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Characterization of the Influence of Moisture Content on Single Wheat Kernels Using Machine Vision

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Abstract. The moisture content of grain affects the physical properties of kernels that must be understood for designing and operating post-harvest bulk handling systems. Changes in the physical properties of wheat were quantified using digital image processing. Three classes of western Canadian wheat namely Canada Western Red Spring (CWRS), Canada Western Amber Durum (CWAD), and Canada Prairie Spring White (CPSW) were used for this study. Single wheat kernels of these 3 classes were conditioned to 12.5, 13.9, 15.9, 18.0, and 19.7% moisture content (wet basis) using headspaces above various concentrations of potassium hydroxide (KOH) solutions. Colour images of individual kernels were acquired using a camera (7.4 x 7.4 μm pixel resolution) with an inter-line transfer CCD image sensor. Machine vision algorithm developed by the Canadian Wheat Board Centre for Grain Storage Research, University of Manitoba was implemented to extract 49 morphological features from the wheat kernel images. Of the 49 features extracted, 24, 11, and 7 morphological features of CWRS, CWAD, and CPSW, respectively, were significantly (α=0.05) different, as the moisture content increased from 12.5 to 19.7%. Generally the morphological features such as area, perimeter, length, and radius of kernels of all three wheat classes were linearly increased with increase in moisture content whereas all the moment and Fourier descriptor features decreased as moisture content increased.

Keywords: machine vision; moisture content; individual wheat kernels; morphological features.

INTRODUCTION

Canada is the second largest exporter of wheat in the world with annual exports averaging 20 MT in 2006-07 (Agriculture and Agri-Food Canada, 2008). Grain movement takes place in the midst of highly changing weather conditions in and out of storage facilities. Machine vision has been widely explored as a modern tool for automating grain handling and quality inspection operations. Implementation of image analysis to characterize and identify wheat cultivars using morphological parameters by Keefe and Draper (1986) proved that machine vision can be potentially employed in the grain industry. Zayas et al. (1989) used image analysis for discriminating wheat and non-wheat components in grain samples which emphasized the capability of machine vision systems in solving a variety of problems in grain industries.

Appropriate algorithms are essential to meet operational requirements of the grain handling and inspection systems that measure and extract features of grain kernels. Majumdar and Jayas (2000 a, b, c, d) developed algorithms to classify individual kernels of Canada Western Red Spring (CWRS) wheat, Canada Western Amber Durum (CWAD) wheat, barley, oats and rye based on morphological, color, and textural features of the kernels. Firatligil-Durmus et al. (2008) have developed a methodology for measuring geometrical features to analyze the size distribution of lentils. The results of their study provided increased confidence that the machine vision technology can be an effective tool for determining geometrical features and engineering properties of grain kernels.

In general, machine vision algorithms for extracting grain kernel features have been developed based on mathematical models. Majumdar and Jayas (2000a) developed an algorithm capable of extracting 23 morphological features and, for instance, they calculated the perimeter, by adding Euclidean distances between all successive pairs of pixels around the circumference, of the kernels. These types of measurements are made, by and large, on the assumptions of physical parameters of grain kernels. However changes in parameters, particularly moisture content (mc) of grain, may affect the working of an algorithm during a decision-making process. Urasa et al. (1999) demonstrated a third-order polynomial relationship that exists between moisture and pixel ratio of the soybean grain kernel features. Moreover, the grain size was determined by developing an equation, and their study suggested the feasibility of using pixels to measure the volume of soybean kernels.

In addition, Tahir et al. (2001) studied the effect of moisture content on the classification accuracy when using digital image analysis, and found that moisture content had high impact in classifying bulk kernels in comparison with the individual kernels. It was suggested that use of a high resolution camera would be helpful in analyzing the individual kernels. The effect of moisture content on physical properties of sorghum and millet using four different moisture contents ranging from 12 to 25%, dry mass basis, was examined by Lazaro et al. (2005). The results revealed that linear dimensions, geometric mean diameter, sphericity, surface area, volume, kernel density, and porosity of sorghum and millet had a linear relationship with moisture content.

Isik and Unal (2007) examined the dependence of physical properties such as geometric mean diameter, true density, porosity, and static coefficient of friction of red kidney bean when conditioned to various moisture levels from 9.77-19.62%. Experimental studies by Altuntas and Yildiz (2007) suggested that the physical and mechanical properties such as length, width, thickness, geometric mean diameter, sphericity, thousand grains mass, and angle of repose of faba bean kernels were increased as a result of moisture increase from 9.89 to 25.08% dry basis. Recently, Shimizu et al. (2008) tested the feasibility of using image analysis in measuring rice kernels during moisture absorbing tests and they found that both the length and width of the rice kernels increased. The results of these studies prove that moisture content of grain can potentially affect the physical appearance and kernel morphology, which in turn can affect the grain handling properties.

While developing machine vision algorithms for the grain kernel feature analysis, it is important to consider the influence of moisture content on grain kernel features. The changes due to moisture content would be more pronounced in individual kernels rather than bulk grain samples. The objective of present study was to measure the effects of moisture content in the range of 12.5-19.7% wet basis (wb) on 49 morphological features including area, perimeter, length, radius, shape moment, and Fourier descriptor features of individual kernels of wheat using a machine vision system.

MATERIALS AND METHODS

Sample preparation

One hundred individual kernels of CWRS, CWAD, and Canada Prairie Spring White (CPSW) wheat classes were selected randomly from the composite mixture of wheat. Prior to selecting the individual kernels from the bulk sample, all the three grain samples were treated with 2% sodium hypochlorite (NaClO) solution to prevent fungal infection. Five different concentrated potassium hydroxide (KOH) solutions were used to create different headspaces with 60, 70, 80, 85, and 90% relative humidity at 25°C (Solomon 1951), which approximately corresponded to 12.5, 13.9, 15.9, 18.0, and 19.7% wb moisture content (mc) of wheat kernels, respectively. The wheat kernels were conditioned from lower to higher moisture content to prevent hysteresis effect on kernel morphology and to minimize the potential of mold growth on samples.

Equilibration period for attaining respective moisture contents was determined by measuring the mass, as well as moisture content, of 10 g samples on a daily basis until <0.01g change in mass of the samples was observed. Based on these experiments, the grain kernels required seven days to be stored in the headspace of KOH solutions to attain constant mass and moisture content. The grain kernels were placed individually without touching each other on a sample wire mesh holder, which was above the KOH solution stored in a plastic pail. A small fan (2.5×10^{-3} m^3/s airflow rate) was kept under the wire mesh inside the pail to hasten the equilibration process. The plastic pail with the KOH solution and the grain samples was closed with a tight lid and wrapped with duct tape to prevent exchange of ambient air with wheat samples. Each kernel of the samples was placed on the respective wire-mesh with numbered spacing above the KOH headspace inside the pail. The same 100 kernels were used for conditioning to different moisture levels by following the above procedure after each set of imaging.

Imaging operation

Colour camera of 7.4 x 7.4 µm pixel resolution (Dalsa, Model- DS-22-02M30, ON, Canada), with an inter-line transfer CCD image sensor, was employed to acquire images of individual kernels of each wheat class using Helios/CL dual interface, Matrox Intellicam 8.0 (Matrox Electronic Systems Ltd, Dorval, QC). Illumination for the images was provided using a 32 W fluorescent lamp (FC12T9, Philips Electronics Ltd, ON), and a dome made of steel, which was painted and smoked with magnesium oxide and used as a light diffuser. Before imaging every sample, the camera was calibrated for constant light settings by using a grey card. To prevent moisture loss from kernels before imaging, samples were moved swiftly between pails and image acquisition system and approximately 20 min was required for each sample to be imaged. In addition, each kernel of the samples was imaged in such a way that the maximum exposure time to illumination was maintained around 2-3 min.

Feature extraction and analysis

Forty nine morphological features including area, perimeter, major axis length, minor axis length, maximum radius, minimum radius, mean radius, 2 shape moment features, 20 perimeter Fourier descriptor (PeriFD) features, and 20 radial Fourier descriptor (RadialFD) features of individual kernels of all three wheat classes were extracted using the machine vision algorithm developed by The Canadian Wheat Board Centre for Grain Storage Research group, Department of Biosystems Engineering, University of Manitoba. Shape moment and Fourier descriptor features were mainly incorporated to acquire information about shape characteristics of the wheat kernels. Information on the development of algorithm and the method of extracting these 49 morphological features are given in Majumdar and Jayas (2000a), Paliwal (2002), Visen (2002), and Paliwal et al. (2003). Forty nine morphological features mentioned above were extracted for all the 100 kernels at 5 moisture levels.

Significance of moisture influence was analyzed using 'Proc Mixed' and 'Proc GLM' models (SAS 9.1.3, SAS Institute Inc, NC, USA) and paired t-test results were produced by considering every kernel as a block in a randomized block design. The effects of five moisture treatments on the morphological features of every sample kernel were studied. In addition, feature measurements were predicted against different intermediate moisture levels based on the observed measurements of each feature and these findings were utilized in developing regression curves to relate moisture content with kernel morphology.

RESULTS AND DISCUSSION

The analysis of the morphological features by general linear models (GLM) and the mixed procedures (SAS 9.1.3) showed that 24, 11, and 7 out of 49 morphological features of CWRS, CWAD, and CPSW, respectively, were significantly ($\alpha=0.05$) different as the moisture content increased from 12.5 to 19.7%. Area of all three wheat class kernels increased with increase in moisture content. There was an initial significant increase in area of CWRS kernels when moisture increased from 12.5 to 13.9%, followed by a statistically constant value during 15.9 and 18.0% mc, and final increase at 19.7% mc (Figure 1). However, area of CPSW kernels was increased linearly as moisture content increased. Figure 2 shows a linear relationship between moisture content and area of CWRS, CWAD, and CPSW wheat kernels and similar trend was reported in green wheat in the moisture range of 9.3 to 41.5% by Al-Mahasneh and Rababah (2007).

Generally the perimeter of all three wheat classes increased with an increase in moisture content which has similar trend as increase in area. This is expected because area and perimeter are inter-related dimensions (Figure 3 and 4). Axial and radial dimensions of CWRS, CWAD, and CPSW wheat kernels such as major axis length, minor axis length, maximum radius, minimum radius, and mean radius were generally increased with an increase in moisture content (Figure 5 and 6). Statistical grouping of the basic morphological features at five moisture contents are shown in Table 1. Details of the predicted linear models are given in Table 2. Similar increasing trends of area, perimeter, length, and radii features with increase in moisture content were reported by Lazaro et al. (2005), Isik and Unal (2007), and Altuntas and Yildiz (2007) when they mechanically determined the effect of moisture content in sorghum and millet, red kidney bean, and faba bean, respectively. Urasa et al. (1999) established a third-order polynomial increase in the pixel ratio of soy beans with increase in moisture content using image analysis.

In all cases the moment and Fourier descriptor features decreased as moisture content increased from the lowest value of 12.5% to the highest value studied of 19.7% (Figure 7). At in-between moisture contents the values were either similar to values at 12.5% moisture content or to values at 19.7% moisture content (Table 3). The decrease in the moment and Fourier descriptor features correlated with the increase in axial and radial dimensions of the kernels, as both happened at about the same moisture levels. The lower frequency descriptors intend to acquire general shape information whereas the higher frequency descriptors give smaller/finer information about the object. From the results, it can be understood that moisture content had significant effect only on the general shape features, not on the features intended to extract finer shape details of the kernels.

Thus the significantly varying morphological features such as area, perimeter, length, and radius of kernels of three wheat classes should be considered in the design and development of post-harvest machinery, for instance in designing appropriate aperture size during grain cleaning.

CONCLUSION

The influence of moisture content on the morphological features of CWRS, CWAD, and CPSW wheat kernels has been characterized using the machine vision algorithm. Generally the basic morphological features such as area, perimeter, major axis length, minor axis length, maximum radius, minimum radius, and mean radius were linearly increased with increase in moisture content. In all cases the moment and Fourier descriptor features decreased as moisture content increased from 12.5 to 19.7%.

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REFERENCES

Agriculture and Agri-Food Canada. 2008. Canada: Grains and Oilseeds Outlook released on 24th October, 2008.

Al-Mahasneh, M.A. and T.M. Rababah. 2007. Effect of moisture content on some physical properties of green wheat. *Journal of Food Engineering* 79: 1467-1473.

Altuntas, E. and M. Yildiz. 2007. Effect of moisture content on some physical and mechanical properties of faba bean (*Vicia faba* L.) grains. *Journal of Food Engineering* 78: 174-183.

ASABE. 2003. Moisture measurement – Unground Grain and Seeds. ASAE S352.2. In *ASAE standards* 2003, 555. St. Joseph, MI: ASAE.

Firatligil-Durmus, E., E. Sarka and Z. Bubnik. 2008. Image vision technology for the characterization of shape and geometrical properties of two varieties of lentil grown in Turkey. *Czech Journal of Food Science* 26(2): 109-116.

Isik, E. and H. Unal. 2007. Moisture-dependent physical properties of white speckled red kidney bean grains. *Journal of Food Engineering* 82: 209-216.

Keefe, P.D. and S.R. Draper. 1986. The measurement of new characters for cultivar identification in wheat using machine vision. *Seed Science and Technology* 14(3): 715-724.

Lazaro, E.L., N.B. Shayo and A.B. Gidamis. 2005. The effect of moisture on physical properties of sorghum and millet. *Journal of Agriculture, Science and Technology* 7(1): 30-40.

Majumdar, S. and D.S. Jayas. 2000a. Classification of cereal grains using machine vision: I. Morphology models. *Transactions of the ASAE* 43(6): 1669-1675.

Majumdar, S. and D.S. Jayas. 2000b. Classification of cereal grains using machine vision: II. Color models. *Transactions of the ASAE* 43(6): 1677-1680.

Majumdar, S. and D.S. Jayas. 2000c. Classification of cereal grains using machine vision: III. Texture models. *Transactions of the ASAE* 43(6): 1681-1687.

Majumdar, S. and D.S. Jayas. 2000d. Classification of cereal grains using machine vision: IV. Morphology, color and texture models. *Transactions of the ASAE* 43(6): 1689-1694.

Paliwal, J. 2002. Digital image analysis of grain samples for potential use in grain cleaning. Unpublished PhD thesis. Winnipeg, MB: Department of Biosystems Engineering, University of Manitoba.

Paliwal, J., N.S. Visen and D.S. Jayas. 2003. Cereal grain and dockage identification using machine vision. *Biosystems Engineering* 85: 51-57.

SAS 9.1.3. 2008. *SAS user's guide: Statistics.* SAS Institute Inc. Cary, NC.

Shimizu, N., M.A. Haque, M. Andersson and T. Kimura. 2008. Measurement and fissuring of rice kernels during quasi-moisture sorption by image analysis. *Journal of Cereal Science* 48: 98-103.

Solomon, M.E. 1951. Control of humidity with potassium hydroxide, sulphuric acid, or other solutions. *Bulletin of Entomological Research* 42: 130-141.

Tahir, A.R., S. Neethirajan, M.A. Shahin, S.J. Symons and N.D.G. White. 2007. Evaluation of the effect of moisture content on cereal grains by digital image analysis. *Food Research International* 40: 1140-1145.

Urasa, R., S. Tanaka, K. Morita and F. Tanaka. 1999. Imaging size changes relationship with moisture during soybean hydration. ASAE Paper No. 996087. Toronto, ON: ASABE.

Visen, N. S. 2002. Machine vision based grain handling system. Unpublished PhD thesis. Winnipeg, MB: Department of Biosystems Engineering, University of Manitoba.

Zayas, I., Y. Pomeranz and F.S. Lai. 1989. Discrimination of wheat and non-wheat components in grain samples by image analysis. *Cereal Chemistry* 66: 233-237.

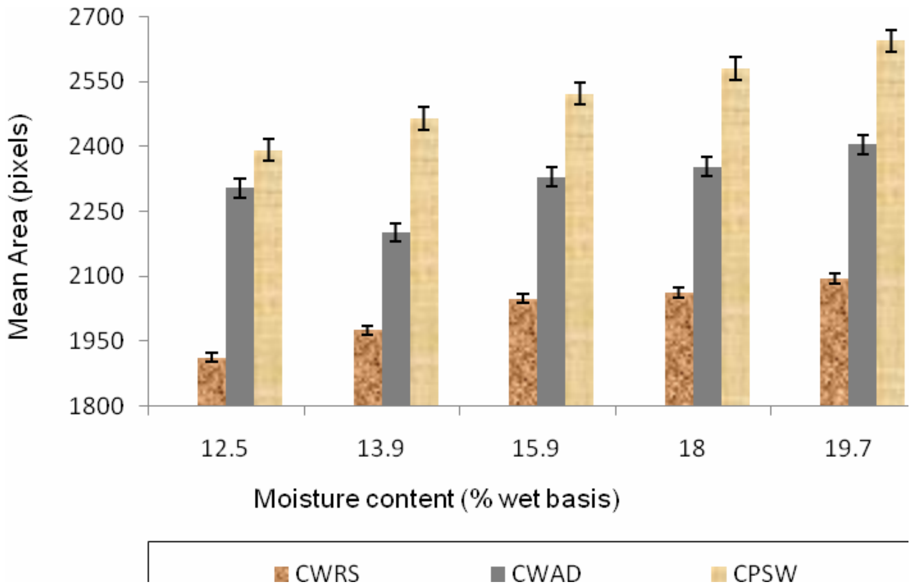
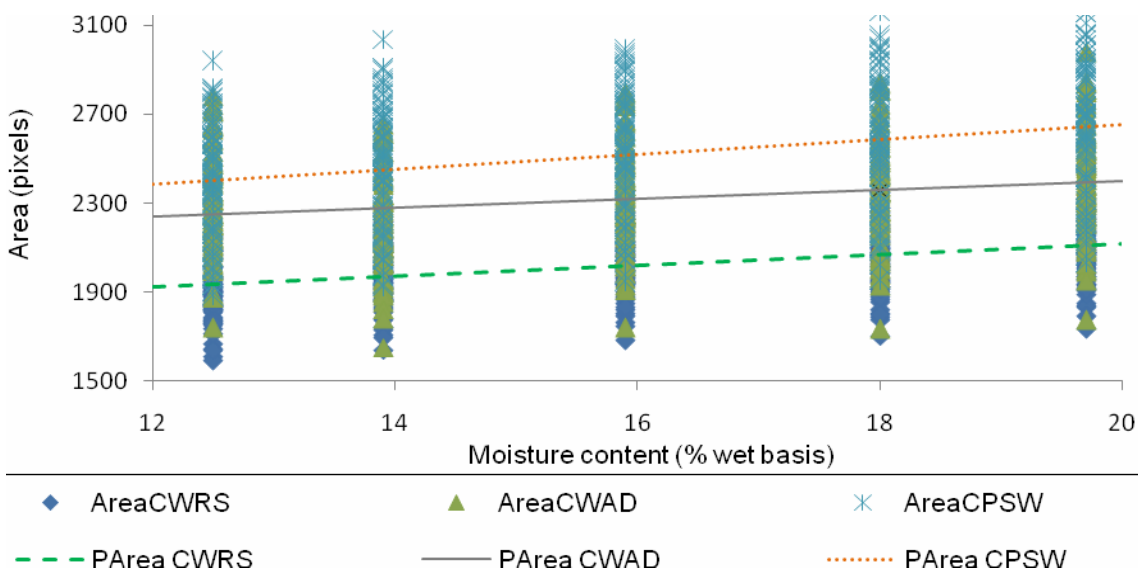


Figure 1. Area of kernels of all three wheat classes with the increase in moisture content from 12.5 to 19.7% wet basis (mean based on 100 kernels for each class)



PArea- predicted area across range of moisture content

Figure 2. Observed and predicted values of area of CWRS, CWAD, and CPSW wheat kernels at different moisture treatments.

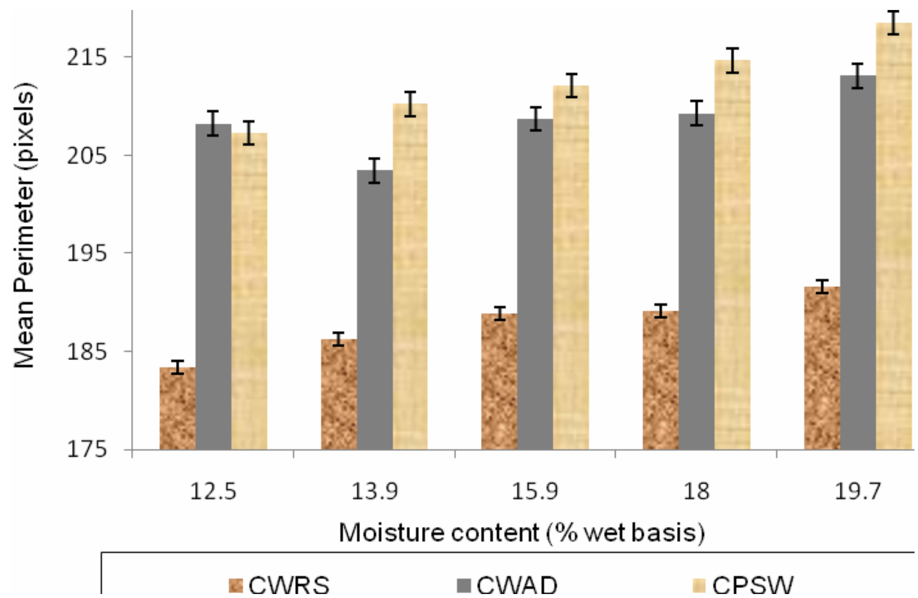
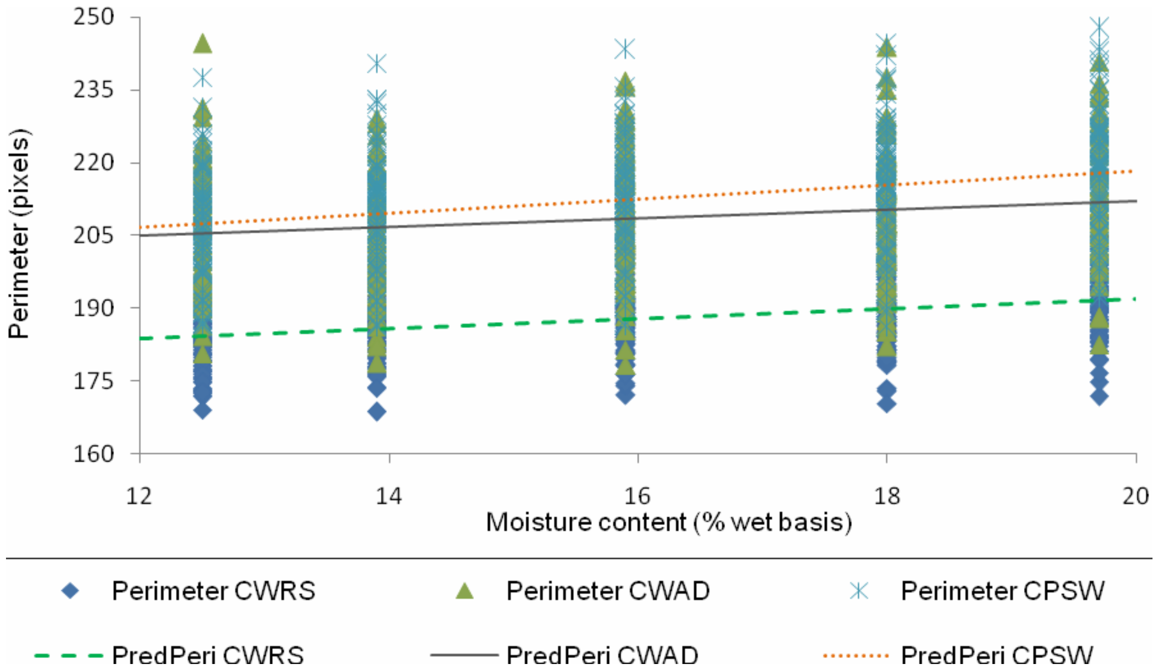
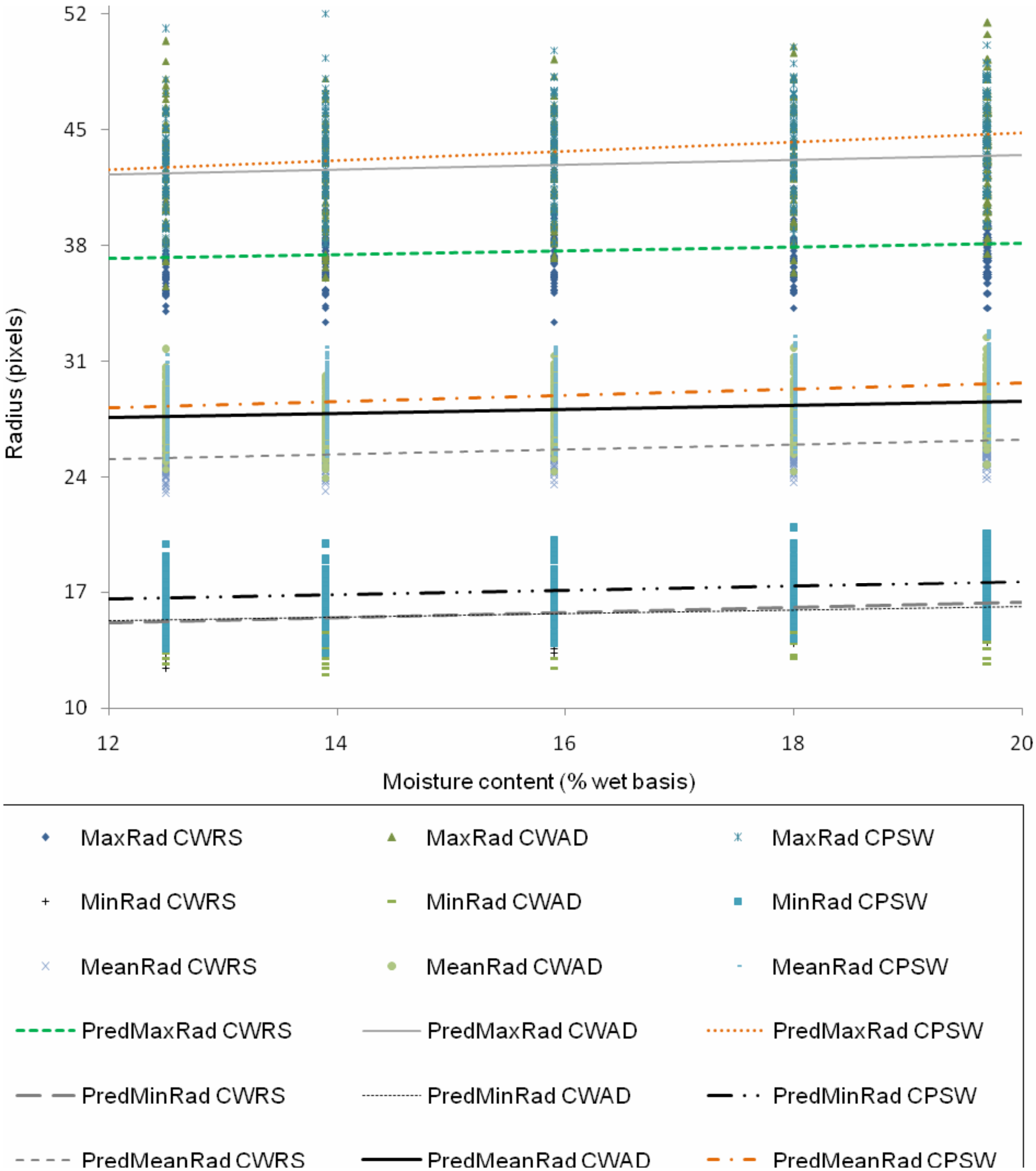


Figure 3. The perimeter of kernels of all three wheat classes with the increase in moisture content from 12.5 to 19.7% wet basis (mean based on 100 kernels for each class)



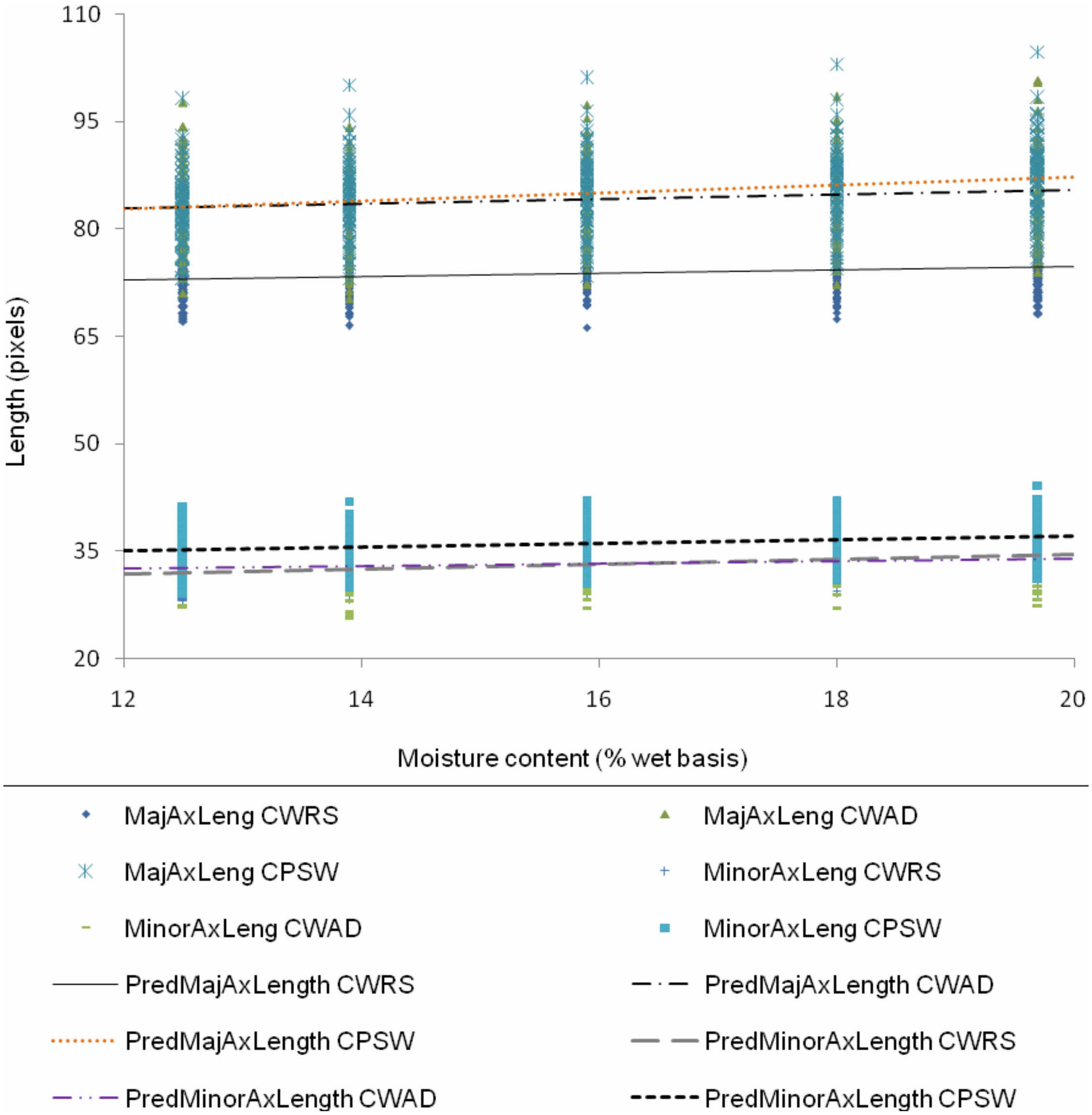
PredPeri – predicted perimeter across range of moisture content.

Figure 4. Observed and predicted values of perimeter of CWRS, CWAD, and CPSW wheat kernels at moisture treatments.



Pred - predicted

Figure 5. Observed and predicted values of maximum, minimum, and mean radii features for CWRS, CWAD, and CPSW wheat kernels at different moisture treatments.



Pred - predicted

Figure 6. Observed and predicted values of major and minor axis length of CWRS, CWAD, and CPSW wheat kernels at different moisture treatments.

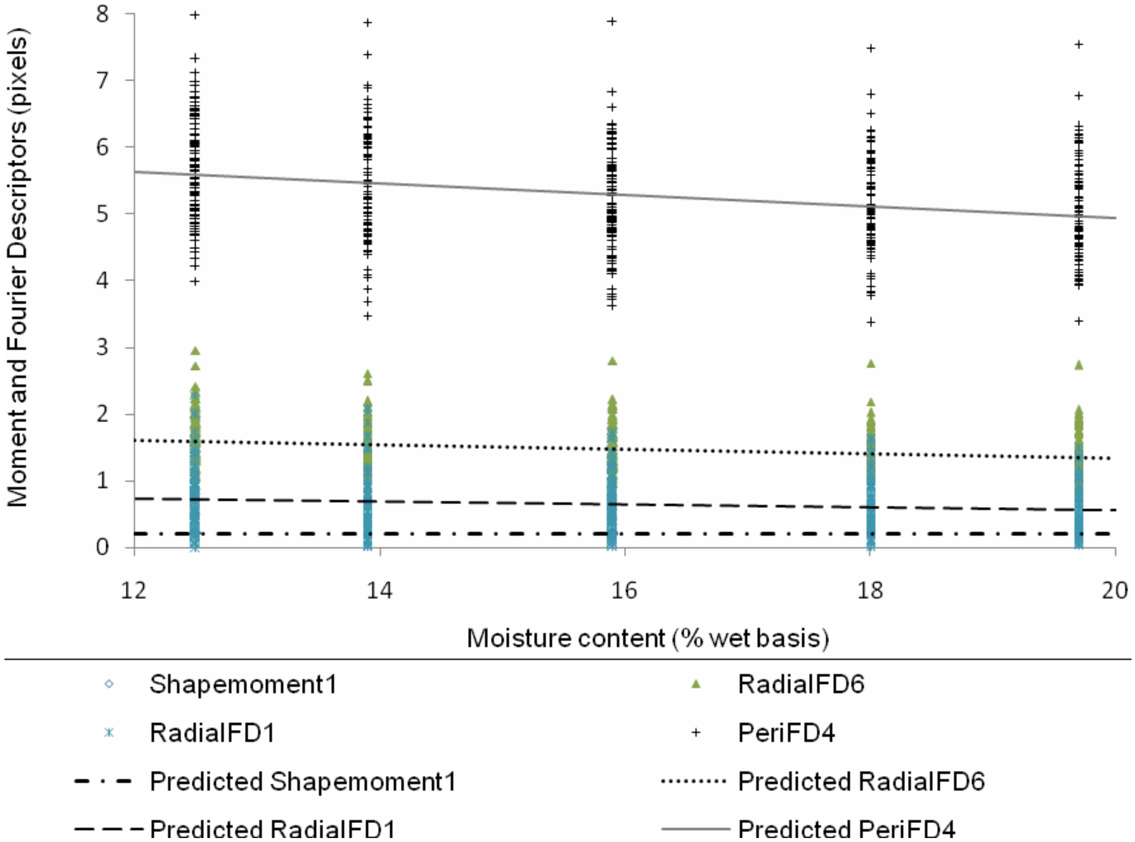


Figure 7. Observed and predicted values of some of the moment and Fourier descriptor features of CWRS wheat kernels at different moisture treatments.

Table 1. Statistical grouping of CWRS, CWAD, and CPSW kernel features for five different moisture treatments. (Treatments with same letter indicate that they were not significantly different)

Wheat Class	Features	Treatment Grouping based on T-test at α=0.05				
		12.5%	13.9%	15.9%	18.0%	19.7%
CWRS	Area	a	b	a c	c	d
	Perimeter, Maximum Radius, Mean Radius, and Major Axis Length	a	b	a	a	c
	Minimum Radius and Minor axis length	a	b	a c	c d	d
CWAD	Area	a	b	a c	c	d
	Perimeter, Maximum Radius, Mean Radius, and Major Axis Length	a	b	a	a	c
	Minimum Radius and Minor axis length	a	b	a c	c d	d
CPSW	Area and Maximum Radius	a	b	c	d	e
	Perimeter	a	b	b	c	d
	Minimum Radius	a	a	b	b c	c
	Mean Radius	a	b	b	c	d
	Major Axis Length	a	b	b c	c	d
	Minor Axis Length	a	b	c	c d	d

Table 2. Linear models of some of the morphological features with their co-efficient of determination values for CWRS, CWAD, and CPSW kernels at different moisture contents.

Feature name	Wheat class	Regression equation Moisture content (mc) in wet basis	Co-efficient of determination, R^2	Relationship with moisture increase from 12.5 to 19.7%
Area	CWRS	24.122(mc) + 1633	0.785091	Linear increment
	CPSW	33.229(mc) + 1989	0.677969	Linear increment
	CWAD	19.84(mc) + 2001	0.636130	Linear increment
Mean Radius	CWRS	0.1422(mc) + 23.388	0.781161	Linear increment
	CPSW	0.1938(mc) + 25.831	0.666197	Linear increment
	CWAD	0.1172(mc) + 26.206	0.629460	Linear increment
PeriFD 4	CWRS	-0.0859(mc) + 6.6509	0.597715	Linear decrement
Shape moment1	CWRS	-0.0009(mc) + 0.2249	0.688105	Linear decrement
RadialFD1	CWRS	-0.0227(mc) + 1.0131	0.444006	Linear decrement
RadialFD5	CWAD	-0.014(mc) + 0.9609	0.590041	Linear decrement
RadialFD6	CWRS	-0.0317(mc) + 1.9787	0.604632	Linear decrement

Table 3. Statistical grouping of moment and Fourier descriptor features for five different moisture treatments. (Treatments with same letter indicate that they were not significantly different)

Wheat Class	Feature Name	Treatment Grouping based on T-test at α=0.05				
		19.7	18.0%	15.9%	13.9%	12.5%
CWRS	PeriFD 2, PeriFD 4, PeriFD 6, PeriFD 20, RadialFD 2, RadialFD 4, and RadialFD 6	a	a	a	b	c
	PeriFD 3	a	a	a b	c	c b
	PeriFD 5	a	a	a	a b	b c
	PeriFD 16 and PeriFD 18	a	a	a b	b	c
	PeriFD 17	a	a	a b	b c	c
	PeriFD 19	a	a	a b	b	a b
CWAD	RadialFD 5	a	a	a b	b	b
	PeriFD 3	a	a b	a b	a b	b
	PeriFD 4 and PeriFD 19	a	a	a b	b	a b