The use of hyperspectral imaging to detect mildew damage in soft red winter wheat samples

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Introduction

Mildew is a major degrading factor in wheat that has a negative impact on the milling yield and quality of flour.[1] Mildew is a fungal contamination caused by adverse growing conditions that imparts a grey discoloration initially on the brush end of the kernel, which begins to encompass the entire kernel as damage increases. The grey color is caused mainly by spores of *Alternaria* and *Cladosporium* fungi. Wheat milling performance decreases as mildew damage increases. Current grading systems are based on a relatively slow and subjective human visual inspection by trained inspectors. Fast and accurate instrumental methods are needed to quantify the extent of mildew damage.

The identification of damaged regions of individual kernels by imaging appears to be a logical solution; however, variations in the discoloration of the damaged regions and the colour of underlying kernels make this impossible to achieve using a traditional imaging platform. Hyperspectral imaging (HSI) can provide a workable solution in this situation as it combines the powers of conventional imaging and spectroscopy. Recently, HSI technology has emerged as a research tool for food quality and safety control.[2] Applications of HSI have been reported for quality assessment of cereal grains.[3–5] Recent studies have shown that hyperspectral imaging could distinguish sprout damaged[6,7] as well as stained and fungal infected[8,9] wheat kernels from sound kernels. Spectral characteristics of mildewed wheat kernels have been reported to be significantly different from those of sound undamaged kernels.[10] These spectral differences can be utilized to determine the extent of mildew damage in wheat samples. The objective of this study was to investigate the use of hyperspectrtal imaging as an objective method to quantify the extent of mildew damage in wheat samples.

Materials and methods

Samples

Sixty-five samples of Canada Eastern Soft Red Winter (CESRW) with varying degree of mildew damage were received from the inspection division of the Canadian Grain Commission (CGC).

These samples were selected for mildew damage. Each sample was approximately 1 kg. The samples were graded by trained grain inspectors into nine mildew levels on a scale from 1 to 9. A score of 1 corresponded to high quality No. 1 grade while 9 corresponded to the lowest acceptable No. 3 grade.

Image capture and calibration

The samples were scanned and analyzed for mildew damage with a push-broom type hyperspectral imaging system in the 400–1000 nm range (VNIR 100E Lextel Intelligence Systems, Jackson, MS, USA). For imaging, a $16 \times 8 \times 1$ cm wooden tray filled with grains was placed directly under the camera and an 800×400 spatial $\times 300$ spectral hypercube was collected in reflectance mode. Spatial binning of 2 and spectral binning of 4 were used, while the exposure time was set at 60 ms. Dark current and white light reference images were collected before imaging each sample to calibrate spectra at each pixel in terms of percent reflectance value.

Spectral data extraction

Image mean and standard deviation values were computed at each wavelength in the hypercube of a sample to generate what were called the image mean spectrum and image standard deviation spectrum, respectively. Darker areas in the image (voids) were excluded from these calculations. A macro written in IDL software (Version 7.0.2; ITT Visual Information Solutions, Denver, CO, USA) was used to extract image mean and standard deviation spectra for all the samples in a batch mode.

Mildew level predictions

The image mean spectra were peak normalized by dividing each spectrum with its value at 950 nm in order to minimize the effects of moisture variations among samples and lighting inconsistency within the image plane. Partial least squares (PLS) calibrations were developed based on normalized image mean and image standard deviation spectra for predicting mildew levels using the Unscrambler (CAMO Software, Oslo, Norway). One half of the samples was used for calibration with the other half for validation.

Performance of PLS models was evaluated based on coefficient of determination (R^2) and root mean squared error (*RMSE*) as the performance criteria. For mildew level classification, output of the best PLS model was partitioned into nine discrete classes to compare with the inspector scores for nine mildew levels.

Results and discussion

Spectral characteristics of mildewed and sound kernels

Mildewed and non-mildewed (sound) regions of kernels showed significantly different spectral characteristics in terms of the shape as well as the slope of the spectral curves (Figure 4.1). These differences in a sample were observed to have a significant effect on the image mean and standard

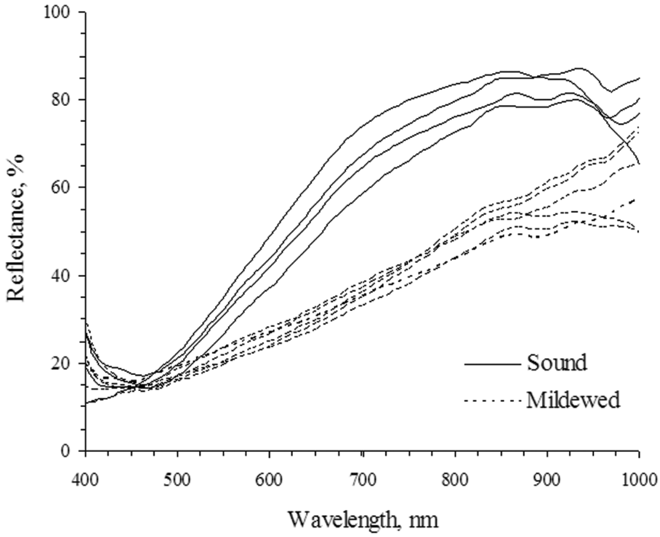

Figure 4.1. Spectral characteristics of sound and mildewed (dotted) wheat kernels.

deviation spectra in relation to the proportions of mildewed and non-mildewed (sound) kernels in the sample.

Mildew level predictions

The image standard deviation spectra showed higher correlation with the mildew levels as compared to the image mean spectra (Table 4.1). A PLS model based on the image mean and standard deviation spectra combined predicted mildew levels highly accurately ($R^2 > 0.87$; $RMSE < 0.73$). Accuracy for predicting 9 mildew levels was 91% for within ± 1 level of inspector scores.

Conclusions

Spectral characteristics of bulk grains were found to be highly correlated with mildew damage in CESRW wheat. PLS regression models predicted mildew levels in CESRW highly accurately

Table 4.1. Performance of PLS regression models for predicting mildew levels based on different input spectra.

PLS model input spectra	Calibration		Validation	
	R^2	*RMSE*	R^2	*RMSE*
Image mean spectra	0.757	1.02	0.667	1.19
Image standard deviation spectra	0.852	0.79	0.839	0.83
Image mean spectra and standard deviation spectra combined	0.894	0.67	0.874	0.73

($R^2 \sim 0.87$; $RMSE = 0.73$) based on image mean and standard deviation spectra. PLS classification results matched the inspector scores with an accuracy approaching 91% for the validation set.

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