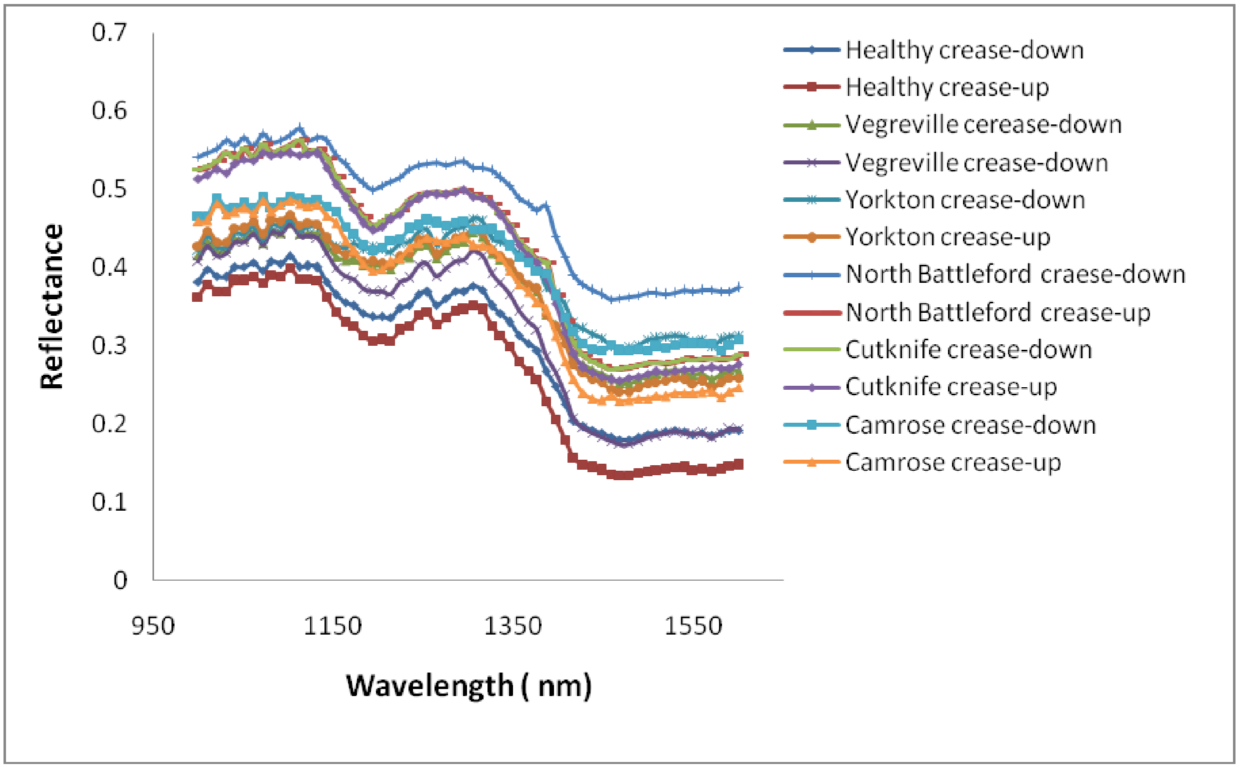


Fig. 3. Reflectance spectra of healthy and midge-damaged kernels.