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Value of Increasing Kernel Uniformity

Byung-Sam Yoon, B. Wade Brorsen, and Conrad P. Lyford

Kernel uniformity is an important quality attribute that can now be measured at low cost. This study analyzes the profitability of sorting to increase wheat kernel uniformity. Nonlinear programming is used to sort grain loads to maximize flour yield by increasing uniformity of kernel size and kernel hardness. Results of this analysis suggest increases in flour yield due to higher kernel uniformity are not enough to outweigh the costs of sorting.

Key words: kernel uniformity, milling, nonlinear programming, sorting, wheat

Introduction

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 consistency of product quality. Recent advances in testing and processing technology enable processors to impose rigorous product requirements.

The grain industry, in search of uniform quality measures, 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 which determine value.

Current U.S. standards for wheat determine grades based on test weight, total defects, and other material [U.S. Department of Agriculture (USDA)]. Recently, however, processors have become more interested in such characteristics as greater kernel size and kernel size uniformity (U.S. Wheat Associates).

For flour millers, kernel size uniformity is a potentially important physical quality attribute for processing efficiency, quality control, and milling yield. In the flour milling process, 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, and consequently require additional processing. This additional processing requires more milling time and energy costs. Furthermore, additional processing may decrease quality of the flour (Li).

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With uniform wheat, the wheat kernels are ground more evenly in the milling process, leading to higher extraction of flour. Since wheat kernels must pass through five or more of the breaking rollermills before the bran is completely removed, more uniform kernel size may increase milling efficiency, flour quality, and flour yield. This study determines the potential benefits from increased flour yield due to an increase in kernel size and hardness uniformity, achieved by sorting.

It is not an easy task to achieve benefits from increased kernel uniformity in the current grain marketing system. Because uniformity of kernel size is not one of the grading standards for wheat,[1] and an increased kernel size uniformity is not rewarded, grain elevators and millers are not strongly motivated to develop and implement various strategies to increase kernel size uniformity.

Kernel size uniformity may be increased by sorting rather than blending various truckloads of wheat with different kernel sizes. Previous studies on grain sorting and blending (e.g., Johnson and Wilson; Adam, Kenkel, and Anderson; Hennessy and Wahl) have been largely prompted by concerns about declining U.S. export market share and complaints by foreign buyers of poor quality grain. These studies analyze the costs and benefits of cleaning wheat to reduce dockage levels. Wilson and Dahl note within-lot variability as one type of quality uniformity of particular concern to export buyers. Vandeburg, Fulton, and Dooley estimate the costs of handling value-added grains, and thus include estimates for the cost of segregation. However, none of these studies compare costs and benefits that accrue to processors from sorting to achieve kernel uniformity.

The remainder of the article proceeds as follows. In the section below, we provide a description of the two distinct data sets used in the analysis. Procedures are then developed to determine optimal grain sorting strategies based on kernel size uniformity. Next, the size of potential benefits from sorting is determined and compared to the cost of sorting. Specifically, a percent flour yield equation is estimated to relate flour yield to wheat quality attributes and to measure the benefits of sorting. An equation approximating milling income is used to assess the monetary value of increasing kernel uniformity, and our results are compared to costs from segregation derived by Vandeburg, Fulton, and Dooley. Concluding remarks are offered in the final section.

Data

Data for this study were collected from two sources. The first data set was used to estimate a percent flour yield equation as well as to perform an optimization-by-sorting procedure. These data cover a four-year time period and span all major U.S. production areas of hard red winter wheat. From 1995 through 1998, samples of hard red winter wheat were collected from elevator bins during the Hard Red Winter Wheat (HRWW) Crop Survey (Deyoe et al.).

HRWW samples were provided from elevators in 22 survey districts. Texas and Oklahoma were covered by four districts, Kansas was represented by nine districts, eastern Colorado by two districts, Nebraska by five districts, and South Dakota and Montana each were treated as separate districts. From each district, seven samples on average were randomly collected over four years, resulting in a total of 609 wheat samples.

[1] Shrunken and broken kernels are among the grade determining factors. The kernel size uniformity referred to here is the uniformity of kernels after shrunken and broken kernels are moved.

Table 1. Summary Statistics for Wheat Quality Characteristics and Percent Flour Yield, U.S. Data Set, 1995–1998

	Single-Kernel Characteristics									
Year/Statistic	*KW*	*KWS*	*KD*	*KDS*	*KH*	*KHS*	*KM*	*KMS*	*TW*	*PFY*
1995 (*n* = 148):										
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
Minimum	22.75	5.89	2.03	0.33	56.98	13.66	8.33	0.37	54.00	67.10
Maximum	35.53	10.79	2.66	0.55	78.95	21.60	12.57	1.72	63.00	75.07
1996 (*n* = 156):										
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
Minimum	22.19	6.31	1.89	0.38	57.67	13.24	9.46	0.32	55.65	66.01
Maximum	34.99	10.24	2.59	0.57	85.09	21.85	14.96	0.78	63.18	73.77
1997 (*n* = 136):										
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
Minimum	22.37	6.77	1.95	0.38	49.24	13.19	9.82	0.33	56.07	67.77
Maximum	37.35	11.61	2.65	0.58	81.43	27.00	15.16	1.31	63.42	73.07
1998 (*n* = 169):										
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
Minimum	23.44	6.50	1.93	0.35	50.67	12.21	9.87	0.32	58.30	67.65
Maximum	36.99	9.24	2.64	0.48	82.92	27.23	14.09	0.86	63.78	74.65

Notes: *n* = number of observations in each of the four years; *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 (pounds/bushel), and *PFY* is the percent flour yield (%).

Because the data are from several regions, the data can be used to analyze the profitability of a regional miller sorting to create uniformity.

Each HRWW sample collected was tested using the Single Kernel Characterization System (the machine used was the Perten SKCS 4100) in the Grain Science and 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. A test can be completed in about three minutes, and calculates mean and standard deviation for single-kernel weight, single-kernel diameter (size), single-kernel hardness, and single-kernel moisture. In addition to the single-kernel characteristics, test weight was also included.

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 (model 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. The samples were milled to meet typical commercial ash specifications.

The second data set consists of truckload samples of wheat taken from several Oklahoma Agricultural Statistics Districts during 1998 and 1999 (Kenkel). Samples were obtained using the truck sampling procedures recommended by the USDA's Federal

Grain Inspection Service. Two main regions were sampled: (*a*) Central, consisting of the Central and North Central Agricultural Statistics Districts, and (*b*) West, consisting of the Northwest, West Central, and Southwest Districts. This data set may be used to depict a local elevator receiving grain only from the region. Thus, with the combination of the two data sets, the profitability of sorting can be analyzed from the perspective of both the regional miller and the local elevator.

Table 1 presents summary statistics for wheat quality characteristics and average percent flour yields for the first data set. The data have some limitations. The percent flour yields used here are from fixed roll settings, and thus may underestimate the value of kernel uniformity. In practice, flour millers may be able to increase the milling yield by optimally adjusting the space of rollermills to different kernel sizes. The summary statistics for wheat quality characteristics for the Oklahoma data set are reported in table 2. The Oklahoma data set generally has larger standard deviations for kernel hardness, which means there is greater variation among truckloads than there is across regions.

Model of Flour Yield

An equation relating the percent flour yield (extraction) to wheat quality characteristics is estimated. Milling income is a linear function of percent flour yield, and thus maximizing one is equivalent to maximizing the other. Sorting strategies are evaluated by how much these strategies increase the percent flour yield or milling income relative to no sorting.

The data on wheat quality characteristics and percent flour yield used for the percent flour yield equation consist of 609 observations on the 22 cross-sections of districts over a four-year time period. To estimate a percent flour yield equation, the time-series and cross-sectional data are pooled[2] using the following error-components model:[3]

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

where i represents the districts ($i = 1, 2, ..., 22$), t represents the years ($t = 1995, 1996, 1997$, and 1998), and k denotes the sample number from the ith district in the tth year. Variable definitions are given in table 3. The β's are the fixed-effects coefficients; μ_{it} denotes the random-effects parameters assumed to be independent and normally distributed with $E[\mu_{it}] = 0$ and $E[\mu_{it}^2] = \sigma_\mu^2$; and ε_{kit} represents independent and normally distributed random variables with $E[\varepsilon_{kit}] = 0$, nonconstant variance $E[\varepsilon_{kit}^2] = \sigma_{\varepsilon_{kit}}^2$, and these ε_{kit} are uncorrelated with the μ_{it} (i.e., $E[\mu_{it}\varepsilon_{kit}] = 0$).

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[2] A likelihood-ratio test that the slope parameters in equation (1) were constant across years yielded a test statistic value of 24.5, which is less than the $\chi^2_{[15]}$ critical value of 25.0 at the 5% significance level. Therefore, the null hypothesis of constant slope parameters across years cannot be rejected.

[3] The single-kernel diameter (*KD*) and single-kernel weight (*KW*) may be considered as alternative measures of kernel size (their correlation in the data set was 0.93). To avoid the multicollinearity problem arising 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), and 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 were not statistically significant at the 5% level.

Table 2. Summary Statistics for Wheat Quality Characteristics in Oklahoma Regions, 1998–1999

	Single-Kernel Characteristics								
Year/Region/Statistic	*KW*	*KWS*	*KD*	*KDS*	*KH*	*KHS*	*KM*	*KMS*	*TW*
1998, Central (n = 38):									
Mean	29.52	7.57	2.22	0.44	81.21	16.50	10.31	0.35	62.66
Std. Dev.	2.11	1.10	0.09	0.06	5.21	1.62	1.18	0.05	0.79
Minimum	25.04	5.37	2.00	0.32	71.80	13.03	9.24	0.26	59.90
Maximum	34.80	9.51	2.41	0.54	89.81	19.41	14.49	0.46	63.90
1998, Western (n = 76 or 78):									
Mean	29.89	7.92	2.18	0.45	78.51	16.28	13.17	0.33	60.36
Std. Dev.	4.15	1.06	0.20	0.05	6.08	2.06	1.55	0.06	2.12
Minimum	18.70	5.78	1.58	0.31	63.64	12.75	9.63	0.23	54.90
Maximum	38.54	11.14	2.57	0.59	93.08	24.22	17.02	0.58	64.40
1999, Central (n = 54):									
Mean	31.45	8.36	2.28	0.46	71.77	17.85	13.57	0.30	60.04
Std. Dev.	3.12	0.87	0.15	0.05	7.23	1.76	0.39	0.05	2.24
Minimum	24.16	6.35	1.93	0.33	58.96	14.30	12.80	0.23	51.50
Maximum	36.50	9.98	2.52	0.58	85.72	22.34	14.43	0.41	63.10
1999, Western (n = 34):									
Mean	29.76	8.05	2.23	0.45	74.89	17.96	13.94	0.32	59.74
Std. Dev.	3.98	0.93	0.19	0.05	8.14	1.82	0.33	0.04	1.63
Minimum	20.04	5.94	1.71	0.30	56.05	14.14	13.30	0.26	57.30
Maximum	37.76	10.15	2.53	0.56	89.02	21.27	14.75	0.39	65.00

Notes: n = number of observations in each of the two regions for 1998 and 1999; *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, and *TW* is the test weight (pounds/bushel).

Expected signs of the fixed-effect coefficients, shown in table 3, were ascertained from past research. Test weight (*TW*) has long been used in wheat marketing and can be expected to increase milling yield. Increased test weight generally means more dense kernels, and as such there is more material in a unit of wheat to be made into flour. Many researchers have noted increases in flour extraction with increases in test weight (e.g., Swanson; Kremer).

Kernel diameter (*KD*) measures a physical property of the wheat. Larger diameters would be expected to have a positive relationship with milling yield because larger objects have more volume relative to surface area. The endosperm that yields the flour is inside the kernel, while the bran coat which is a large part of millfeeds is on the outside.

Williams described increases in milling yield when wheat becomes softer (i.e., when *KH* declines) in hard to very hard wheat (the opposite is true in soft wheat). In the present study, only hard red winter wheat was analyzed, and a linear term was used with an expected negative sign on the *KH* coefficient.

Variability in either kernel diameter or kernel hardness is expected to reduce flour yield. The physical operation of a flour mill is expected to be more efficient in extracting flour when kernels are similar.

The model was fit using PROC NLMIXED in SAS version 8.0, as both random effects and heteroskedasticity are present. The data are assumed normally distributed and the

Table 3. Variable Definitions and Expected Sign of the Relationship with Percent Flour Yield

Independent Variable	Definition	Expected Sign
KD_{it}	Average single-kernel diameter (mm)	+
KDS_{it}	Standard deviation of single-kernel diameter	−
KH_{it}	Average single-kernel hardness (hardness index)	−
KHS_{it}	Standard deviation of single-kernel hardness	−
TW_{it}	Test weight (pounds/bushel)	+

mean (expected value) of the data is a linear function of explanatory variables and the random-effects parameters, i.e.,

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

The random-effects parameters μ_{it} enter the model linearly. This study also considered average single-kernel moisture (*KM*) and standard deviation of single-kernel moisture (*KMS*), but these variables were dropped because they were not statistically significant. The standard deviation of single-kernel moisture (*KMS*) should not matter because each sample was tempered to 16% moisture.

Pretests indicated the only relevant variable in the variance equation was kernel moisture. The variance of the error terms ε_{kit} is an exponential function of the explanatory variable:

$$(3) \qquad \sigma^2_{\varepsilon_{kit}} = \exp\left[\alpha_1 KM_{kit}\right],$$

where α_1 is a coefficient to be estimated.

Finally, the estimated percent flour yield (*PFY*) equation is specified as:

$$(4) \qquad \begin{array}{lllllll} PFY = & 48.24 & + 1.32KD & - 2.25KDS & - 0.07KH & - 0.04KHS & + 0.44TW, \\ & (29.58) & (3.19) & (-2.30) & (-7.95) & (-1.84) & (13.14) \end{array}$$

where the variables are the same as defined in equation (1), and the t-statistics of the coefficients are presented in parentheses. The estimate of α_1 was -0.065 with a t-value of -12.52, indicating the prediction equation is not as accurate for low-moisture grain. The estimate of σ^2_M was 0.494, and the likelihood-ratio test statistic of no random effect was 234, which is immensely greater than the $\chi^2_{[1]}$ critical value.

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 depend upon the curvature attributes of the yield-quality schedule. Generally, if yield is a concave function of quality, blending all grain together is best. In contrast, sorting is desirable when yield is a convex function of quality. The negative coefficients on the standard deviation terms (*KDS*, *KHS*) in equation (4) are quadratic terms in *KD* and *KS*. Thus, their negative coefficients yield a function convex in *KD* and *KS*, so sorting is optimal in this case.

To estimate the monetary benefits of increased kernel uniformity due to increased flour yield, we need an estimate of milling income. Milling income (*MI*), in dollars per bushel, is approximated as:

(5)
$$\begin{aligned} MI &= (1 - PFY)MFP + (PFY)FP \\ &= 1.68(1 - PFY) + 5.52PFY \\ &= 1.68 + 3.84PFY, \end{aligned}$$

where MFP and FP are millfeed price and flour price, respectively. Prices are taken from Lyford and converted to dollars per bushel. Lyford reports the price of millfeeds as \$56/ton, and the price of flour as \$9.2/cwt. Thus, milling income is approximated as the sum of incomes[4] generated by flour yield and mill feed.

Sorting Strategy

Elevators and millers often rearrange grain by blending and sorting to take advantage of profit opportunities. To simplify the analysis, the elevator or miller is assumed to know the distribution of wheat quality characteristics before the loads of wheat are delivered to the elevator. In practice, an elevator would need to start with an initial estimate of wheat quality and then adjust the estimates as samples were taken from initial loads. The elevators or millers may allocate 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 mathematical programming.

For the 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, and total quantity of wheat in bin j is denoted by QTY_j. Because Oklahoma elevators use about three bins[5] to store grain, three bins are assumed in our model. The objective is to maximize the total milling income. But because milling income and flour yield are linearly and positively related, we can equivalently maximize total flour yield from all wheat contained in the bins. The objective function, using equation (4), is defined as:

(6)
$$\begin{aligned} &\underset{QTY}{\text{Max}} \sum_j PFY(\overline{KD}_j, \overline{KDS}_j, \overline{KH}_j, \overline{KHS}_j, \overline{TW}_j)QTY_j = \\ &\underset{QTY}{\text{Max}} \sum_j \left(48.24 + 1.32\overline{KD}_j - 2.25\overline{KDS}_j - 0.07\overline{KH}_j - 0.04\overline{KHS}_j + 0.44\overline{TW}_j\right)QTY_j, \end{aligned}$$

where $\overline{KD}_j$ is the average single-kernel diameter for wheat in bin j, $\overline{KDS}_j$ is the standard deviation of single-kernel diameter in bin j, $\overline{KH}_j$ is the average single-kernel hardness for wheat in bin j, $\overline{KHS}_j$ is the standard deviation of single-kernel hardness in bin j, and $\overline{TW}_j$ 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)
$$QTY_j = \sum_i X_{ij}, \quad j = 1, 2, 3.$$

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[4] The sensitivity of the conclusions with respect to changes in prices can be calculated directly from (5). If mill feed price increased 10% with no change in flour price, the value of uniformity would decrease 4.375% [(0.1 - 1.68)/3.84].

[5] Using five bins for the Oklahoma Western region in 1999 increased marginal revenue by 0.16¢/bushel. The time required to solve the model increases exponentially with the number of bins. As little difference in revenue was achieved, five bins were not considered for the other data sets.

For simplicity, each truckload is treated as one unit. Consequently, the sum of wheat quantities allocated from truckload i over all bins should be one. That is, $\Sigma_j X_{ij} = 1$. The model allows a load to be partially allocated into different bins to avoid the extra complexity of integer programming. Only a small number of loads (usually two) are not allocated to a single bin at convergence.

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:

(8) $$\overline{KD}_j = \sum_i p_{ij} KD_i,$$

where

$$p_{ij} = \frac{X_{ij}}{\sum_i X_{ij}}.$$

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

(9) $$\overline{KD}_j = \sum_i p_{ij} KH_i,$$

and finally, the average test weight for wheat in bin j is written as:

(10) $$\overline{TW}_j = \sum_i p_{ij} TW_i.$$

When grain from truckloads differing in kernel size is combined in the bin, the variation of kernel size in bin j results from two sources: within-load variation and between-load variation. Within-load variation is the variation of kernel size within a load, i.e., the difference between each kernel size and its load mean; between-load variation is 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 rearranging the loads cannot alter it, and so it does not alter the optimal solution. However, combining the loads of similar kernel size when truckloads are allocated into the bins can reduce the between-load variation. A smaller between-load variation, in turn, indicates a smaller total variation of kernel size in the bin.

Calculating the standard deviation of kernel size of each bin directly led to so many nonlinearities that convergence could not be obtained. Instead, the mean absolute deviation was calculated and then converted to a standard deviation.[6] This approach is analogous to using MOTAD to approximate a quadratic programming problem.

[6] The authors thank Paul Preckel for suggesting this approach.

Under normality, the expected value of an absolute deviation is equal to 1/1.25 times the expected value of the standard deviation (Taylor, pp. 98–99). Taylor's formula was verified using Monte Carlo integration.

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 $KD_i - \overline{KD}_j$, be denoted by u_{ij}^+ if it is positive, and by u_{ij}^- if it is negative. Then, $\Sigma_i\,(u_{ij}^+ + u_{ij}^-)$ measures the sum of the absolute deviations for average single-kernel diameter. The mean absolute deviation times 1.25 is used to approximate the between-load standard deviation of kernel diameter.

Combining the within-load mean absolute deviation (MAD) and the between-load MAD, the MAD of kernel diameter for wheat in bin j ($\overline{KDMAD}_j$) is calculated as:

$$\overline{KDMAD}_j = \left[\sum_i p_{ij}\frac{KDS_i}{1.25} + \sum_i p_{ij}\left(u_{ij}^+ + u_{ij}^-\right)\right]. \tag{11}$$

The first term in parentheses is the within-load MAD, and the second term is the between-load MAD. Multiplying (11) by 1.25 converts the MAD into a standard deviation and yields:

$$\overline{KDS}_j = \sum_i p_{ij}\left[KDS_i + 1.25\left(u_{ij}^+ + u_{ij}^-\right)\right].$$

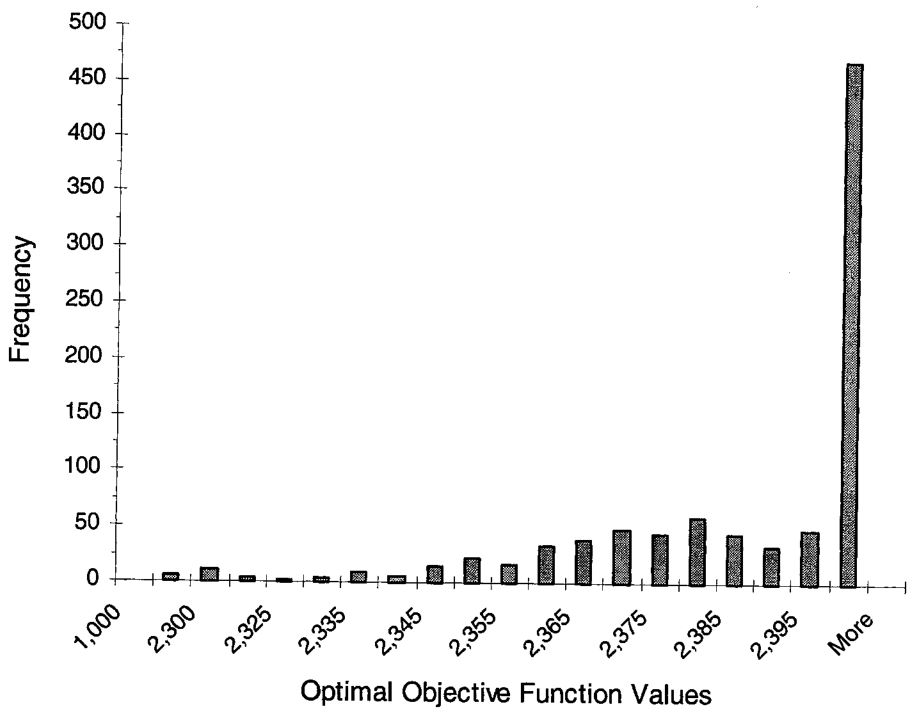
Similarly, the average standard deviation of kernel hardness for wheat in bin j is estimated by:

$$\overline{KHS}_j = \sum_i p_{ij}\left[KHS_i + 1.25\left(v_{ij}^+ + v_{ij}^-\right)\right]. \tag{12}$$

The elevator's or miller's maximization problem is solved using the MINOS5 solver in GAMS, a general nonlinear optimizer. Nonlinearities occur in several constraints and, as with many problems related to nonlinear constraints, there are multiple local optima.

To address the problem of multiple local optima, the method of random restarts is used. With random restarts, the non-convex model is solved with numerous different starting values for a selected variable (Brooke et al., p. 154). Specifically, the starting values for X_{ij}, the amount of load i allocated to bin j, were varied by random numbers generated from a uniform distribution and scaled to impose the following condition: $\Sigma_{j=1}^{3} X_{ij} = 1$. The model was solved 1,000 times, and the solution giving the largest objective value was selected as the optimum. This method guarantees reaching the global optimum as the number of random restarts approaches infinity.

Figure 1 shows the distribution of optima achieved using random starts with 1,000 repetitions using the 1999 Western Oklahoma data. Most values tend to concentrate close to the apparent global maximum, forming a left-tailed distributional shape. Distributions for the other data sets also showed this negative skewness. The shape of this distribution suggests a sufficient number of random starts were used to identify the global optimum. Because of the greater number of observations with the U.S. data set, it likely has more local optima, and thus there is a greater risk of not being close to the global optimum with the U.S. data set. The median local optimum in figure 1 is 2,395, which translates into a percent flour yield of 70.441. Using the median of local optima would miss 60% of the advantage of sorting [(70.773 - 70.441)/(70.773 - 70.218)].



Notes: The global optimum was 2,406.28. The optimum can be divided by the number of truckloads (34) to convert it into a percent flour yield of 70.773. The frequencies do not sum to 1,000 because the 86 which did not converge are not included.

Figure 1. Histogram of optima using random starting values: Western Oklahoma wheat region, 1999

Results

The estimated wheat quality characteristics and percent flour yield assuming all loads are blended for each year for the first data set (several U.S. regions) are presented in table 4. 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 4 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 at 70.52, and highest in 1998 at 71.66. The predicted average percent flour yields are generally lower than the actual average percent flour yields presented in table 1, because they are based on the increased standard deviation of single-kernel diameter and single-kernel hardness.

Tables 5 and 6 show the results of the global optimization for the first and second data sets, respectively. A few loads were partially allocated into the bins, and thus the total quantities of loads allocated into each bin are not round numbers. For the U.S. data set, average percent flour yields are slightly higher than those for the whole sample without sorting. For the Oklahoma data set, a similar pattern is observed, although the increase in flour yield due to segregation is larger. The higher gain to segregation can be partly explained by the larger standard deviations for kernel diameter and kernel hardness in the Oklahoma data set. The 1998 Oklahoma Central data, however, do not

Table 4. Average Wheat Quality Attributes and Predicted Percent Flour Yield from U.S. Data Without Sorting, 1995–1998

Year	No. of Observations	Single-Kernel Characteristics					
		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: *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, *TW* is the test weight (pounds/bushel), and *PFY* is the predicted percent flour yield (%). *KDS* and *KHS* are calculated by combining the within-load standard deviation and the between-load standard deviation. The *PFY* is calculated using equation (4).

Table 5. Optimal Wheat Quality Characteristics with Three Bins for Several U.S. Regions, 1995–1998

Year	Variable	Bin Number		
		1	2	3
1995	*QTY*	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	*QTY*	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	*QTY*	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	*QTY*	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: *QTY* is the total number of truckloads 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, *TW* is the test weight (pounds/bushel), and *PFY* is the percent flour yield (%).

Table 6. Optimal Wheat Quality Characteristics for Oklahoma Regions with Three Bins, 1998–1999

Year/Region	Variable	Bin Number 1	2	3
1998, Central	*QTY*	11.321	2.747	23.932
	KD	2.220	2.339	2.215
	KDS	0.359	0.357	0.200
	KH	75.524	76.947	84.379
	KHS	14.983	13.542	16.016
	TW	62.854	62.771	62.558
	Average *PFY*		71.861	
	PFY w/o sorting		71.405	
1998, Western	*QTY*	53.875	13.177	10.948
	KD	2.193	1.901	2.474
	KDS	0.200	0.470	0.417
	KH	77.561	74.810	71.753
	KHS	20.033	17.843	15.450
	TW	60.601	57.985	62.004
	Average *PFY*		70.957	
	PFY w/o sorting		70.398	
1999, Central	*QTY*	13.634	11.953	28.413
	KD	2.392	2.293	2.234
	KDS	0.416	0.460	0.200
	KH	66.863	79.691	70.772
	KHS	19.146	16.831	19.857
	TW	60.858	61.278	59.279
	Average *PFY*		71.226	
	PFY w/o sorting		70.734	
1999, Western	*QTY*	6.746	9.022	18.232
	KD	2.388	1.996	2.270
	KDS	0.398	0.448	0.200
	KH	64.300	79.389	75.951
	KHS	18.658	20.045	19.164
	TW	59.922	58.470	60.271
	Average *PFY*		70.773	
	PFY w/o sorting		70.218	

Notes: *QTY* is the total number of truckloads 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, *TW* is the test weight (pounds/bushel), and *PFY* is the percent flour yield (%).

have a larger standard deviation, but do have a larger gain in flour yield. This unexpected relationship could be due to the Oklahoma data set having clusters of wheat with similar characteristics.

The fact that flour yield varies little when going from no segregation to segregation immediately suggests there are limited gains from sorting to increase flour yield. Table 7 reports the marginal revenue from segregating by kernel diameter and kernel hardness. Segregation increases flour yield in all cases, slightly more for the local elevator than for the regional miller. Estimating the cost of segregation in handling value-added grains, Vandeburg, Fulton, and Dooley considered several scenarios and never found a

Table 7. Increase in Percent Flour Yield, and Benefits from Sorting

Sample		Year	*PFY* with Blending[a]	*PFY* Optimal Sorting	*PFY* Increase	Marginal Revenue from Sorting (¢/bushel)
Several U.S. Regions:		1995	71.01	71.33	0.32	1.23
		1996	70.52	70.89	0.37	1.42
		1997	71.32	71.67	0.35	1.34
		1998	71.66	71.91	0.25	0.96
Oklahoma:	▸ Central	1998	71.40	71.86	0.46	1.77
	▸ Western	1998	70.40	70.96	0.56	2.15
	▸ Central	1999	70.73	71.73	0.50	1.92
	▸ Western	1999	70.22	70.77	0.55	2.11

Notes: *PFY* represents the percent flour yield. Increases in *PFY* are calculated relative to the *PFY* from blending all samples. Three bins are used for the optimal sorting.

[a] The *PFY* with blending is calculated by taking the average for each characteristic and plugging the averages into equation (4).

cost of segregation below 4¢/bushel. Thus, all the marginal revenues reported in table 7 are below marginal cost. Sivaraman, Lyford, and Brorsen estimated revenues from using three bins to sort by protein at 3.3¢/bushel. Most local elevators do not sort by protein, which offers further support for Vandeburg, Fulton, and Dooley's estimates for small firms. However, some large elevators do sort by protein. Thus, there may be instances when sorting to create uniformity would be profitable.

Conclusions

Kernel uniformity is an important physical attribute that can now be measured at low cost. The potential benefits from sorting grain to increase kernel uniformity were estimated. Nonlinear programming was used to sort loads to increase kernel size uniformity.

Data came from two sources. One set was comprised of elevator samples from several U.S. wheat regions, and was used to depict the situation of a miller receiving grain from several regions. The second data set was used to analyze the situation from a local elevator's perspective because it contained truckload samples from two Oklahoma wheat regions.

Sorting wheat by truckload at the local elevator provides more benefits than sorting wheat by region, partly because wheat size and hardness vary more by truckload than by location. In no scenario were benefits enough to offset the costs, but benefits were close to breakeven levels. Thus, increases in flour yield alone are not enough to justify sorting to increase kernel uniformity. There are other potential benefits derived from kernel uniformity, such as dough quality, and sorting for both uniformity and other factors, such as protein, is a possibility. These possibilities should be considered in future research before abandoning the idea of sorting to increase kernel uniformity.

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