Secondary Density Correction for Low Test Weight Corn

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ABSTRACT

Unusual weather patterns in the U.S. delayed the maturity of corn in some areas and resulted in abnormally low test weight (bulk density) for a portion of the 2009 corn crop. The Landau-Lifshitz, Looyenga mixture equation was not completely successful in correcting for the extreme bulk density variations within the 2009 corn crop. Based on 668 corn samples, we developed a secondary density correction which drastically reduced the moisture measurement discrepancies caused by low bulk density for corn. Furthermore, the correction significantly reduced the scatter of the moisture error for the samples with normal bulk density. This correction was unnecessary for grains other than corn.

Keywords: density-correction, corn, moisture.

1 INTRODUCTION

Moisture content is one of the most important quality factors in marketing grain, since it determines both the quantity of dry matter traded and the storability of the grain. So it is essential to measure grain moisture before storage and commercial transactions. Because of its cost and speed, the RF dielectric method is the most widely used technology for determining grain moisture content during grain marketing.

Dielectric-type grain moisture measurement results are affected by many factors, such as packing density, temperature, and grain constituent variations between crop years. Additionally, different measurement technologies provide different results, which make moisture measurement uniformity impossible [1],[2].

In response to these challenges, USDA-Grain Inspection, Packers and Stockyards Administration (GIPSA) developed an improved grain moisture measurement method, the Unified Grain Moisture Algorithm (UGMA) [3],[4]. The UGMA has the potential to provide improved accuracy, better calibration stability, reduced calibration development effort, and calibrations that are transferable among different moisture meter models that are built to conform to the basic algorithm.

The basic steps of the method are: 1) measure complex reflection coefficients (or impedances) at 149 MHz with a parallel-plate transmission line test cell, 2) convert reflection coefficient to bulk material complex permittivity with a mathematical model and iterative solver, 3) apply density correction to the dielectric constant using the Landau-Lifshitz, Looyenga (LLL) mixture equation [5], 4) apply grain-group-specific unifying parameters, 5) apply a single polynomial equation to convert to moisture content, and 6) apply temperature correction [3],[4].

One of the major improvements in this algorithm is applying the LLL. Nelson found that the Landau-Lifshitz, Looyenga mixture equation works best for grain [6]. He rearranged the LLL equation to form a density correction to calculate the dielectric constant for a defined target bulk density from a dielectric constant measured at a different bulk density.

$$\varepsilon_{den} = \left[\left(\varepsilon_{meas}{}^{1/3} - 1\right) \cdot \frac{\rho_{target} \cdot V}{m} + 1\right]^3 \quad (1)$$

Where ε_{den} is the density corrected dielectric constant, ε_{meas} is the sample's measured dielectric constant , ρ_{target} is the target density (g/ml), V is the volume of the test cell, and m is the mass of the sample (g).

This permits normalizing measured dielectric constants with diverse densities to a common bulk density- thereby dramatically reducing the variations caused by packing density [5]. The approach reduces density-induced errors from test cell filling methods, grain moisture level, and kernel density and shape. Furthermore it causes the relationship between dielectric constant and moisture content to be more linear and to be similar for all grain types. This shape-similarity is the basis of the unified algorithm [3],[4].

In 2009, unusual weather patterns in the U.S. delayed the maturity of corn in some areas and resulted in abnormally low test weight (bulk density) for a portion of the corn crop. We were surprised to find that the LLL mixture equation was not very effective in correcting for the extreme bulk density variations within the 2009 corn crop. Samples with low test weight showed significantly lower moisture results by UGMA with respect to tests by the air oven moisture method. The goal of this study was to develop a strategy to correct these moisture measurement errors.

2 MATERIALS AND METHODS

2.1 Measurement System

We used a parallel-plate transmission-line type test cell terminated with a precision 50 Ω load. The test cell was constructed of three parallel 3.2 mm thick aluminum plates. The spacing between the plates was 27.7 mm. The height of the plates was 76.2 mm. The total length of the test cell was 245 mm and the length of the grain-filled section was 101.7 mm. The volume of the test cell 429.58 ml.

A funnel-type loading mechanism (Ohaus 4321 Filling Hopper) was used to over-fill the test cell. The excess grain was struck off to achieve a constant sample volume in the test cell. An Hewlett Packard[1] 4291A Material/Impedance Analyzer was used to measure the reflection coefficients at from 1 MHz to 501 MHz with a 2 MHz increment. The measurement setup was previously described in detail [5]. An ABCD matrix model was used to calculate the dielectric constant values [6].

2.2 Samples

The samples were collected from all growing areas the US as part of the National Type Evaluation Program moisture meter on-going calibration performance review. In this study, 668 yellow dent corn samples were analyzed. Corn samples were classified as "low" or "normal" bulk density according to an arbitrary moisture-dependent threshold function (2). The fraction of samples with low density was much larger in 2009 than in 2008 or 2010.

$$Threshold = -0.00687\ g/ml \cdot AOM + 0.785\ g/ml \quad (2)$$

Where AOM is moisture of the sample (%M) determined by the air oven.

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[1] The mention of firm names or trade products does not imply that they are endorsed or recommended by the U.S. Department of Agriculture over other firms or similar products not mentioned.

Table 1: *Corn Samples*

	2008	2009	2010	Total
Low Density	7	49	6	62
Normal Density	226	153	197	576
Total	233	202	203	638

Thirty additional corn samples were dried down below 10% moisture to extend the applicable moisture range. We assessed the transferability of the secondary density correction to other loading methods by applying the correction to 207 corn measurements from 2007. These samples were loaded into the test cell by a fast-drop mechanism rather than funnel loading.

Wheat results were also studied for comparison to the effects for corn. Samples for five classes of wheat were involved in this study. The categorization of low and normal bulk density for wheat samples was according to another arbitrary moisture-dependent threshold function (2). Table 2 shows the numbers of samples by wheat class. Unlike for corn, the prevalence of low bulk density samples was not distinctly different for any one crop year.

$$Threshold = -0.00412\ g/ml \cdot AOM + 0.757\ g/ml \qquad (2)$$

Where AOM is moisture of the sample (%M) determined by the air oven.

Table2: *Wheat samples used for density-correction study*

	Low	Normal	Total
Hard Red Winter	9	303	312
Hard Red Spring	4	200	204
Hard White	1	78	79
Soft Red Winter	9	256	265
Soft White	1	148	149
Total	24	985	1009

The reference moisture contents of samples were determined using standard USDA air oven methods [7].

3 RESULTS AND DISCUSSION

3.1 Basic UGMA Calibration Performance

When we observed the density-dependence of UGMA moisture prediction errors for corn, we first suspected that the LLL density correction (1) was at fault. However, comparison of achievable moisture measurement accuracy with and without LLL density correction (Fig. 1) showed that the LLL density correction was, as intended, dramatically reducing moisture measurement error. Fifth-order polynomial regression was used to fit both sets of data. The Standard Error of Calibration (SEC) describes the goodness of fit for the calibrations. The LLL density correction reduced the scatter in the plot of the dielectric constant versus moisture and reduced the achievable moisture measurement error to less than one third of the error observed without LLL density correction. Fig. 2 shows the residual errors (predicted moisture minus reference moisture) for corn and wheat samples with LLL density correction.

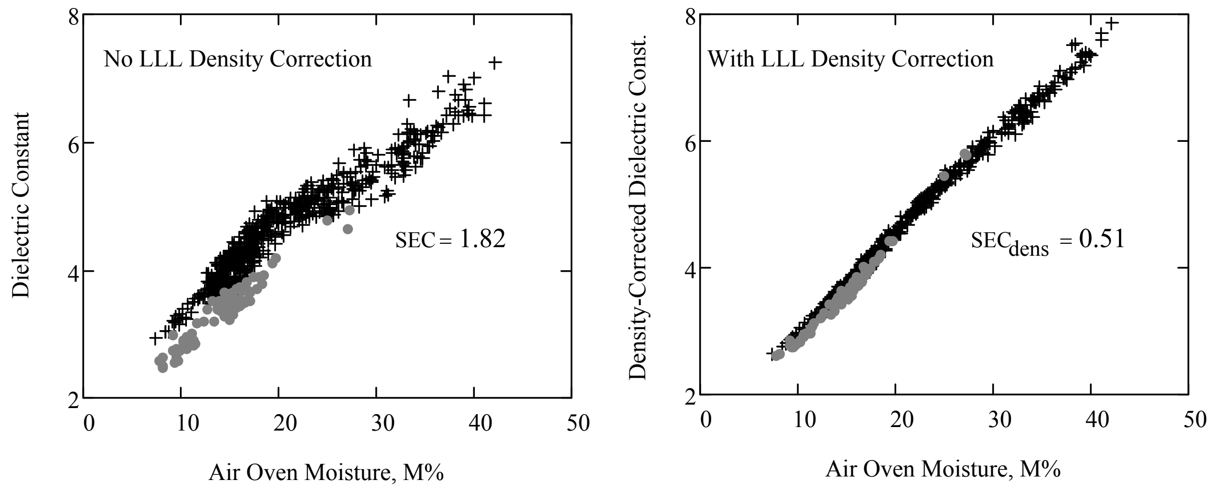

Fig. 1: *Dielectric constants of the corn samples versus air oven moisture with and without Landau-Lifshitz, Looyenga (LLL) density correction. Samples with low density (●). Normal samples (+). The standard error of calibration (SEC) values (% moisture) refer to the performance of 5th order polynomial calibrations.*

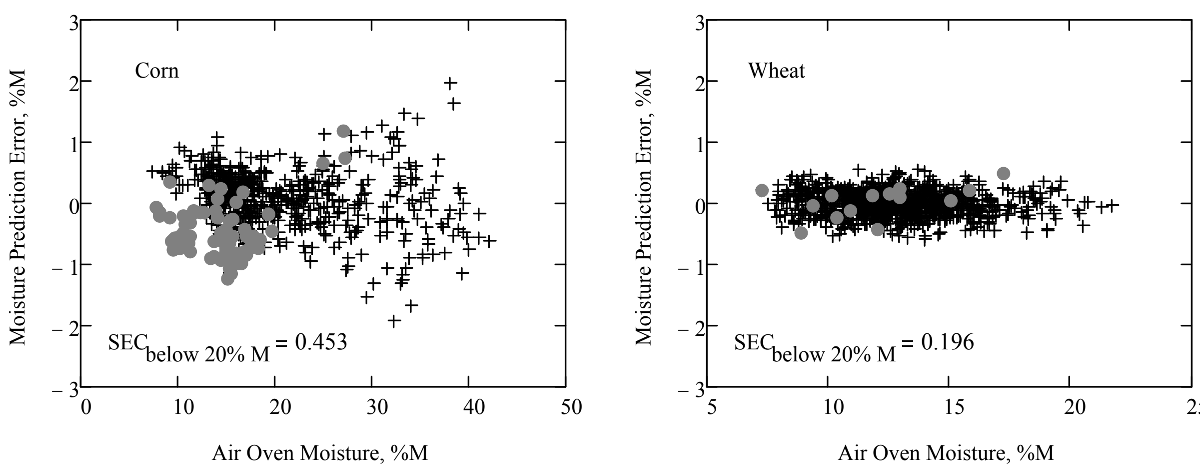

Fig. 2: *Moisture prediction error with Landau-Lifshitz, Looyenga density correction for corn and wheat. Samples with low density (●). Normal samples (+). The standard error of the calibration (SEC) values describe the performance of the 5th order calibrations for samples below 20% moisture.*

Fig. 2 shows that the scatter for corn was much larger than for wheat, and the low bulk density corn samples had negative biases (differences between moisture predictions and air oven moisture values) if the moisture was less than 20% moisture—but the bias was positive for samples above 20% moisture. For wheat, the moisture prediction errors were not separated for the low bulk density samples and the normal samples.

3.2 Analysis of Potential Causes

Why did the corn results show a separation between low density and normal samples—but the wheat results did not? The first hypothesis we investigated was that corn might have had a more extreme range in bulk density. Fig. 3 shows the bulk densities versus moisture content for corn and wheat and the threshold functions defined by (2) and (3). The range of density variation was not significantly greater for corn than for wheat. Therefore, the range of bulk density did not appear to be the cause of the problem.

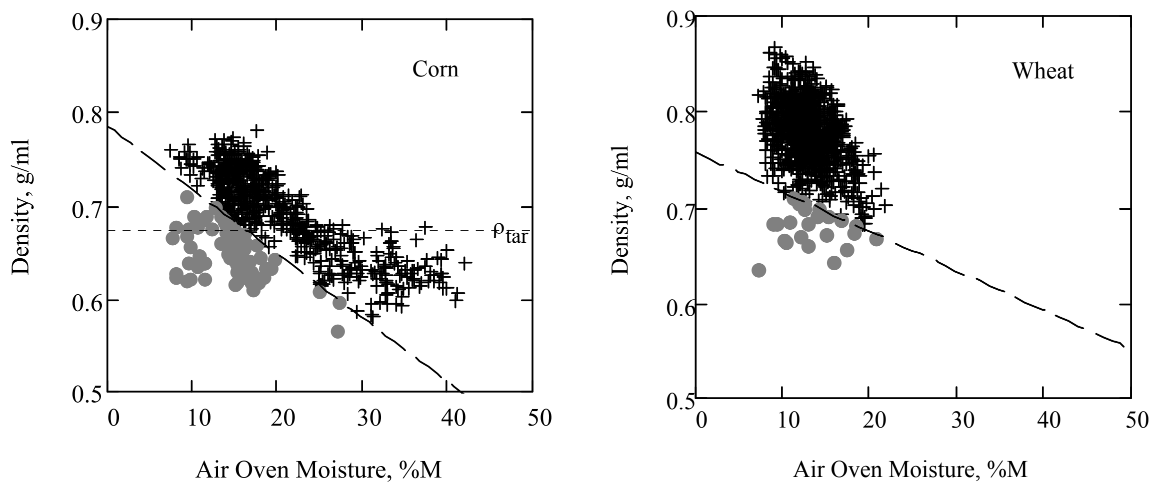

Fig. 3: *The bulk densities versus moisture contents for corn and wheat. Samples with low density (●). Normal samples (+). Low bulk density threshold (— —). Target density for LLL density correction(- -).*

The second hypothesis that we evaluated was that perhaps the low-density corn samples had significantly different chemical composition than the normal-density samples. Since we had near-infrared spectra for these samples, we were able to predict oil and protein contents for each. The results (not shown) did not reveal any consistent correlations between chemical composition, density, and moisture prediction error.

The third hypothesis was that the low-density corn samples had kernels with distinctly different shapes than the normal-density samples. Often, low-density wheat is associated with a shriveled or wrinkled appearance. Visual comparison of the low- and normal-density corn samples did not, however, show consistent differences in kernel shape.

We did notice, though, that the low-density corn samples contained more grain dust than the normal samples. We found that the kernels from the low-density samples could be crushed readily with pliers, whereas the kernels from the normal-density samples were much harder to crush. Also, when placed in water, the kernels from the low-density samples consistently floated—indicating low kernel density.

Evaluation of the geographic origins of the low-density corn samples pointed to the most northern corn-growing regions. In 2009, a cool, wet spring led to late planting and late maturity of the corn crop. In northern regions, frost may have arrested normal kernel development—resulting in porous, low-density kernels.

Investigating the nature of the predicted moisture error, it was found that the moisture error was bulk density dependent in narrow moisture ranges, as shown in Fig. 4. Below 20% moisture, the correlation between bulk density and moisture error was positive and high; above 20% moisture, the correlation was negative and relatively low. The residual bulk density dependence of the moisture error meant that the LLL density correction was not completely successful for corn. The LLL density correction under-corrected low moisture samples and over-corrected above 20% moisture.

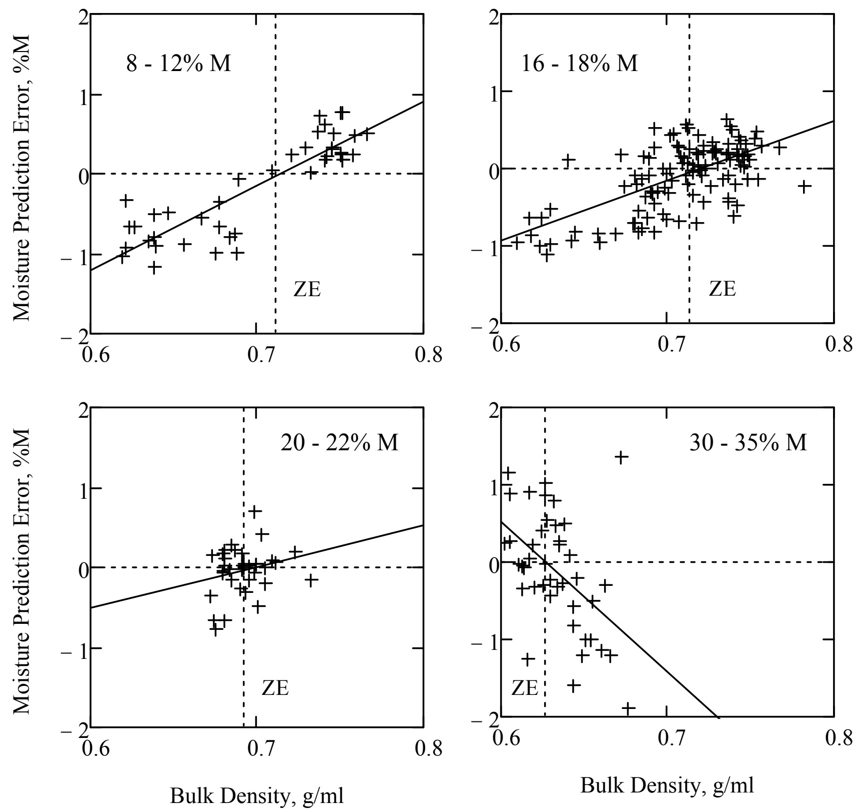

Fig. 4: *Predicted-moisture error versus bulk density in different moisture ranges, the cross sections of the dotted lines shows the bulk densities with no moisture prediction error (ZE).*

When viewed as a 3-dimensional plot, the relationship among corn sample density, dielectric constant without density correction, and moisture content showed a tilted and slightly twisted surface (ribbon) of data points that appeared as high scatter when viewed as a 2-dimensional plot of dielectric constant versus air oven moisture (Fig. 1, left). Wheat data (not shown) appeared similar. The LLL density correction successfully removed the tilt and linearized the data somewhat so that the plot of density-corrected dielectric constant versus air oven moisture (Fig. 1, right) showed much less scatter. However, the LLL density correction did not contain a moisture-density interaction term, so the slight moisture- and density-dependent twist remained uncorrected—resulting in the behavior shown in Fig. 4.

3.3 Secondary Density Correction

We considered several approaches to straighten out this twist. The basic LLL density correction equation could have been modified to include a moisture-dependent term, or a secondary density correction could have been applied to the density-corrected dielectric constant. Either of those approaches would have made calibration development much more complicated. For simplicity, we chose to apply a secondary density correction (1) to the predicted moisture value.

$$M_{final} = M_{pred} + SDC \tag{1}$$

Where M_{final} is the final predicted moisture, M_{pred} is the predicted moisture, and *SDC* is the calculated value of the secondary density correction to be applied.

We found that including the low bulk density samples in the polynomial regression (calibration) caused significant errors both for the normal and the low bulk density samples; therefore we chose to optimize the calibration for the normal density samples. Secondary density correction was applied to the predicted moisture values that were calculated with a 5^{th}-order polynomial that was based on only the normal density samples.

We chose to implement the moisture- and density-dependent correction via linear correction through look-up tables. The correction could have been a multivariate polynomial, but we decided not to use that approach because it might cause unintended results for samples with extreme moisture or density characteristics. The linearity of the error in each moisture range (Fig. 4) supported this decision also. The basic equation is given by (3):

$$SDC = (\rho_{meas} - ZE) \cdot SC \tag{3}$$

Where *SDC* is the calculated magnitude of the secondary density correction, ρ_{meas} is the measured bulk density of the sample, *ZE* is the density (for the sample's predicted moisture level) at which zero moisture prediction error would be expected, and *SC* is the slope of the correction (for the sample's predicted moisture level). Fig. 4, which shows the moisture error versus bulk density, helps with understanding this equation. For a sample at a given (predicted) moisture level, the needed correction is dependent on the bulk density and is proportional to the difference between the sample's measured bulk density ρ_{meas} and the nominal density *ZE* for that moisture level. *SC* is the ratio of the needed density correction and the density difference.

SC and *ZE* both are moisture-dependent. To determine the needed SC and ZE for each moisture level we sorted the samples from lowest to highest moisture and used a 61-sample "moving window" to calculate the slope and the x-axis intercept of the moisture correction needed versus density at each moisture level. Fig. 5shows the calculated slope values and the shape of the interpolation function assigning the *SC* value for any corn sample.

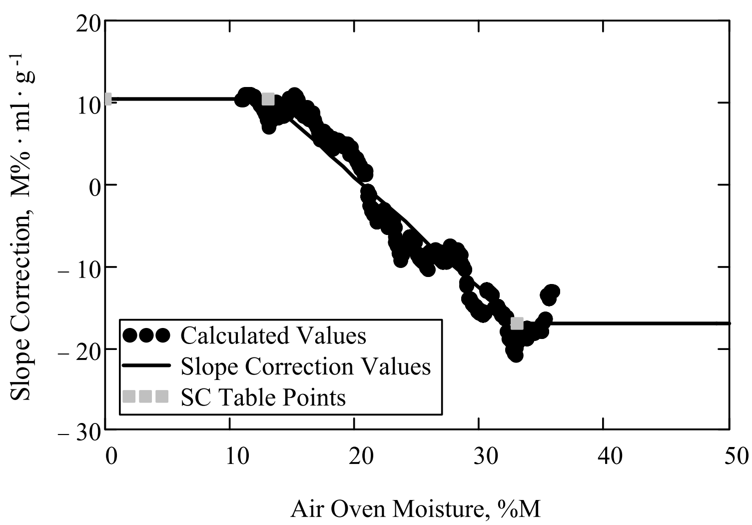

Fig. 5: *Slope correction values (SC).*

The calculated slope values showed an approximately linear relationship with moisture (Fig. 5). However, we did not have sufficient data to calculate slope values below 10% moisture or above 36 % moisture. Also, the behavior at both moisture extremes showed signs of becoming constant rather than continuing on the linear trend. Therefore, we chose to assign constant values for slope below 13%

moisture and above 33% moisture. Fig. 5 also shows the *SC* lookup table points and the resulting piecewise linear *SC* function.

The calculated x-axis intercept values (*ZE*) also showed an "S" shaped curve (Fig. 6). The *ZE* values were essentially the mean density values for "normal" samples at each moisture level. A 3^{rd}-order polynomial was fitted to the computed *ZE* values, and lookup table points were chosen to adequately describe the resulting curve. The lookup table was extended with constant values below 15% moisture and above 33% moisture.

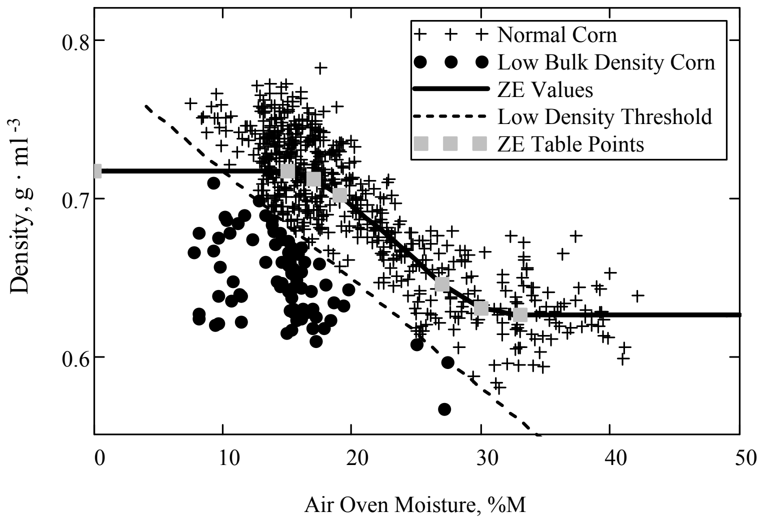

Fig. 6: *Target density curve and the corn samples*

We created lookup tables (Tables 3 and 4) to calculate the coefficients for (2). From the lookup tables, the actual values for a sample can be calculated using linear interpolation.

Table 3: *Target density lookup table (ZE Table) to determine the ZE value by linear interpolation from the measured moisture content.*

Moisture	Nominal Density (*ZE*), g/ml	Moisture	Nominal Density (*ZE*), g/ml
0	0.7168	27	0.6451
15	0.7168	30	0.6297
17	0.7116	33	0.6253
19	0.7018	100	0.6253

Table 4: *Slope correction lookup table (SC Table) to determine the Slope Correction value by linear interpolation from the measured moisture content.*

Moisture	Slope Correction (*SC*), $\%M \cdot ml \cdot g^{-1}$
0	10.4
13	10.4
33	-17
100	-17

The performance of the secondary density correction for corn is shown in Fig. 7. Table 5 summarizes the statistics for corn samples below 20% moisture. Higher scatter above 20% moisture makes the effects of the secondary density correction less apparent in that region.

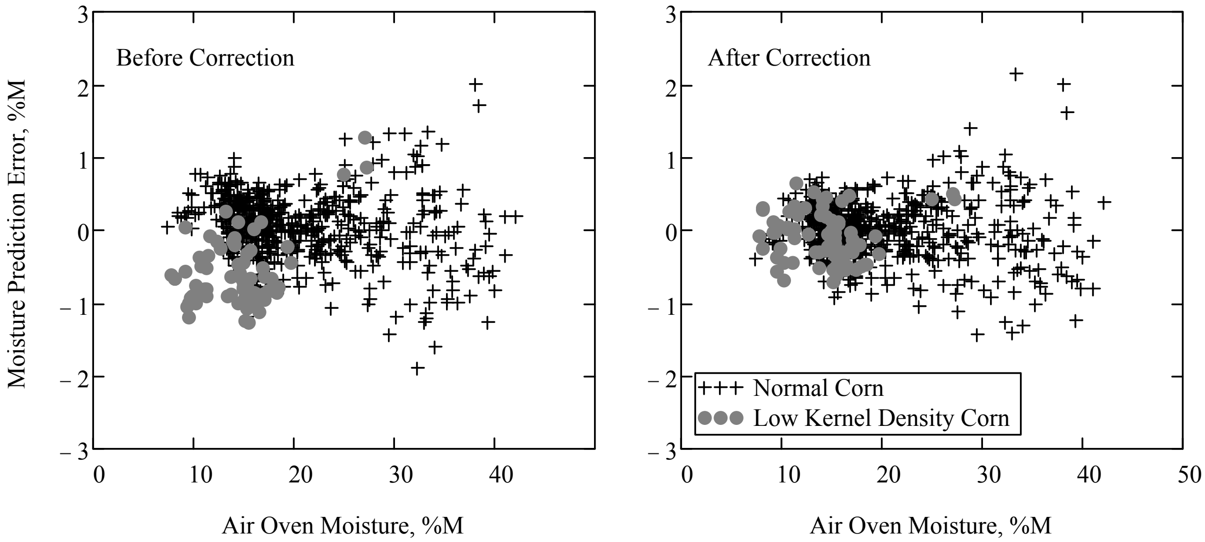

Fig. 7: *Corn sample predicted moisture errors before and after secondary density correction. Samples measured with funnel loading.*

Table 5: *Secondary density correction statistics (Bias, Standard Deviation of Differences (STD), and Slope of prediction errors) for samples less than 20% moisture—before and after application of secondary density correction.*

Before	Bias	STD	Slope
All Samples	-0.04	0.46	-0.01
Low Density	-0.66	0.34	0.00
Normal	0.09	0.36	-0.04

After	Bias	STD	Slope
All Samples	-0.01	0.31	-0.01
Low Density	-0.11	0.32	-0.03
Normal	0.01	0.30	-0.01

Secondary density correction developed for wheat was beneficial only below 12 % moisture. It reduced the standard deviation from 0.19 % moisture to 0.18 % moisture for all samples in that region, and the low bulk density samples' (six samples) bias changed from -0.12 %M to 0.06 %M.

The errors in predicted moisture for low bulk density corn samples (Fig. 7, Table 5) were significantly reduced. Furthermore, the standard deviation of the predicted moisture errors for "normal" samples was improved.

We applied the secondary density correction to dielectric data for 207 corn samples from the 2007 crop that used fast-drop loading for filling the test cell. That sample set contained only one low bulk density sample because low density samples were not common in that year. The *ZE* values in Table 3 were reduced by a constant (0.029) for those samples since the bulk density of samples were lower with fast-drop loading than with funnel loading. The results showed a significant reduction in the predicted moisture error (Fig. 8.) even though the bulk density range was not extreme.

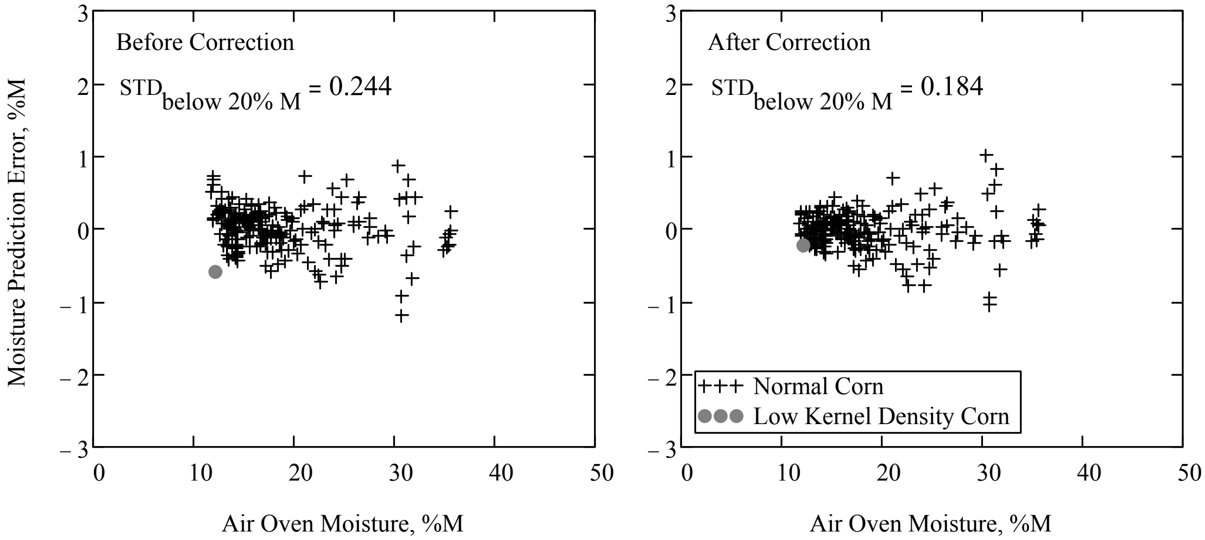

Fig. 8: *Corn sample predicted moisture errors before and after secondary density correction. Samples measured with fast-drop loading.*

4 CONCLUSIONS

The secondary density correction dramatically reduced the moisture measurement errors for corn samples with unusually low bulk densities (test weight). Furthermore, the correction significantly reduced the moisture error for the samples with normal bulk densities. We did not determine the reason why the Landau-Lifshitz, Looyenga density correction was not able to correct the low density problem for corn or why it was not a problem for other grains such as wheat.

The secondary density correction applied to the predicted moisture value was effective for measurements with fast-drop loading as well as funnel loading. Therefore, this correction approach may be broadly applicable for improving density corrections for corn moisture measurements by dielectric methods.

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