Value of Increasing Kernel Uniformity

by

Byung-Sam Yoon

B. Wade Brorsen

Conrad P. Lyford

Correspondence Author: B. Wade Brorsen
Department of Agricultural Economics
Oklahoma State University
414 Agricultural Hall
Stillwater, Oklahoma 74078-6026
Tel: (405) 744-6836
Fax: (405) 744-8210
E-mail: brorsen@okstate.edu

Paper presented at the Western Agricultural Economics Association Annual Meetings, Logan, Utah, July, 2001.

Byung-Sam Yoon is a Ph.D. graduate, B. Wade Brorsen is a regents professor and Jean & Patsy Neustadt chair, and Conrad P. Lyford is an assistant professor in the Department of Agricultural Economics at Oklahoma State University. Financial support was provided by the Targeted Research Initiative Program (TRIP) at Oklahoma State University.

Value of Increasing Kernel Uniformity

Abstract

Kernel size uniformity is an important physical quality attribute in terms of processing efficiency, quality control, and milling yield. This study developed optimal grain sorting strategies for elevators to use to increase kernel size uniformity and determined the size of potential benefits from sorting. Cluster analysis and global optimization were used to sort grain loads to increase kernel size uniformity. Cluster analysis and global optimization increased the percent flour yield relative to no sorting by 0.13% and 0.32% respectively. Cluster analysis and global optimization increased the daily milling income relative to no sorting by 105 dollars (5%) and 266 dollars (13%) respectively.

Key words: cluster analysis, global optimization, kernel uniformity, milling, sorting, wheat

Value of Increasing Kernel Uniformity

While consumers demand diverse food products with higher quality, food processors require uniform raw materials with specific quality attributes. In virtually all areas of food processing, processors desire uniform raw materials to improve the efficiency of production and product quality. Recent advances in quality testing and processing technology enable processors to impose rigorous product requirements.

In the grain industry, the search for equitable, uniform measures of quality has established grades and grade requirements, but the appropriate grading factors and factor limits for designating numerical grades have been a persistent issue in grain markets (Hill, 1990). Moreover, Hill (1988) argues that grain grades lack economic rationale and fail to accurately measure the factors that determine value.

Current U.S. standards for wheat determine grades based on test weight, total defects, and other material (USDA). However, these generic grades and standards are becoming less meaningful in effectively describing wheat, because processors are becoming more interested in and demanding such characteristics as greater kernel size and kernel size uniformity (U.S. Wheat Associates).

For flour millers, kernel size uniformity is an important physical quality attribute in terms of processing efficiency, quality control, and milling yield. In the flour milling process, the tempered wheat is first ground on a series of rollermills to separate the endosperm (starch and protein) from the outer bran skins. When there is a wide variation in kernel size, small kernels pass through the rollermills unground or are only partially broken in the initial breaking process, thus requiring additional processing. This additional processing requires more milling time and energy costs, and further decreases the overall quality of the flour due to higher ash content (Li). However, with uniform wheat, the wheat kernels are ground more evenly in the milling process, which leads to higher extraction of flour with a lower ash content. Considering the fact that the wheat kernels must pass through five or more of the breaking rollermills before the bran is completely removed, the increased kernel size uniformity will significantly contribute to an increase in milling efficiency, extraction rate and flour quality.

However, it is not an easy task to achieve the benefits from increased kernel uniformity in the current grain marketing system. Since wheat kernel size uniformity is not among the grade determining factors and the increased kernel size uniformity is not properly rewarded, grain elevators are not strongly encouraged to develop and implement various strategies to increase kernel size uniformity. The kernel size uniformity can be increased by sorting rather than blending various truckloads of wheat with different kernel sizes when wheat is delivered to grain elevators.

The previous studies on grain sorting (Johnson and Wilson; Adam, Kenkel, and Anderson; Hennessy and Wahl) were largely motivated by the concerns about declining U.S. export market share and foreign buyer complaints about poor quality grain. These studies analyze the costs and benefits of cleaning wheat to reduce dockage levels, but do not consider the benefits to processors from sorting to achieve kernel uniformity.

The primary objective of this study is to develop procedures for determining optimal grain sorting strategies based on kernel size uniformity and to determine the size of potential benefits from sorting to achieve kernel uniformity. Specifically, a percent flour yield equation is estimated to relate flour yield to wheat quality attributes and to measure the effect of sorting. A daily milling income equation is used to assess the monetary value of increasing kernel uniformity by evaluating the percent flour yields obtained from sorting strategies. Cluster analysis and global optimization are used to sort grain loads to increase kernel size uniformity.

Value Equations

Two value equations are used to evaluate the performance of wheat sorting strategies. One is the percent flour yield equation that relates the percent flour yield (extraction) to the wheat quality characteristics. The other is the daily milling income equation that estimates the milling income from the percent flour yield. Sorting strategies are evaluated by how much they increase the percent flour yield or daily milling income relative to no sorting.

The data on wheat quality characteristics and percent flour yield consist of 609 observations on the 22 cross-sections of districts over the 4-year time period. To estimate a percent flour yield equation, this study pools the time-series and cross-sectional data using the following error components model: [1]

$$PFY_{it} = \beta_0 + \beta_1 KD_{it} + \beta_2 KDS_{it} + \beta_3 KH_{it} + \beta_4 KHS_{it} + \beta_5 TW_{it} + \mu_i + \varepsilon_{it}, \quad (1)$$

where i represents the districts (i = 1, 2, …, 22), t represents the years (t = 1995, 1996, 1997, and 1998), PFY_{it} is the percent flour yield (%), KD_{it} is the average single kernel diameter (mm), KDS_{it} is the standard deviation of single kernel diameter, KH_{it} is the average single kernel hardness (hardness index), KHS_{it} is the standard deviation of single kernel hardness, and TW_{it} is the test weight (lb/bu). The βs are the fixed-effects coefficients, the μ_i are the random-effects parameters assumed to be independent and identically distributed with $E[\mu_i] = 0$ and $E[\mu_i^2] = \sigma_\mu^2$, and the ε_{it} are independent and identically distributed random variables with $E[\varepsilon_{it}] = 0$, $E[\varepsilon_{it}^2] = \sigma_\varepsilon^2$, and uncorrelated with the μ_i. That is, $E[\mu_i \varepsilon_{it}] = 0$.

The model was fit using PROC NLMIXED in SAS version 8.0. The data are assumed normally distributed and the mean (expected value) of the data is linear in terms of a set of explanatory variables and the random-effects parameters, i.e.,

$$E[PFY_{it}] = \beta_0 + \beta_1 KD_{it} + \beta_2 KDS_{it} + \beta_3 KH_{it} + \beta_4 KHS_{it} + \beta_5 TW_{it} + \mu_i. \quad (2)$$

The random-effects parameters μ_i enter the model linearly. This study also considered average single kernel moisture (*KM*) and standard deviation of single kernel moisture (*KMS*), but dropped them because they were not statistically significant. Further, the standard deviation of single kernel moisture (*KMS*) should not matter since each sample is tempered to 16% moisture. The ordinary least squares (OLS) estimates of the coefficients were used as the starting values for the coefficients of the mean model. The variance and covariance of the data is an exponential function of a linear combination of explanatory variables, i.e.,

$$\sigma_\varepsilon^2 = \exp[\alpha_0 + \alpha_1 KD_{it} + \alpha_2 KDS_{it} + \alpha_3 KH_{it} + \alpha_4 KHS_{it} + \alpha_5 TW_{it}]. \quad (3)$$

Finally, the estimated percent flour yield equation is

$$PFY = 48.24 + 1.32KD - 2.25KDS - 0.07KH - 0.04KHS + 0.44TW \tag{4}$$
$$(29.58) \quad (3.19) \quad (-2.30) \quad (-7.95) \quad (-1.84) \quad (13.14)$$

where *PFY* is the percent flour yield (%), *KD* is the average single kernel diameter (mm), *KDS* is the standard deviation of single kernel diameter, *KH* is the average single kernel hardness (hardness index), *KHS* is the standard deviation of single kernel hardness, and *TW* is the test weight (lb/bu). The *t*-statistics of the coefficients are presented in parentheses.

The percent flour yield equation is linear with respect to all explanatory variables. Hennessy, and Hennessy and Wahl show that the elevator's decisions on blending and sorting are dependent upon the curvature attributes of the yield-quality schedule. Generally, a concave yield-quality schedule is associated with blending and a convex schedule with sorting. The negative coefficients on the standard deviation terms (*KDS*, *KHS*) in equation (4) yield a convex function, which is necessary for sorting to be optimal.

Equation (4) shows that flour yield is expected to increase with increases in single kernel diameter (*KD*) and test weight (*TW*), but decrease with increases in single kernel hardness (*KH*), standard deviation of single kernel diameter (*KDS*), and standard deviation of single kernel hardness (*KHS*).[2]

To assess the monetary value of increasing kernel uniformity, the percent flour yields obtained from sorting strategies are evaluated by the following milling income equation (Lyford):

$$MI = 1408.30 * PFY * TW + 13.02 * TW - 2295.64 * PFY - 57475.70, \tag{5}$$

where *MI* is the milling income in dollars per day, *PFY* is the percent flour yield, and *TW* is the test weight. The milling income equation is estimated on the basis of daily throughput of 15,500 bushels of wheat, represented by a medium-sized mill.

Data

Data used in this study were collected over a four-year time period and span all major U.S. hard red winter wheat producing areas (Deyoe et al.). From 1995 through 1998, hard red winter wheat samples were collected during the Hard Red Winter Wheat (HRW) Crop Survey. HRW samples were provided from 22 survey districts when wheat was delivered to elevators during harvest. Texas and Oklahoma were covered by 4 districts, Kansas was represented by 9 districts, eastern Colorado by 2 districts, Nebraska by 5 districts, and South Dakota and Montana were treated as one district for each state. From each district, 7 samples on average were randomly collected over 4 years, resulting in a total of 609 wheat samples.

Each HRW sample collected was tested using the Single Kernel Characterization System (Perten SKCS 4100) in the Grain Science & Industry Department at Kansas State University. The Single Kernel Characterization System (SKCS) measures a variety of physical characteristics of wheat kernels by individually selecting and analyzing 300 kernels per sample. This device completes a test in about 3 minutes, and simultaneously reports mean and standard deviation data for single kernel weight, single kernel diameter (size), single kernel hardness, and single kernel moisture. Besides the single kernel characteristics, test weight was measured as a basic wheat quality attribute.

After initial SKCS tests on the individual survey samples, each sample was tempered to 16% moisture for 18 hours. The tempered samples were milled using fixed roll settings from the Buhler laboratory mill (MLU-202). Milling performance, reported as percent flour yield (PFY), was calculated as the percentage of flour out of total product recovered from the Buhler laboratory mill.

Table 1 presents summary statistics for wheat quality characteristics and average percent flour yields. The data do have some limitations. The percent flour yield data used here are from fixed roll settings and thus may underestimate the value of kernel uniformity. In practice, flour millers can increase the milling yield by optimally adjusting the space of rollermills to different kernel sizes. The wheat samples from 22 districts across 7 states may result in an overestimation of the variability of kernel size when they are combined. The kernel size of wheat from several different regions may be more variable than that from a single region or geographically close regions. This study would have benefited from the measurements of ash content during the milling process to accurately evaluate the value of kernel uniformity in reducing ash content.

Sorting Strategies

Cluster analysis and global optimization are used to sort grain loads to increase kernel size uniformity. Cluster analysis is easy to implement, but may not lead to an optimal solution. On the other hand, global optimization results in an optimal solution, but is harder to implement or may not be practical to implement in certain cases.

Cluster Analysis

Cluster analysis is commonly used to group observations into clusters such that each cluster is as homogeneous as possible with respect to certain characteristics. The clusters formed should be highly internally homogeneous, i.e., observations in each cluster are similar to each other, and highly externally heterogeneous, i.e., observations of one cluster should be different from the observations of other clusters (Sharma).

Cluster analysis can be used to group a large number of grain loads into a desired number of clusters in which each load is similar to one another with respect to kernel size. Since the loads in any cluster are homogeneous with respect to kernel size, the variability of kernel size among individual loads is minimal. This suggests that the variation of kernel size between loads can be reduced by forming homogeneous groups or clusters, and further implies that the overall variation of kernel size can be reduced when various loads of grain are mixed in the bin.

This study employs a two-stage clustering procedure suggested by Punj and Stewart. Two-stage clustering procedure is characterized by the complementary use of hierarchical and nonhierarchical clustering techniques. In other words, in a two-stage clustering procedure, nonhierarchical clustering is used to refine the clustering solution obtained from the hierarchical method. A two-stage cluster analysis is based on the results of simulation studies showing that nonhierarchical clustering techniques are quite sensitive to the selection of the initial seeds, i.e., local optima can be numerous. However, their performance is much superior when the results from hierarchical clustering methods are used to form the initial or starting seeds.

In the first stage, one of the hierarchical clustering methods that has demonstrated superior performance in terms of within-standard deviation and R^2 is used to obtain *k* initial cluster centroids or seeds. In this study five primary hierarchical clustering methods are evaluated: (1) centroid method, (2) single-linkage or nearest-neighbor method, (3) complete-linkage or farthest-neighbor method, (4) average-linkage method, and (5) Ward's or minimum variance method.

For hierarchical clustering, PROC CLUSTER in SAS 8.0 is used. After the data are first subjected to hierarchical clustering, the PROC TREE is used to specify the number of clusters desired (*k*). Then, the PROC MEANS is used to compute the means of each clustering variable for each cluster. The *k* cluster means or centroids for each clustering variable is used as the initial or starting seeds.

In the second stage, the *k* initial cluster centroids or seeds obtained from the hierarchical clustering are submitted to the nonhierarchical clustering technique for refinement of the clusters. In the nonhierarchical clustering, each observation is initially assigned to the cluster to which it is the closest. In the next iterative procedure, the observation is reassigned or reallocated to one of the *k* clusters until the convergence criterion is satisfied. Since this nonhierarchical clustering algorithm uses *k* initial cluster centroids or seeds as starting points and produces exactly *k* different clusters of greatest possible distinction, it is commonly referred to as *k*-means clustering method. For nonhierarchical clustering, PROC FASTCLUS in SAS 8.0 is used.

Since the primary interest of the study lies in the kernel size uniformity, loads for each year are clustered with respect to the average single kernel diameter (*KD*). Three cluster solutions are used because kernel size can be simply classified into three categories, i.e., small, medium, and large kernels.

Global Optimization

The basic function of grain elevators is to store grain delivered from farmers and then sell it to processors or other merchandisers. The elevators often rearrange grain by blending and/or sorting high-quality grain with or from low-quality grain to take advantage of profit opportunities. The elevator is assumed to have a prior knowledge of the distribution of wheat quality characteristics before the loads of wheat are delivered to the elevator. The elevator allocates truckloads of wheat with different quality attributes into a number of storage bins such that total flour yield from all wheat stored in the bins is maximized. This optimization problem is solved using a mathematical programming approach (Hazell and Norton).

For a mathematical programming model, truckloads are indexed by i (i = 1, 2, …, N), each containing wheat with different levels of quality attributes. Storage bins are indexed by j. Considering the fact that grain grades can be simply classified into three categories, i.e., low, medium, and high quality, three storage bins (j = 1, 2, 3) are used. Total quantity of wheat in bin j is denoted by QTY_j.

The objective is to maximize the total flour yield from all wheat contained in the bins, and the objective function is defined as:

(6)
$$\begin{aligned} &\underset{QTY}{Max} \sum_j PFY(KD_j, KDS_j, KH_j, KHS_j, TW_j) QTY_j \\ &= \underset{QTY}{Max} \sum_j (48.24 + 1.32 KD_j - 2.25 KDS_j - 0.07 KH_j - 0.04 KHS_j + 0.44 TW_j) QTY_j, \end{aligned}$$

where KD_j is the average single kernel diameter for wheat in bin j, KDS_j is the standard deviation of single kernel diameter in bin j, KH_j is the average single kernel hardness for wheat in bin j, KHS_j is the standard deviation of single kernel hardness in bin j, and TW_j is the test weight for wheat in bin j.

The maximization problem is subject to a number of constraints concerning wheat allocation and quality attributes. Let X_{ij} denote the quantity of wheat allocated from load i to bin j, then the total quantity of wheat available in bin j is:

(7)
$$QTY_j = \sum_i X_{ij}.$$

For simplicity, each truckload is treated as one unit and then the proportion of load i allocated into bin j is summed to 1. That is, $\sum_j X_{ij} = 1.$ The model allows a load to be partially allocated into different bins to avoid the extra complexity of integer programming.

One of the useful properties of grains of different quality is that they can be readily mixed, and for many quality characteristics the effects of mixing can be easily computed. These quality attributes include kernel diameter, kernel hardness, and test weight. This ability to compute the physical quality characteristics of mixed grain arises from the linear homogeneity attributes of mixing. Denote the proportion of load *i* allocated into bin *j* by p_{ij}, and let the average single kernel diameter for wheat in load *i* be KD_i, then the average single kernel diameter for wheat in bin *j* is given by

$$KD_j = \sum_i p_{ij} KD_i \quad \text{where} \quad p_{ij} = \frac{X_{ij}}{\sum_i X_{ij}}. \tag{8}$$

Similarly, the average single kernel hardness for wheat in bin j is given by

$$KH_j = \sum_i p_{ij} KH_i \quad \text{where} \quad p_{ij} = \frac{X_{ij}}{\sum_i X_{ij}}. \tag{9}$$

Finally, the average test weight for wheat in bin *j* is given by

$$TW_j = \sum_i p_{ij} TW_i \quad \text{where} \quad p_{ij} = \frac{X_{ij}}{\sum_i X_{ij}}. \tag{10}$$

When grain from separate truckloads that differ in kernel size is combined in the bin, the variation of kernel size in bin *j* results from two sources. One is the within-load variation and the other is the between-load variation. Within-load variation means the variation of kernel size within a load, i.e., the difference between each kernel size and its load mean, and between-load variation means the variation of kernel size across loads, i.e., the difference between the mean kernel size of each load and the overall mean kernel size of the bin. Thus, the total variation of kernel size in the bin is calculated as the sum of the variation within each load and the variation between loads.

The within-load variation is inherent to each load in the sense that it can not be altered by rearranging the loads and so it does not influence the optimal solution. However, the between-load variation can be reduced by combining the loads of similar kernel size when truckloads are allocated into the bins. The smaller between-load variation in turn means the smaller total variation of kernel size in the bin.

In equation (6), the standard deviation of single kernel diameter (KDS_j) reflects the variation of kernel size in bin j. The standard deviation of kernel diameter for wheat in bin j can be approximated using mean absolute deviations. Specifically, the within-load standard deviation of kernel diameter for wheat in bin j is approximated by mean absolute deviation estimator. This is based on the theoretical results by Taylor (pp.98-99). Taylor presented that the expected value of absolute deviation is equal to $1/1.25$ times the expected value of the standard deviation. Since the standard deviation of single kernel diameter in load i is readily available, we can obtain the mean absolute deviation estimator as an approximation to the within-load standard deviation of kernel diameter.

On the other hand, the between-load standard deviation of kernel diameter for wheat in bin j is estimated by the expected absolute deviation of the load average kernel diameter from the bin average kernel diameter. Let the deviation of the average single kernel diameter for wheat in load i from the average single kernel diameter for wheat in bin j, or $KD_i - KD_j$, be denoted by u_{ij}^{+} if it is positive, and by u_{ij}^{-} if it is negative. Then, $\sum_i \left(u_{ij}^{+} + u_{ij}^{-}\right)$ measures the sum of the absolute deviations for average single kernel diameter. Taking the expected value of $\sum_i \left(u_{ij}^{+} + u_{ij}^{-}\right)$, we can obtain the mean absolute deviation estimator as an approximation to the between-load standard deviation of kernel diameter.

With the within-load standard deviation and the between-load standard deviation combined together, the average standard deviation of kernel diameter for wheat in bin j is

$$\text{(11)} \qquad KDS_j = \sum_i p_{ij} \frac{KDS_i}{1.25} + \sum_i p_{ij} (u_{ij}^{+} + u_{ij}^{-})$$

$$= \sum_i p_{ij} \left[\frac{KDS_i}{1.25} + \left(u_{ij}^{+} + u_{ij}^{-}\right) \right], \text{ where } p_{ij} = \frac{X_{ij}}{\sum_i X_{ij}}.$$

Similarly, the average standard deviation of kernel hardness for wheat in bin j is estimated by

(12) $$KHS_j = \sum_i p_{ij} \frac{KHS_i}{1.25} + \sum_i p_{ij} (u_{ij}^+ + u_{ij}^-)$$

$$= \sum_i p_{ij} \left[\frac{KHS_i}{1.25} + \left(u_{ij}^+ + u_{ij}^- \right) \right], \text{ where } p_{ij} = \frac{X_{ij}}{\sum_i X_{ij}}.$$

The elevator's maximization problem is solved using the MINOS5 solver in GAMS, a general nonlinear optimizer. Nonlinearities occur in several constraints and the feasible region for the problem is not convex. Due to the non-convexity, there is no guarantee that a local optimum found is actually global.

To deal with this problem, a global optimization method is required. A global optimization method solves the non-convex model with numerous different starting values for a selected variable (Brooke, Kendrick, Meerhaus, and Raman, p. 154). In this study, the global solution was tracked by randomizing the starting values up to 1000 times. Specifically, the starting values for variable X_{ij}, i.e., amount of load allocated, were varied by random numbers generated from uniform distribution, within a range of 0.0001 and 1/3. The model was repetitively solved and the solution that gave the largest objective value was selected as a global maximum.

Results

The wheat quality characteristics and percent flour yield assuming all loads for each year are blended are presented in Table 2. The standard deviation of single kernel diameter (*KDS*) and standard deviation of single kernel hardness (*KHS*) are generally larger than the average values reported in Table 1. This is because the standard deviation of the two variables in Table 2 reflects the between-load standard deviation as well as the within-load standard deviation. The percent flour yield (*PFY*) predicted by equation (4) is lowest in 1996 with 70.52 and highest in 1998 with 71.66. The predicted average percent flour yields are generally lower than the actual average percent flour yields presented in Table 1, since they are based on the increased standard deviation of single kernel diameter and single kernel hardness.

The cluster solutions from 1995 to 1998 are reported in Tables 3 and 4. The first column of Table 3 indicates the hierarchical clustering algorithm that gave the best solution in the first stage of two-stage clustering. There were only slight differences in the solutions obtained when the centroids from the single-linkage, complete-linkage, centroid, average-linkage, and Ward's methods were used as initial seeds or starting points. The R^2s ranging from 0.76 to 0.85 are quite large, suggesting that the clusters are quite homogeneous and well separated. The low values of within standard deviation ranging from 0.05 to 0.06 further confirm this conclusion.

The cluster solution can be labeled using the cluster means of each cluster. For example, considering 1995 sample in Table 4, cluster 1 consists of loads that have medium kernels and therefore this cluster can be labeled as medium-kernel cluster. Similarly, cluster 2 can be labeled as small-kernel cluster, and cluster 3 as large-kernel cluster.

Table 5 exhibits the average wheat quality attributes of the clusters in each year and the estimated percent flour yield. The overall mean of the percent flour yield is 71.13 for 1995, 70.69 for 1996, 71.46 for 1997, and 71.74 for 1998. The percent flour yields obtained from clustering are higher than those without sorting across the board. This result is from the fact that by sorting the loads for each year into homogeneous clusters, the between-load variations of single kernel diameter and single kernel hardness are decreased, and in turn the average standard deviations of single kernel diameter and single kernel hardness are decreased.

Table 6 shows the results of the global optimization. A small number of loads were partially allocated into the bins, and thus the total quantities of loads allocated into each bin are not round numbers. The average percent flour yield is 71.33 for 1995, 70.89 for 1996, 71.67 for 1997, and 71.91 for 1998. The yields are higher than those from cluster analysis as well as whole sample without sorting.

Table 7 summarizes the results in Tables 2, 5 and 6. The results show slight increases in percent flour yield from two sorting methods. Specifically, the cluster analysis and global optimization increase the percent flour yield relative to the whole sample without sorting by 0.13% and 0.32% respectively.

This implies that when one million bushels of wheat are milled, the cluster analysis will increase flour yield by 1,300 bushels, and the global optimization will increase flour yield by 3,200 bushels.

Table 8 reports the milling incomes per day from whole sample without sorting, cluster analysis, and global optimization. Cluster analysis increases the milling income relative to the whole sample without sorting by 104.99 dollars (5%) on average, and global optimization increases the milling income relative to whole sample without sorting by 265.90 dollars (13%) on average.

Conclusions

Kernel size uniformity is an important physical quality attribute in terms of processing efficiency, quality control, and milling yield. This study developed grain sorting strategies for elevators to use to increase kernel uniformity and determined the size of potential benefits from sorting.

Cluster analysis and global optimization were used to sort loads to increase kernel size uniformity. Cluster analysis and global optimization increased the percent flour yield relative to no sorting by 0.13% and 0.32% respectively. Cluster analysis increased the daily milling income relative to no sorting by 105 dollars (5%), and global optimization increased the milling income by 266 dollars (13%). The results show that cluster analysis is vastly inferior to global optimization.

This study was unable to consider all the potential benefits of kernel uniformity. The milling yield data used here are from fixed roll settings on small-scale mill tests. In practice, flour millers can optimally adjust the space of rollermills to take advantage of the kernel size uniformity. The benefits of uniformity could be different under large-scale commercial milling operations. Future grain science research needs to look at the possibility of optimally adjusting roller settings. There is also the possibility of improving flour quality (reduced ash content) from increased kernel uniformity. Future grain science research should also address flour quality. These additional benefits of kernel uniformity may need to be considered before firms would adopt sorting strategies to increase kernel uniformity.

Footnotes

1. The single kernel diameter (*KD*) and single kernel weight (*KW*) may be considered as alternative measures of kernel size. To avoid the multicollinearity problem that arises from including two measures of the same thing, the following model was estimated separately:

$$PFY_{it} = \beta_0 + \beta_1 KW_{it} + \beta_2 KWS_{it} + \beta_3 KH_{it} + \beta_4 KHS_{it} + \beta_5 TW_{it} + \mu_i + \varepsilon_{it},$$

where KW_{it} is the average single kernel weight (mg), KWS_{it} is the standard deviation of single kernel weight. However, the results of *t*-tests showed that the estimated coefficients β_1 *and* β_2 are not statistically significant at the 5% level.

2. Milling yield increases when wheat becomes softer in hard wheat. However, milling yield increases as hardness increases in soft wheat.

References

Adam, B.D., P. Kenkel, and K. Anderson. "The Economics of Cleaning Winter Wheat for Export: An Evaluation of Proposed Federal 'Clean Grain' Standards." *Journal of Agricultural and Resource Economics* 19(December 1994): 280-98.

Brooke, A., D. Kendrick, A. Meeraus, and R. Raman. *GAMS: A User's Guide*, Washington DC: GAMS Development Corporation, 1998.

Deyoe, C., Y. Chen, P.V. Reddy, P. McCluskey, J. Gwirtz, and D. Eustace. "Utilization of the SKWCS Information in Hard Red Winter Wheat Surveys for Quality Evaluations." *Association of Operative Millers-Bulletin* (July 1998): 7131-7140.

Hazell, P.B.R., and R.D. Norton. *Mathematical Programming for Economic Analysis in Agriculture*. New York: Macmillan Publishing Company, 1986.

Hennessy, D.A. "The Economics of Purifying and Blending." *Southern Economic Journal* 63(July 1996): 223-32.

Hennessy, D.A., and T.I. Wahl. "Discount Schedules and Grower Incentives in Grain Marketing." *American Journal of Agricultural Economics* 79(August 1997): 888-901.

Hill, L.D. *Grain Grades and Standards: Historical Issues Shaping the Future*. Urbana IL: University of Illinois Press, 1990.

_________. "Grain Grades: They Lack Economic Rationale." *Choices* (1st Quarter 1988): 24-27.

Johnson, D.M., and W.W. Wilson. "Wheat Cleaning Decisions at Country Elevators." *Journal of Agricultural and Resource Economics* 18(December 1993): 198-210.

Li, Yuzhou. "The Influence of Kernel Size on the Millability of Wheat." Unpublished M.S. Thesis, Kansas State University, 1987.

Lyford, C.P. "Grain Quality Characteristics to Predict Flour Yield in Hard Red Winter Wheat." Unpublished manuscript, Oklahoma State University, Stillwater, Oklahoma, 2000.

Punj, G., and D.W. Stewart. "Cluster Analysis in Marketing Research: Review and Suggestions for

Application." *Journal of Marketing Research* (May 1983): 134-48.

Sharma, S. *Applied Multivariate Techniques.* New York: John Wiley & Sons, Inc., 1996.

Taylor, S. *Modelling Financial Time Series*. New York: John Wiley & Sons, Inc., 1986.

U.S. Department of Agriculture, Federal Grain Inspection Service. *Official United States Standards for Grain*. Washington DC: U.S. Government Printing Office, 1999.

U.S. Wheat Associates. "Survey of Importers' Quality Needs". Unpublished internal information, 1996, 1997.

Table 1. Summary Statistics for Wheat Quality Characteristics and Actual Percent Flour Yield, 1995–1998

Year	Statistics	Single Kernel Characteristics								TW	PFY
		KW	KWS	KD	KDS	KH	KHS	KM	KMS		
1995	Mean	27.87	7.74	2.29	0.42	67.56	17.34	10.70	0.64	59.41	71.75
	Std.Dev.	2.59	0.81	0.12	0.04	4.28	1.35	0.80	0.19	2.09	1.48
	Min	22.75	5.89	2.03	0.33	56.98	13.66	8.33	0.37	54.00	67.10
	Max	35.53	10.79	2.66	0.55	78.95	21.60	12.57	1.72	63.00	75.07
	Obs.	148	148	148	148	148	148	148	148	148	148
1996	Mean	28.21	8.00	2.23	0.46	70.81	17.18	13.00	0.51	59.40	70.74
	Std.Dev.	2.91	0.79	0.14	0.04	6.11	1.37	0.86	0.08	1.38	1.50
	Min	22.19	6.31	1.89	0.38	57.67	13.24	9.46	0.32	55.65	66.01
	Max	34.99	10.24	2.59	0.57	85.09	21.85	14.96	0.78	63.18	73.77
	Obs.	156	156	156	156	156	156	156	156	156	156
1997	Mean	30.23	8.53	2.31	0.47	69.36	17.47	12.58	0.48	60.71	71.29
	Std.Dev.	2.82	0.90	0.14	0.04	5.84	1.98	1.05	0.12	1.37	0.93
	Min	22.37	6.77	1.95	0.38	49.24	13.19	9.82	0.33	56.07	67.77
	Max	37.35	11.61	2.65	0.58	81.43	27.00	15.16	1.31	63.42	73.07
	Obs.	136	136	136	136	136	136	136	136	136	136
1998	Mean	30.16	7.67	2.31	0.42	72.78	15.86	12.12	0.47	61.56	71.80
	Std.Dev.	1.94	0.47	0.10	0.03	6.70	1.89	0.89	0.09	1.21	1.29
	Min	23.44	6.50	1.93	0.35	50.67	12.21	9.87	0.32	58.30	67.65
	Max	36.99	9.24	2.64	0.48	82.92	27.23	14.09	0.86	63.78	74.65
	Obs.	169	169	169	169	169	169	169	169	169	169

Notes: *KW* is the average single kernel weight (mg), *KWS* is the standard deviation of single kernel weight, *KD* is the average single kernel diameter (mm), *KDS* is the standard deviation of single kernel diameter, *KH* is the average single kernel hardness (hardness index), *KHS* is the standard deviation of single kernel hardness, *KM* is the average single kernel moisture (%), *KMS* is the standard deviation of single kernel moisture, *TW* is the test weight (lb/bu), and *PFY* is the percent flour yield (%).

Table 2. Average Wheat Quality Attributes and Predicted Percent Flour Yield from Whole Sample without Sorting, 1995–1998

Year	Obs.	KD	KDS	KH	KHS	TW	PFY
1995	148	2.29	0.43	67.56	17.22	59.41	71.01
1996	156	2.23	0.48	70.81	18.80	59.40	70.52
1997	136	2.31	0.48	69.36	18.56	60.71	71.32
1998	169	2.31	0.41	72.78	17.89	61.56	71.66

Notes: *Obs.* is the number of observations, *KD* is the average single kernel diameter (mm), *KDS* is the standard deviation of single kernel diameter, *KH* is the average single kernel hardness (hardness index), *KHS* is the standard deviation of single kernel hardness, and *TW* is the test weight (lb/bu), and *PFY* is the percent flour yield (%). *KDS* and *KHS* are calculated by combining the within-load standard deviation and between-load standard deviation.

Table 3. Summary Statistics for Two-Stage Cluster Analysis, 1995 – 1998

Year	Hierarchical Clustering Method	Total Standard Deviation	Within Standard Deviation	R^2
1995	Single-Linkage	0.12	0.05	0.81
1996	Single-Linkage	0.14	0.06	0.85
1997	Complete-Linkage	0.14	0.06	0.82
1998	Centroid	0.10	0.05	0.76

Note: Loads are clustered with respect to average single kernel diameter (*KD*) in each cluster.

Table 4. Cluster Means and Standard Deviation, 1995 – 1998

Year	No. of Clusters	No. of Loads	Cluster Mean	Cluster Std. Dev.
1995	1	62	2.29	0.04
	2	54	2.17	0.05
	3	32	2.46	0.08
1996	1	78	2.24	0.05
	2	42	2.04	0.06
	3	36	2.42	0.06
1997	1	27	2.10	0.07
	2	75	2.31	0.05
	3	34	2.48	0.06
1998	1	88	2.31	0.03
	2	46	2.42	0.06
	3	35	2.17	0.07

Note: Loads are clustered with respect to average single kernel diameter (*KD*) in each cluster.

Table 5. Clusters, Average Quality Attributes and Percent Flour Yield, 1995-1998

Year	Cluster	Obs	KD	KDS	KH	KHS	TW	PFY	Mean PFY
	1	62	2.29	0.37	68.63	17.41	59.66	71.19	
1995	2	54	2.17	0.37	66.05	17.13	57.98	70.48	71.13
	3	32	2.46	0.42	68.02	16.78	61.36	72.12	
	1	78	2.24	0.41	68.89	18.45	59.52	70.89	
1996	2	42	2.04	0.39	73.78	18.87	58.33	69.81	70.69
	3	36	2.42	0.45	71.50	17.43	60.37	71.28	
	1	27	2.10	0.43	69.80	18.91	59.06	70.39	
1997	2	75	2.31	0.42	70.43	18.18	60.94	71.50	71.46
	3	34	2.48	0.42	66.63	18.60	61.51	72.22	
	1	88	2.31	0.36	72.14	18.97	61.58	71.76	
1998	2	46	2.42	0.37	72.43	16.57	62.24	72.26	71.74
	3	35	2.17	0.38	74.81	17.00	60.62	71.00	

Notes: *Obs* is the number of observations, *KD* is the average single kernel diameter (mm), *KDS* is the standard deviation of single kernel diameter, *KH* is the average single kernel hardness (hardness index), *KHS* is the standard deviation of single kernel hardness, and *TW* is the test weight (lb/bu), *PFY* is the percent flour yield (%), and *Mean PFY* is the average PFY of the clusters.

Table 6. Globally Optimal Wheat Quality Characteristics with Three Bins, 1995-1998

Year	Variables	Bin Number		
		1	2	3
1995	Quantity	70.92	32.34	44.74
	KD	2.28	2.45	2.17
	KDS	0.20	0.42	0.37
	KH	69.71	66.84	64.67
	KHS	16.71	16.86	16.56
	TW	59.79	61.07	57.62
	Average PFY		71.33	
1996	Quantity	69.02	45.00	41.98
	KD	2.23	2.39	2.04
	KDS	0.41	0.46	0.39
	KH	67.26	72.38	74.98
	KHS	17.87	17.06	18.25
	TW	59.30	60.38	58.50
	Average PFY		70.89	
1997	Quantity	58.54	33.89	43.57
	KD	2.41	2.13	2.33
	KDS	0.44	0.45	0.30
	KH	66.54	68.82	73.53
	KHS	17.47	18.95	16.86
	TW	61.18	59.33	61.16
	Average PFY		71.67	
1998	Quantity	35.85	52.46	80.69
	KD	2.31	2.23	2.37
	KDS	0.39	0.20	0.38
	KH	62.51	75.48	75.57
	KHS	17.98	15.69	15.09
	TW	60.44	61.28	62.25
	Average PFY		71.91	

Notes: *Quantity* is the total number of loads allocated into the bin, *KD* is the average single kernel diameter (mm), *KDS* is the standard deviation of single kernel diameter, *KH* is the average single kernel hardness (hardness index), *KHS* is the standard deviation of single kernel hardness, and *TW* is the test weight (lb/bu), and *PFY* is the percent flour yield (%).

Table 7. Predicted Average Percent Flour Yield from Whole Sample without Sorting, Cluster Analysis, and Global Optimization, 1995-1998

Year	Whole Sample Without Sorting	Cluster Analysis		Global Optimization	
		PFY	Increase	PFY	Increase
1995	71.01	71.13	0.12	71.33	0.32
1996	70.52	70.69	0.17	70.89	0.37
1997	71.32	71.46	0.14	71.67	0.35
1998	71.66	71.74	0.08	71.91	0.25
Average	71.13	71.26	0.13	71.45	0.32

Note: PFY represents the percent flour yield and increases in PFY are calculated relative to the PFY from whole sample without sorting.

Table 8. Milling Incomes per Day from Whole Sample without Sorting, Cluster Analysis, and Global Optimization, 1995-1998

Year	Whole Sample without Sorting	Cluster Analysis			Global Optimization		
		Milling Income	Dollar Increase	Percent Increase	Milling Income	Dollar Increase	Percent Increase
1995	$1,079.53	$1,177.17	$97.65	9%	$1,339.91	$260.39	24%
1996	$670.74	$809.05	$138.31	21%	$971.77	$301.02	45%
1997	$2,654.42	$2,770.90	$116.48	4%	$2,945.62	$291.21	11%
1998	$3,806.18	$3,873.70	$67.52	2%	$4,017.18	$211.00	6%
Average	$2,052.72	$2,157.71	$104.99	5%	$2,318.62	$265.90	13%

Note: Dollar increases and percent increases are calculated relative to the milling income from whole sample without sorting. The mill is assumed to process 15,500 bushels of wheat per day.