Seed Science Research

cambridge.org/ssr

Multispectral imaging – a new tool in seed quality assessment?

Birte Boelt[1], Santosh Shrestha[1], Zahra Salimi[1], Johannes Ravn Jørgensen[1], Mogens Nicolaisen[1] and Jens Michael Carstensen[2,3]

[1]Department of Agroecology, Aarhus University, DK-4200 Slagelse, Denmark; [2]Videometer A/S, DK-2970 Hørsholm, Denmark and [3]Technical University of Denmark, DK-2800 Lyngby, Denmark

Review Paper

Cite this article: Boelt B, Shrestha S, Salimi Z, Jørgensen JR, Nicolaisen M, Carstensen JM (2018). Multispectral imaging – a new tool in seed quality assessment? *Seed Science Research* **28**, 222–228. https://doi.org/10.1017/S0960258518000235

Received: 12 January 2018
Accepted: 4 May 2018
First published online: 27 June 2018

Keywords:
chlorophyll; seed development; seed health; seed quality

Author for correspondence:
Birte Boelt, Email: Birte.Boelt@agro.au.dk

Abstract

Multispectral imaging is a new technology that is being deployed to assess seed quality parameters. Examples of applications in the detection and identification of fungi on seeds are presented, together with an example of the technology used for maturity determination in sugar beet seed. Results from multispectral imaging are compared with reference methods, and a high correlation is found. Applications of the technique for varietal discrimination and insect damage are also presented. There is a need for non-destructive, reliable and fast techniques, and it is concluded that multispectral imaging has potential for seed quality assessment, in particular for those components associated with surface structure and chemical composition, seed colour, morphology and size.

Introduction

Seed quality is a multiple component characterization of seeds, including varietal and analytical purity, germination capacity, vigour, seed health and uniformity. Currently, testing for seed quality relies on physical and chemical as well as visual inspections, which are costly and time consuming. Furthermore, visual inspections are subjective and difficult to reproduce.

Visible features like colour, surface structure, morphology and seed size are determined by machine vision, primarily based on RGB (red, green and blue) cameras. Another optical sensing technology is near-infrared spectroscopy (NIRS) for the determination of chemical composition, both on the seed surface and internally. Hyperspectral imaging combines the two technologies and provides information on both spatial and spectral aspects (Huang *et al.*, 2015). Rahman and Cho (2016) have reviewed a number of non-destructive measurement techniques including machine vision, spectroscopy and hyperspectral imaging for the assessment of quality parameters of agricultural seeds. In particular, they found hyperspectral imaging to be a promising tool for seed quality aspects, as it combines machine vision and spectroscopy into one instrument. Applications of hyperspectral imaging in seed quality assessment are variety identification and classification, quality grading, detection of insect damage and fungi infection, and prediction of chemical composition (Huang *et al.*, 2015). The spectral regions employed cover a broad range of spectra in the visible (380–780 nm) and NIR (780–2500 nm) region (Huang *et al.*, 2015; Rahman and Cho, 2016). However, adoption of hyperspectral imaging by the seed industry requires a decrease of costs without compromising the accuracy of analysis (Dell'Aquila, 2007; Huang *et al.*, 2015; Rahman and Cho, 2016).

Selecting only those spectra providing specific information about the quality aspect in question is one way of reducing costs, yet still maintaining the high quality assessment. Multispectral imaging (MSI) systems include light sources providing a restricted number of wavelengths, which will provide the specific spectra. Examples are reported from the food industry where the spectra from four wavelength bands provide 100% correct classification of damaged mushrooms (Esquerre *et al.*, 2012), and similarly Xing *et al.* (2010) were able to distinguish sprouted from non-sprouted wheat kernels by the use of four specific wavelength bands.

The Organisation for Economic Co-operation and Development (OECD) defines the standards for the certification of seeds in the international trade, and the International Seed Testing Association (ISTA) develops, approves and disseminates methods for harmonized and standardized seed quality analysis. The Association of Official Seed Analysts (AOSA) has a similar function in the USA and Canada. The procedures of seed quality assessments are consolidated and globally accepted, and new technologies need to be thoroughly documented before approval is obtained. Both ISTA and AOSA recognize the need for new technologies for non-destructive, fast and reliable seed quality assessment to improve seed quality analysis and to reduce the cost of labour-intensive tests.

This review provides examples of applications of MSI for the assessment of physiological characteristics and determination of fungal infection. In addition, the results obtained by MSI in seed quality assessments are reviewed.

© Cambridge University Press 2018

CAMBRIDGE UNIVERSITY PRESS

Seed development and maturity

Crops like sugar beet (*Beta vulgaris*) and spinach (*Spinacia oleracea*) have an indeterminate flowering pattern, which consequently leads to a non-uniform seed development and maturity pattern. Furthermore, the climatic conditions during seed production may affect the interval from anthesis to harvest time, resulting in seed lots with non-uniform maturity levels. Distinguishing empty or underdeveloped seeds from fully matured seeds is hardly possible by visual inspection, but their effect on the germination potential of a seed batch is significant (Tekrony and Hardin, 1969). In many studies on sugar beet seed performance, the underdeveloped seeds are considered to be the predominant reason for poor field establishment (TeKrony, 1969; TeKrony and Hardin, 1969; Snyder, 1971; Śliwińska *et al.*, 1999). Sugar beet is an important commercial biennial crop with a global production of 185 million metric tons in 2017 (USDA, 2017). It is direct-seeded and the seed quality greatly affects field emergence uniformity and crop yield (Agrawal and Rakwal, 2012).

During maturation, the amount of chlorophyll in the seed coat of many seed species decreases (Dell'Aquila, 2009), and Jalink *et al.* (1998) reported chlorophyll fluorescence (CF) as a non-destructive marker for seed maturity and performance in white cabbage (*Brassica oleracea*). Following this finding, CF has been demonstrated to correlate with seed germination in pepper (*Capsicum annuum*) and spinach (Deleuran *et al.*, 2013; Kenanoglu *et al.*, 2013).

X-ray provides a non-destructive evaluation method of the internal seed morphology associated with seed development (Dell'Aquila, 2009), and its application to predict germination capacity has been reported in bell pepper (*Capsicum annuum*) and tomato (*Solanum lycopersicum*) seeds (van der Burg *et al.*, 1994; Gagliardi and Marcos-Filho, 2011; Gomes-Junior *et al.*, 2012; Silva *et al.*, 2013).

With the aim of comparing multispectral image analysis results from a non-uniform sugar beet seed lot, 20 sugar beet seeds in each of three maturity classes based on CF sorting according to Deleuran *et al.* (2013) were analysed by MSI technology. Multispectral images were captured by the VideometerLab multispectral imaging system (Videometer A/S, Hørsholm, Denmark). High resolution images (2056 × 2056 pixels) constituted images from 19 wavelengths ranging from 375 to 970 nm. The multispectral images of the sugar beet seeds were analysed by a normalized canonical discriminant analysis (nCDA) (Olesen *et al.*, 2015; Shrestha *et al.*, 2015) to discriminate between maturity classes. The mean reflectance from the surface of the sugar beet seeds in the maturity classes 1 to 3 were different across the 19 wavelengths. The immature seeds (class 1) generally had a higher reflection in the visible range of the spectrum, whereas all three classes showed differences in the NIR spectrum. Chlorophyll fluorescence is correlated with the reflectance in wavelengths 435, 645 and 660 nm of this MSI system. As indicated in Fig. 1, the immature seeds have a higher reflectance compared with maturity classes 2 and 3 in those wavelengths, but the reflectance of classes 2 and 3 is almost overlapping in the visible spectrum.

In order to extract information from the multispectral images, 17 variables (representing seed shape, colour and binary features) were evaluated. The RegionMSImean calculates a trimmed mean of MSI transformed pixel values within the blob (each single seed) and RegionMSIthresh returns a relative number of pixels exceeding the threshold of MSI-transformation in blob region based on the nCDA model (derived from all three classes) in their setting. The output of the image analysis was exported for the statistical

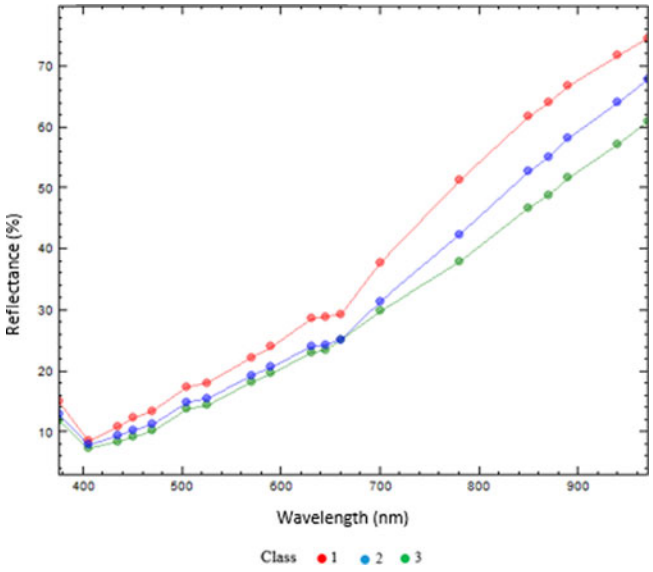


Figure 1. The mean reflectance (%) of the seed coat of sugar beet seeds in three maturity groups [group 1 (red): underdeveloped seeds; group 2 (blue): physiologically developed and ready for harvest; group 3 (green): seeds have passed physiological maturity].

data analysis. Canonical discriminant analysis (CDA) in SAS (SAS, 9.3) was used as statistical method. CDA is a dimension-reduction technique related to principal component analysis and canonical correlation. By the use of a classification variable and several interval variables, the CDA derives canonical variables (linear combinations of the interval variables) that summarize between-class variation.

For the characterization of differences between the three maturity classes, stacked photos of one seed per maturity class and a selected CT (computed tomography) slice from the 3D X-ray image of the same seeds were acquired (Fig. 2). North Star Imaging Europe, Inspection Services Group provided the CT scans. The seed development and maturity levels are illustrated in Fig. 2A with the least mature seed (class 1) to the left. In parallel with this, the slice of CT scan in Fig. 2B illustrates the internal structure of the seed, which is not yet fully developed and has free cavity space.

The CDA based on the surface characteristics from the MSI analysis classifies the sugar beet seeds into three distinctive classes (Fig. 3), which are identical with the three maturity levels from the CF reference analysis. The collection of seed colour, shape, texture and binary features identified three individual seed classes: (1) undeveloped, (2) physiologically developed seed, ready for harvest, and (3) seed past physiological maturity.

Figure 3 shows the scatter plot of the examined seeds classified into three classes according to the statistical analysis of the spectral information by plotting two derived variables of CDA (can1 and can2) for each assessed seed. Of the 60 seeds investigated in this study, 57 were classified in accordance with the CF classes, with a resulting 95% accuracy of classification in total. Comparing the MSI of each seed and the related CT scan (Fig. 2B) shows a good relationship between classification by the use of seed surface characteristics and seed development. MSI is therefore suggested as a reliable, non-destructive technology for the classification of seed development in sugar beet. The number of sugar beet seeds available, in particular the class 1, immature seed, did not allow for the characterization of germination capacity in this study. In castor bean (*Ricinus cimmunis*) MSI provided a model

https://doi.org/10.1017/S0960258518000235 Published online by Cambridge University Press

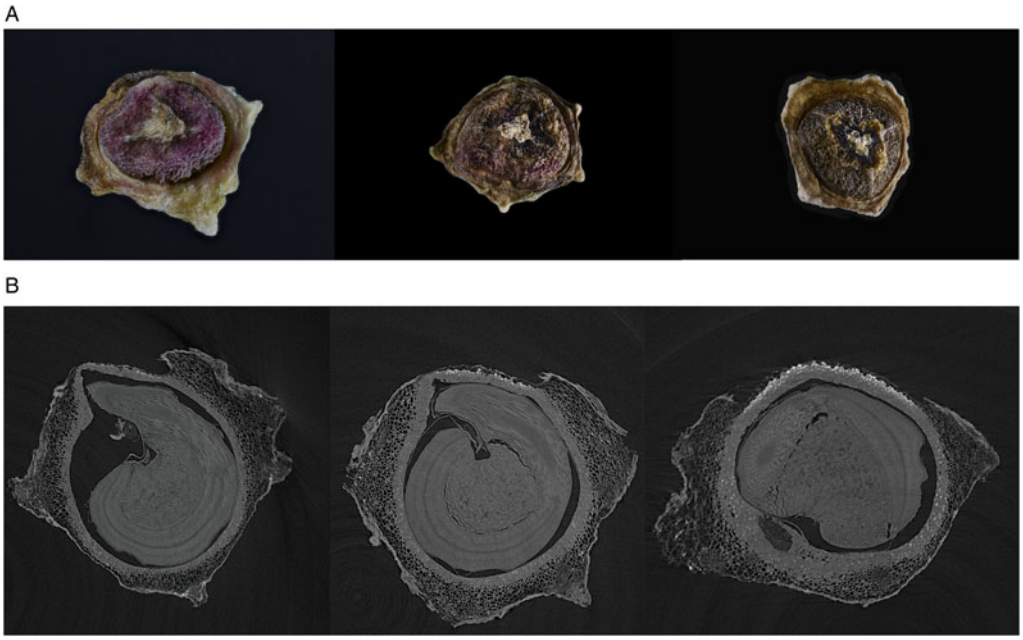


Figure 2. Three maturity groups of sugar beet seed. (A) RGB photo with maturity group 1 to the left; (B) slides of CT scan. Scans provided by North Star Imaging Europe, Inspection Services Group.

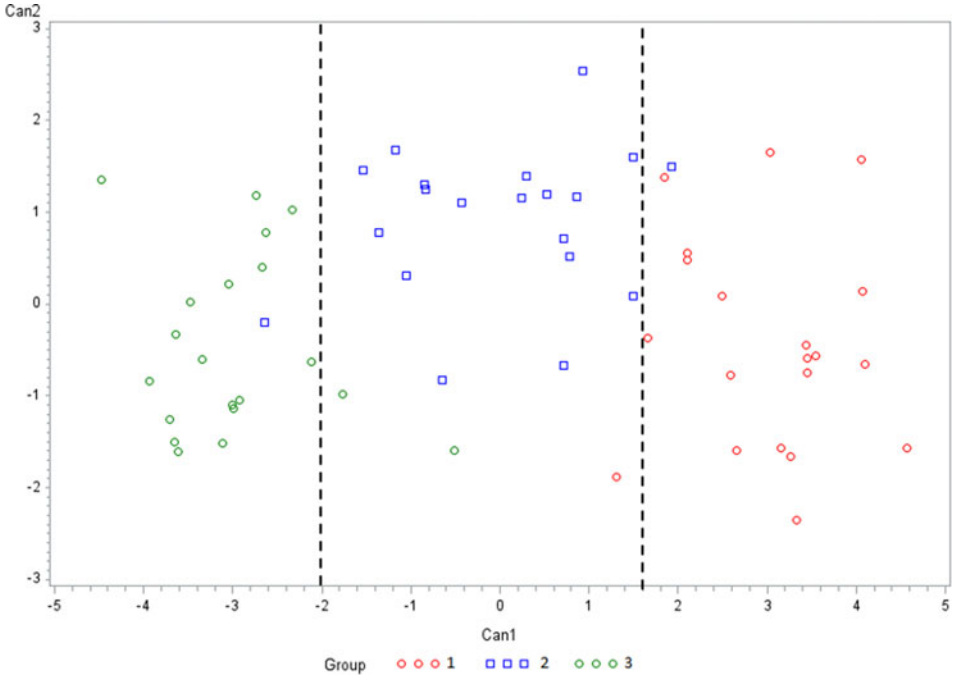


Figure 3. Classification of sugar beet seeds in three maturity groups (1–3) by plotting the can1 *versus* can2, derived from canonical discriminant analysis. Group 1: underdeveloped seeds, 2: physiologically developed and ready for harvest; 3: seeds have passed physiological maturity.

to predict viable from dead seed with an accuracy of 92% (Olesen *et al.*, 2015).

Multispectral imaging technology has been used in many studies for evaluating fruit maturity but not in seeds (Hahn, 2002; Lleó *et al.*, 2009; Baiano *et al.*, 2012; Rajkumar *et al.*, 2012; Qin *et al.*, 2013). However, evaluating seed maturity by different methods shows that differences in the level of embryo development as a probable effect of insects, other species pollen stimulation, application of synthetic hormones, extreme temperature or inappropriate nutrition condition of plant may affect seed quality (Gustafson, 1942; Hills, 1963; Tekrony and Hardin, 1969).

Seed health

Seed deterioration caused by fungi is an important factor in seed quality during storage, processing and propagation (Barton, 2016). Detection of fungi on seed is performed by inspection of the dry seed, washing tests, incubation methods, embryo count method or seedling symptom tests (Mathur and Kongsdal,

https://doi.org/10.1017/S0960258518000235 Published online by Cambridge University Press

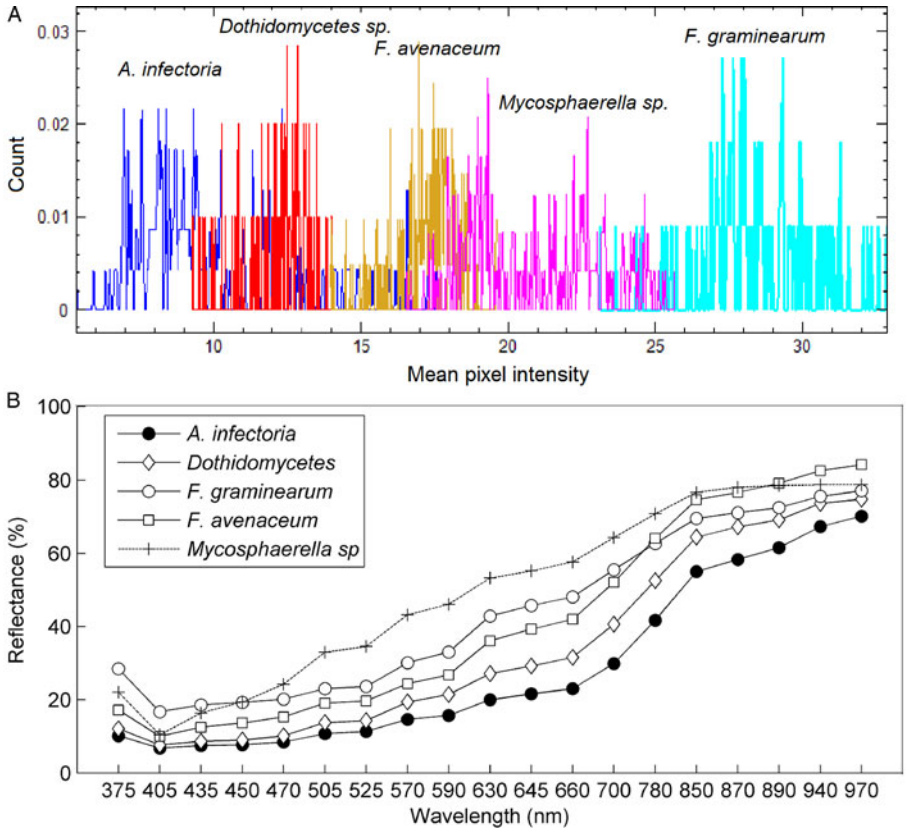


Figure 4. Mean pixel intensity (a) and mean reflectance (b) of barley seeds infected with *Alternaria infectoria*, *Dothidomycetes* sp., *Fusarium graminearum*, *Fusarium avenaceum* and *Mycosphaerella tassiana*.

2003). The preferred test method depends on the location of the spores, inoculum, etc. Furthermore, identification often requires sporulation and also expert knowledge (Lievens and Thomma, 2005).

The combinations of the features from multispectral images captured by visual light wavelengths and NIR wavelengths have proved to be useful in the separation of infected seeds from uninfected seeds in several species (Bodevin *et al.*, 2009; Olesen *et al.*, 2011; Jaillais *et al.*, 2015; Vrešak *et al.*, 2016). In spinach seeds, multispectral imaging has been used to discriminate uninfected seeds from seeds infected by *Stemphylium botryosum*, *Cladosporium* spp., *Fusarium* spp., *Verticillium* spp. or *Alternaria alternata* with 80–100% classification rate (Olesen *et al.*, 2011). The potential of using spectral characteristics of specific fungal species is to provide a fast optical screening method for fungal contamination of seeds; however, development of new methods depends on reliable reference methods.

Seeds of barley (*Hordeum vulgare*) can be infected by a high number of fungi, including pathogens such as *Fusarium graminearum*, *F. culmorum*, *F. poae*, *F. avenaceum* and *Pyrenophora teres* but also a high number of non-pathogenic or slightly pathogenic taxa such as *Alternaria*, *Epicoccum*, *Cryptococcus* and *Dioszegia*. *Fusarium* spp. is a widely distributed fungus of high relevance in agriculture as it causes yield reductions in a range of agricultural crops, and many species in the genus produce mycotoxins responsible for serious quality deterioration. In malting barley, *Fusarium* also has a negative effect by causing gushing in beer (Christian *et al.*, 2011).

With the aim of comparing multispectral image analysis data with DNA-based data from infected barley seeds, approximately 200 barley seeds assumed to be infected by fungi from different origins (Europe) and years (2012–2016) of cultivation were tested by multispectral analysis and by next generation sequencing (NGS) of the ITS (Internal Transcribed Spacer) from total DNA (Nicolaisen *et al.*, 2014).

Prior to NGS evaluation, multispectral images of all the barley seeds were captured by a VideometerLab multispectral imaging system (Videometer A/S). A multispectral image consisted of images of 19 different wavelengths from visible to the near-infrared region in a range from 375 to 970 nm. Spectral information from the surface of seeds may be combined with information about size, shape and texture of the seeds for detection of fungal infection. The MS images of the barley seeds were analysed by an nCDA (Olesen *et al.*, 2015; Shrestha *et al.*, 2015) to discriminate fungi. A more detailed description of nCDA data analysis can be found in Shrestha *et al.* (2018) and Olesen *et al.* (2015).

From the NGS, approximately 2–4000 reads were obtained from each seed and these were subsequently identified to species level. The main fungal genera identified were *Fusarium*, *Pyrenophora*, *Epicoccum*, *Didymella*, *Alternaria*, *Bipolaris* and *Microdochium*. The fungal composition and quantities on each seed varied significantly. Some seeds were infected mainly by a single fungus and some were infected by multiple fungi. A total of 48 seeds primarily infected by a single fungus species viz. *Alternaria infectoria*, *Dothidomycetes* sp., *Fusarium graminearum*, *Fusarium avenaeum* and *Mycosphaerella tassiana* were used for the multivariate data analysis to identify the causal fungal species.

The barley seeds infected with the different fungal species showed considerable variation in mean pixel intensities (Fig. 4a). The seeds infected with *F. graminearum* and *Mycosphaerella tassiana* had distinct differences in mean pixel intensities (Fig. 4a). The remaining infected seeds also showed variations, although the mean intensities of groups overlapped each other. A similar trend observed in Fig. 4b was that the

https://doi.org/10.1017/S0960258518000235 Published online by Cambridge University Press



Figure 5. Raw images of the barley seeds and corresponding transformed image by the nCDA model.

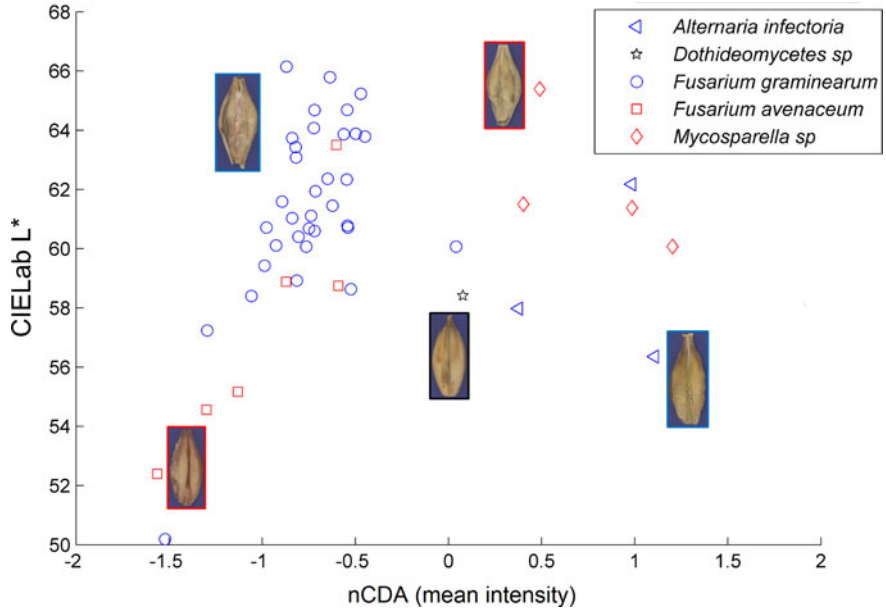


Figure 6. nCDA scores plot showing the clustering of the barley seeds infected by the five different fungi species. Each score is a mean intensity of the nCDA transformed seed image.

spectral signatures of the infected seeds had variation in mean reflectance. The variation in spectral signatures showed the possibility of developing a chemometric method for separating the infected seeds.

An nCDA analysis involving five classes (i.e. each fungus class) of infected seeds showed differences among the infected seeds (Fig. 5). Each pixel of an nCDA-transformed image represented a score calculated by the nCDA model. It determined the score in a way that maximized variation between the classes and reduced variation within a class (Olesen *et al.*, 2015). The nCDA model showed contrasting differences between *Fusarium* spp. and others (Fig. 5). The nCDA model did not show significant differences between the two *Fusarium* spp.; however, a colour feature CIELab L*, which relates to the brightness/darkness, showed a tendency of separation between them (Fig. 6). The results suggest the possibility of using multispectral imaging for identifying different fungal species in barley seeds. However, the nCDA model can be significantly enhanced by using additional steps such as hierachical/step-wise factorial classification or pairwise comparisons (Shrestha *et al.*, 2015; Kimuli *et al.*, 2018) to acquire distinctive discrimination among the fungal species. For instance, a step-wise classification between the two *Fusarium* species can significantly increase the separation, as shown in Fig. 7.

A proper validation of a developed model is essential for a multivariate image analysis to assess the robustness and reproducibility of the results (Shetty *et al.*, 2011). However, the nCDA model could not be validated due to availability of only few and disproportionate samples of the five fungal infected seeds. Previous studies have shown the potential of multispectral imaging in detecting or identifying a specific fungus species (Bauriegel *et al.*, 2011; Dammer *et al.*, 2011; Jaillais *et al.*, 2015; Leplat *et al.*, 2018) in wheat seeds with high accuracy. The study dealt with identifying several fungal species in barley seeds. The seeds examined had a diverse background such as

https://doi.org/10.1017/S0960258518000235 Published online by Cambridge University Press

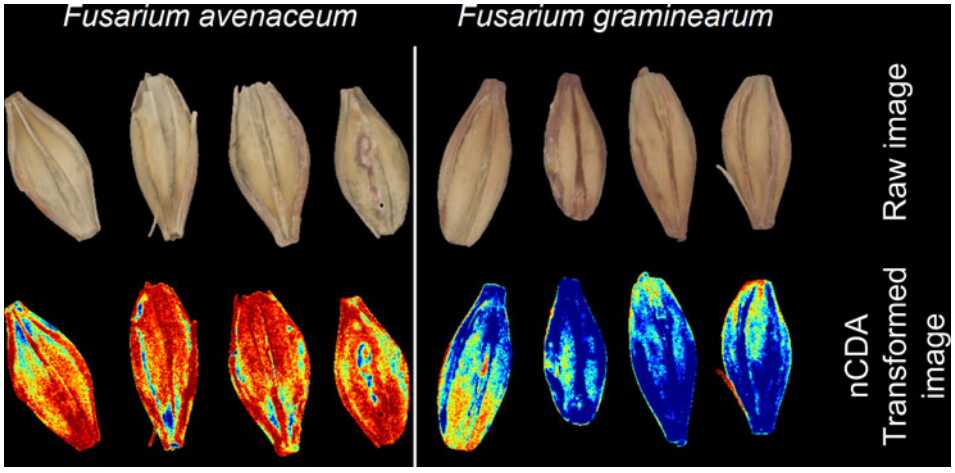


Figure 7. A stepwise nCDA classification of *Fusarium avenaceum* and *Fusarium graminearum* (top: raw image; bottom: subsequent transformed image).

genetic (different varieties), environment (year and region of cultivation) and ageing apart from the fungal infection. These factors have an influence on the discriminatory ability of the imaging system (Shrestha *et al.*, 2016). Considering this, the results obtained are promising and show the prospect of developing a method that can identify several fungal infections in seeds simultaneously.

Other applications of multispectral imaging

Varietal purity is a very important aspect in plant breeding programmes, seed production, genebank management and in the trading of seed in general. Therefore, any non-destructive, fast and reliable method for the identification and discrimination of varietal purity will be of interest. Recent studies have shown the potential of MSI combined with chemometric methods for the varietal identification of transgenic *Bacillus thuringiensis* rice seeds (*Oryza sativa*) and the discrimination of two varieties, respectively conventional and glyphosate-resistant soybean seeds (*Glycine max*) and their hybrid descendants (Liu *et al.*, 2014, 2016). In tomato, Shrestha *et al.* (2015) examined eleven varieties/accessions either all together or pairwise with their offspring for varietal identification and discrimination. By the use of MSI and multivariate data analysis the classification accuracy obtained was between 100 and 86%. International genebanks handle a large number of seed accessions and the evaluation of seed phenotype is usually done by visual inspection. Seed accessions are evaluated on arrival to the genebank to determine if the accession is new or already exists in store. Furthermore, the phenotype is evaluated when accessions have been regenerated to assure that the newly harvested seed is true to type to the stored sample. These procedures are very time consuming and require highly skilled and patient staff. Hansen *et al.* (2015) demonstrated that MSI could classify 20 diverse rice varieties with 93% accuracy.

A further application of MSI is the determination of insect damage (Ma *et al.*, 2015; Sendin *et al.*, 2018) and other crop and weed seeds (Sendin *et al.*, 2018) have recently been documented.

Concluding remarks

From the applications presented and reviewed, it is concluded that MSI has a potential for seed quality assessment, in particular for those components associated with surface structure and chemical composition, seed colour, morphology and size. MSI is a non-destructive, reliable and fast tool with a potential for the detection and characterization of fungi, insect damage, varietal purity and components associated with seed development and quality aspects.

References

Agrawal GK and Rakwal R (2012) *Seed Development: OMICS Technologies Toward Improvement of Seed Quality and Crop Yield*. Available at: https://link.springer.com/content/pdf/10.1007%2F978-94-007-4749-4.pdf (accessed 19 December 2017).

Baiano A, Terracone C, Peri G and Romaniello R (2012) Application of hyperspectral imaging for prediction of physico-chemical and sensory characteristics of table grapes. *Computers and Electronics in Agriculture* **87**, 142–151.

Barton SA (2016) Cereals: Grain Defects, pp. 68–73 in Wrigley C.W., Corke H, Seetharaman K and Faubion J (eds), *Encyclopedia of Food Grains*. New York: Academic Press.

Bauriegel E, Giebel A, Geyer M, Schmidt U and Herppich WB (2011) Early detection of *Fusarium* infection in wheat using hyper-spectral imaging. *Computers and Electronics in Agriculture* **75**, 304–312.

Bodevin S, Larsen TG, Lok F, Carstensen JM, Jørgensen K and Skadhauge B (2009) A rapid non-destructive method for quantification of fungal infection on barley and malt. Poster presented at 32nd EBC Congress, Hamburg, Germany, 10–14 May 2009.

Christian M, Titze J, Ilberg V and Jacob F (2011) Novel perspectives in gushing analysis: a review. *Journal of The Institute of Brewing* **117**, 295–313.

Dammer K.-H., Möller B, Rodemann B and Heppner D (2011) Detection of head blight (*Fusarium* ssp.) in winter wheat by color and multispectral image analyses. *Crop Protection* **30**, 420–428.

Deleuran LC, Olesen MH and Boelt B (2013) Spinach seed quality: potential for combining seed size grading and chlorophyll fluorescence sorting. *Seed Science Research* **23**, 271–278.

Dell'Aquila A (2007) Towards new computer imaging techniques applied to seed quality testing and sorting. *Seed Science and Technology* **35**, 519–538.

Dell'Aquila A (2009) Development of novel techniques in conditioning, testing and sorting seed physiological quality. *Seed Science and Technology* **37**, 608–624.

Esquerre C, Gowen AA, Downey G and O'Donnell CP (2012) Wavelength selection for development of a near infrared imaging system for early detection of bruise damage in mushrooms (*Agaricus bisporus*). *Journal of Near Infrared Spectroscopy* **20**, 537–546.

Gagliardi B and Marcos-Filho J (2011) Relationship between germination and bell pepper seed structure assessed by the X-ray test. *Scientia Agricola* **68**, 411–416.

Gomes-Junior FG, Yagushi JT, Belini UL, Cicero SM and Tomazello-Filho M (2012) X-ray densitometry to assess internal seed morphology and quality. *Seed Science and Technology* **40**, 102–107.

Gustafson FG (1942) Parthenocarpy: natural and artificial. *The Botanical Review* **8**, 599–654.

https://doi.org/10.1017/S0960258518000235 Published online by Cambridge University Press

Hahn F (2002) Multi-spectral prediction of unripe tomatoes. *Biosystems Engineering* **81**, 147–155.

Hansen MAE, Hay FR, Carstensen JM (2015) A virtual seed file: the use of multispectral image analysis in the management of genebank seed accessions. *Plant Genetic Resources: Characterization and Utilization* **14**(3), 238–241.

Hills OA (1963) *Insects Affecting Sugar Beets Grown for Seed*. Washington, DC: Agricultural Research Service, US Department of Agriculture.

Huang M, Wang QG, Zhu QB, Qin JW and Huang G (2015) Review of seed quality and safety tests using optical sensing technologies. *Seed Science and Technology* **43**, 337–366.

Jalink H, Frandas A, van der Schoor R and Bino JB (1998) Chlorophyll fluorescence of the testa of *Brassica oleracea* seeds as an indicator of seed maturity and seed quality. *Scientia Agricola* **55**, 88–93.

Jaillais B, Roumet P, Pinson-Gadais L and Bertrand D (2015) Detection of *Fusarium* head blight contamination in wheat kernels by multivariate imaging. *Food Control* **54**, 250–258.

Kenanoglu BB, Demir I and Jalink H (2013) Chlorophyll fluorescence sorting method to improve quality of *Capsicum* pepper seed lots produced from different maturity fruits. *HortScience* **48**, 965–968.

Kimuli D, Wang W, Lawrence KC, Yoon S.-C., Ni X and Heitschmidt GW (2018) Utilisation of visible/near-infrared hyperspectral images to classify aflatoxin B_1 contaminated maize kernels. *Biosystems Engineering* **166**, 150–160.

Leplat J, Mangin P, Falchetto L, Heraud C, Gautheron E and Steinberg C (2018) Visual assessment and computer-assisted image analysis of Fusarium head blight in the field to predict mycotoxin accumulation in wheat grains. *European Journal of Plant Pathology* **150**, 1065–1081.

Lievens B and Thomma B.P.H.J. (2005) Recent developments in pathogen detection arrays: implications for fungal plant pathogens and use in practice. *Phytopathology* **95**, 1374–1380.

Liu C, Liu W, Lu X, Chen W, Chen F, Yang J and Zheng L (2016) Non-destructive discrimination of conventional and glyphosate-resistant soybean seeds and their hybrid descendants using multispectral imaging and chemometric methods. *Journal of Agricultural Science* **154**, 1–12.

Liu C, Liu W, Lu X, Chen W, Yang J and Zheng L (2014) Nondestructive determination of transgenic *Bacillus thuringiensis* rice seeds (*Oryza sativa* L.) using multispectral imaging and chemometric methods. *Food Chemistry* **153**, 87–93.

Lleó L, Barreiro P, Ruiz-Altisent M and Herrero A (2009) Multispectral images of peach related to firmness and maturity at harvest. *Journal of Food Engineering* **93**, 229–235.

Ma F, Wang J, Liu C, Lu X, Chen W, Chen C, Yang J and Zheng L (2015) Discrimination of kernel quality characteristics for sunflower seeds based on multispectral imaging approach. *Food Analytical Methods* **8**, 1629–1636.

Mathur SB and Kongsdal O (2003) *Common Laboratory Seed Health Testing Methods for Detecting Fungi*. Bassendorf: International Seed Testing Association.

Nicolaisen M, Justesen AF, Knorr K, Wang J and Pinnschmidt HO (2014) Fungal communities in wheat grain show significant co-existence patterns among species. *Fungal Ecology* **11**, 145–153.

Olesen MH, Nikneshan P, Shrestha S, Tadayyon A, Deleuran LC, Boelt B and Gislum R (2015) Viability prediction of *Ricinus cummunis* L. seeds using multispectral imaging. *Sensors* **15**, 4592–4604.

Olesen MH, Carstensen JM and Boelt B (2011) Multispectral imaging as a potential tool for seed health testing of spinach (*Spinacia oleracea* L.). *Seed Science and Technology* **39**, 140–150.

Qin J, Chao K, Kim MS, Lu R and Burks TF (2013) Hyperspectral and multispectral imaging for evaluating food safety and quality. *Journal of Food Engineering* **118**, 157–171.

Rahman A and Cho B.-K. (2016) Assessment of seed quality using non-destructive measurement techniques: a review. *Seed Science Research* **26**, 285–305.

Rajkumar P, Wang N, Elmasry G, Raghavan GSV and Gariepy Y (2012) Studies on banana fruit quality and maturity stages using hyperspectral imaging. *Journal of Food Engineering* **108**, 194–200.

Sendin K, Manley M and Williams PJ (2018) Classification of white maize defects with multispectral imaging. *Food Chemistry* **243**, 311–318.

Shetty N, Min T.-G., Gislum R, Olesen MH and Boelt B (2011) Optimal sample size for predicting viability of cabbage and radish seeds based on near infrared spectra of single seeds. *Journal of Near Infrared Spectroscopy* **19**, 451–461.

Shrestha S, Deleuran LC, Olesen MH and Gislum R (2015) Use of multispectral imaging in varietal identification of tomato. *Sensors* **15**, 4496–4512.

Shrestha S, Knapič M, Žibrat U, Deleuran LC and Gislum R (2016) Single seed near-infrared hyperspectral imaging in determining tomato (*Solanum lycopersicum* L.) seed quality in association with multivariate data analysis. *Sensors and Actuators B: Chemical* **237**, 1027–1034.

Shrestha S, Topbjerg HB, Ytting NK, Skovgaard H and Boelt B (2018) Detection of live larvae in cocoons of *Bathyplectes curculionis* (Hymenoptera: Ichneumonidae) using visible/near-infrared multispectral imaging. *Pest Management Science*, doi: 10.1002/ps.4915

Silva VN, Cicero SM and Bennett M (2013) Associations between X-ray visualised internal tomato seed morphology and germination. *Seed Science and Technology* **41**, 225–234.

Śliwińska E, Jing HC, Job C, Job D, Bergervoet JHW, Bino RJ and Groot SPC (1999) Effect of harvest time and soaking treatment on cell cycle activity in sugarbeet seeds. *Seed Science Research* **9**, 91–99.

Snyder FW (1971) Relation of sugarbeet germination to maturity and fruit moisture at harvest. *Journal of the American Society of Sugar Beet Technologists* **16**, 541–551.

TeKrony DM (1969) Seed development and germination of monogerm sugar beets (*Beta vulgaris* L.) as affected by maturity. Available at: https://ir.library.oregonstate.edu/concern/graduate_thesis_or_dissertations/gh93h188s (accessed 24 May 2018).

TeKrony DM and Hardin EE (1969) The problem of underdeveloped seeds occurring in monogerm sugarbeets. *Journal of the American Society of Sugar Beet Technologists* **15**, 625–639.

United States Department of Agriculture (USDA) (2017) *Record Global Production Spurs Record Consumption Sugar Overview*. Available at: apps.fas.usda.gov/psdonline/circulars/sugar.pdf (accessed 24 May 2018).

van der Burg WJ, Aartse JW, van Zwol RA, Jalink H and Bino RJ (1994) Predicting tomato seedling morphology by X-ray analysis of seeds. *Journal of the American Society of Horticultural Sciences* **119**, 258–263.

Vrešak M, Olesen MH, Gislum R, Bavec F and Jørgensen JR (2016) The use of image-spectroscopy technology as a diagnostic method for seed health testing and variety identification. *PLoS ONE* **11**, e0152011. https://doi.org/10.1371/journal.pone.0152011.

Xing J, Symons S, Shahin M and Hatcher D (2010) Detection of sprout damage in Canada Western Red Spring wheat with multiple wavebands using visible/nearinfrared hyperspectral imaging. *Biosystems Engineering* **106**, 188–194.

https://doi.org/10.1017/S0960258518000235 Published online by Cambridge University Press