DEVELOPMENT OF EQUILIBRIUM MOISTURE RELATIONSHIPS FOR STORAGE MOISTURE MONITORING OF CORN

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ABSTRACT. *Commercial systems are currently available to measure grain moisture during storage using relative humidity (RH) and temperature (T) sensors and equilibrium moisture (EMC) models. However, the variability of the EMC relationships between grain lots necessitates that a good model be selected or developed for each specific grain. The objective of this research was to develop modified Chung-Pfost equilibrium moisture models for seven corn samples, examine their prediction accuracy, and evaluate simplification of the experimental procedures used to develop these models. The models that were developed used corn conditioned over a broad range of five moisture levels (5-point models). Models were also developed using a reduced number of levels with a narrower moisture range; models with 4 and 2 moisture levels (4- and 2-point models, respectively). The 4-point model used all data except the highest moisture level while the 2-point model used the extreme moisture levels of the 4-point model. The 5-point models had the highest standard error of estimates (SEE) averaging 0.90 and 0.82 for adsorption and desorption, respectively. The 2-point model was used to predict all of the moisture levels of the 4-point data; the standard errors of prediction (SEP) for these predictions averaged 0.41 and 0.39 for adsorption and desorption, respectively, and are only marginally higher than 4-point models. These results show that a 2-point model can be used for accurate moisture measurement across a range common for stored corn, while reducing the amount of work required for model development. The moisture levels suitable for a 2-point model should be limited to upper and lower moisture contents corresponding to 85% to <90% relative humidity and 35% to 50% relative humidity, respectively.*

Keywords. *Equilibrium moisture, Corn, Grain monitoring, Chung-Pfost.*

Equilibrium moisture content (EMC) relationships for grain can be used for a number of grain operations. Natural-air or low-temperature drying and conditioning are process operations that rely on accurate EMC relationships. More recently the use of EMC sensors for storage monitoring further necessitates the development of accurate EMC prediction for specific grains. EMC sensors can replace traditional temperature monitoring cables as they measure both temperature (T) and relative humidity (RH). They can also be used to augment natural and low-temperature drying by monitoring the process.

Traditionally, conditioning and drying has relied on standardized EMC relationships such as those found in *ASABE Standards* (2009) for controlling process parameters. Bartosik and Maier (2007) alluded to the deficiencies of using a generalized model by showing the EMC differences between yellow dent, white, and waxy corn hybrids and ASAE Standards (D245.6) for the modified Chung-Pfost equation. They also pointed out the lack of available published adsorption data. Several previous studies have examined the development of EMC models and their suitability as generalized models. Chen and Morey (1989a) examined predictions of four isotherm equations for different types of grains and concluded that no model was suitable for all grain types. The modified Chung-Pfost and Henderson equations worked well for starchy grains such as corn or wheat while the modified Halsey equation worked well for high oil and protein seeds.

Chen (2001) examined the accuracy of measuring grain EMC with RH and T sensing. Moisture accuracy for corn was found to be within 1% dry basis moisture content (MCdb) for equilibrium relative humidity (ERH) values below 85%. This earlier work used RH sensors that required individual calibration to obtain this degree of accuracy. Fairly recent miniaturization and integration of RH and T sensing elements provides opportunities for measuring EMC of stored grain using cabled systems similar to temperature monitoring cables. Uddin et al

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(2006) examined the accuracy of measuring EMC with a miniaturized, digital RH and T sensor (model SHT75, Sensirion AG, Zurich, Switzerland). Assuming a perfect EMC model, EMC prediction errors due to sensor error were found to be 0.25% to 0.65% MCdb between the RH ranges of 20% to 70% RH. This particular sensor has better accuracy within this range of RH. As sensor accuracy diminishes above 70% RH and the slope of the EMC/ERH curve increases above 70% RH, EMC prediction error increases substantially. EMC accuracy was also influenced by T error but to a much lesser extent. During simulated aeration of hard red winter wheat (Gonzales et al., 2009), multiple Sensirion sensors were embedded throughout the profile of the wheat mass and were shown to predict MC reasonably well using equation parameters for the modified Chung-Pfost equation taken from ASABE Standards; standard deviation of the difference between predcited EMC and measured MC was 0.51 .

OPI-Integris (Calgary, AB, Canada) has recently developed cabled moisture sensing systems based on EMC prediction from RH and T sensors and can be implemented for multi-point moisture monitoring in a grain storage. A similar Sensirion sensor is used in this system but with some improvement in RH and T accuracy. Regardless, EMC accuracy is still influenced by RH and model accuracy. While sensor accuracy cannot easily be improved, model accuracy for a specific grain lot can be optimized by developing a model specific to the grain. However, development of EMC relationships for a single hybrid or variety is tedious and time consuming resulting in the delay of the information for the process application. There is also a monetary cost. Development of adsorption and desorption curves requires samples to be dried and re-wetted or wetted and dried respectively over a range of moisture levels, equilibrated for a few days and then cycled through a range of temperatures while measuring ERH. Methods that would allow more rapid EMC model development would facilitate better implementation of EMC measurement systems.

Objectives

The goals of this research were to explore methods to simplify the development of EMC/ERH relationships for specific corn samples by reducing the required amount of modeling data. These methods could most likely be used for other grain types as well. The approach was to develop complete EMC/ERH relationships for several corn samples and determine from these sets, a method for developing prediction models that provide good MC prediction but use smaller data sets.

Methods and Procedures

Corn Samples

Corn samples were obtained from a diverse set of commercially harvested, yellow dent corn representing regions from Indiana, Iowa, and Kansas. Initial moisture levels (dry basis) ranged from 15.6% to 18.1%. A total of seven samples were used to obtain EMC, ERH, and temperature data for EMC prediction development. Each sample consisted of approximately 35 kg. In addition, previously published EMC data for a yellow dent, white, and waxy corn type (Bartosik and Maier, 2007) were used to further validate study findings.

Equilibruim Moisture and Relative Humidity Data

The initial sample moisture content was determined for each corn sample (35 kg) using ASAE Standard S352.2 (*ASABE Standards,* 2008). Each sample was then divided, with one half used for adsorption and the other half for desorption model development. For adsorption tests, the half-sample was air-dried to approximately 9% wet basis moisture content (MCwb) and then divided into five subsamples. These subsamples were then wetted to varying moisture levels based on their weight and initial MC. Wetting was done using a spray bottle to wet the grain contained in a plastic bag. Grain was mixed repeatedly during wetting. The target moisture levels were approximately 10%, 12.5%, 15%, 17.5%, and 20% MCwb. These subsamples were stored at 2°C for a minimum of 3 days to allow for equilibration of moisture throughout the kernels and sample. Each subsample was then divided into two or three subsamples for replicate measurements. Subsamples were obtained by hand mixing grain in a large bucket and retrieving a sample from the bucket. Mixing occurred after each sample was retrieved. The range of the target moisture levels was reduced to 10%, 12%, 14%, 16%, and 18% MCwb for a few samples.

For desorption tests, the half-sample was divided into five subsamples and each subsample wetted to approximately 20% MCwb. Subsamples were then divided into two or three subsamples for replicate measurements. These subsamples were stored at 2°C for a minimum of 3 days to allow for equilibration. Replicates were then air-dried at low temperature (45°C or less) to moisture levels based on their weight and conditioned MC. The target moisture levels were the same as for adsorption tests. Replicates were stored at 2°C for a minimum of 3 days to allow for further equilibration.

EMC modeling data was obtained on the above replicate subsamples by placing them in a sealed plastic box (180 × 90 × 110 mm) containing two Sensirion (SHT 75) relative humidity and temperature sensors (fig. 1). The Sensirion sensors were enclosed in a protective housing and are the same as those used in the commercial sensing cable developed by OPI Integris. The error of this sensor is constant at ±1.8% RH between 10% and 90% RH, beyond this range, error increases linearly to approximately ±4% at 0% and 100% RH.

Two sensors per box were used to provide duplicate measurement. Each box contained about 900 grams of corn. The sensor boxes were placed in an environmental chamber (Model #I36VLC8, Percival Scientific, Fontana, Wis.) and cycled once through the temperature range of 0°C, 9°C, 16°C, 27°C, and 35°C. Chamber temperature was initially 0°C or 35°C and incrementally increased or decreased every 24 h. The 24-h period was used for convenience. An equilibration time of 8 h for RH and T between temperature

Figure 1. Instrumented boxes used to determine equilibrium relative humidity and temperature measurements.

increments was also found to be adequate for equilibration but was not used because the chamber required manual control of temperature. Data was logged with a personal computer at 15-min intervals during the test period. Moisture content was determined for each sensor box by oven drying three replicates using ASABE Standard S352.2 (*ASABE Standards,* 2008) and used for the EMC modeling. Data collection and analysis methods used by Bartosik and Maier (2007) were similar to this study although the RH, T and MC data reported were averaged over triplicate measurements, which would reduce the variability of RH and T measurements.

EMC Modelling

EMC predictions, based on the modified Chung-Pfost equation, *ASABE Standards* (2009), were developed from data using non-linear regression provided in XLSTAT (Addinsoft, New York, N.Y.):

$$MCdb = -\frac{1}{B}\ln\left[\frac{-(T+C)\ln(RH)}{A}\right] \quad (1)$$

A, B, and C are regression parameters of the modified Chung-Pfost equation; RH is relative humidity (decimal), MCdb is percent dry basis moisture content, and T is temperature in Celsius.

Models were developed using the entire range of five conditioned MCs (5-point model) and a limited range (4-point model) that excluded the highest MC, which was equivalent to an ERH of 85% to 90% or higher. An additional model (2-point model) was developed using the lowest MC and the second highest MC of the grain equivalent to an ERH of approximately 80% to 90% or less. These models were examined to determine if modeling accuracy could be improved by limiting the range of RH to accommodate the sensor range with greatest

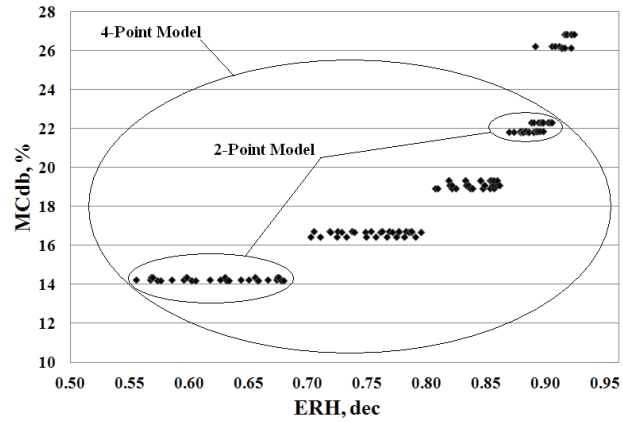

Figure 2. Regions of data used to develop different EMC/ERH models. Desorption data for the USDA2 sample are shown.

accuracy and if the number of samples could be reduced and still obtain a good model. The data these models used are graphically represented in figure 2 for the USDA2 desorption data sample.

Results and Discusion

EMC Modelling

Modeling parameters for the prediction of MCdb for each sample are shown in table 1 for the 5-point models. The standard error of estimate (SEE) was calculated by using model parameters to predict MCdb using individual sensor data collected during tests. The SEE was used as a measure of prediction accuracy and was comparable to the standard error of prediction (SEP) when the 2-point models were used to predict data from sensor readings not contained in the model. SEE is defined in equation 2 where MCdb and MCdb' are the measured and modeled moisture levels, respectively, and N is the number of data points used for modeling.

$$SEE = \sqrt{\frac{\sum (MCdb - MCdb')^2}{N}} \quad (2)$$

SEP is defined in equation 3 where MCdb" are the predicted moisture levels

$$SEP = \sqrt{\frac{\sum (MCdb - MCdb'')^2}{N}} \quad (3)$$

The SEE values are shown in table 2 for the 4-point and 2-point models along with SEP values obtained from predicting the 4-point model data from the 2-point model. The corresponding Chung-Pfost model parameters are shown in table 3.

The models shown in table 1 had average SEE values of 0.90 and 0.82 for adsorption and desorption, respectively, for all samples excluding the literature model data. The lower SEE values obtained from Bartosik and Maier (2007) data were most likely due to averaging of sensor readings which reduced the variability compared to individual

Table 1. Modified Chung-Pfost equation parameters (5-point model) using all five moisture levels of conditioned grain and the standard error of estimate (SEE) of the sensors.

Grain ID		Adsorption					Desorption				
	N[a]	A	B	C	SEE	MCdb[b] Range	A	B	C	SEE	MCdb[b] Range
USDA1	60	363.7	0.130	91.7	1.61	12-24	523.8	0.137	119.7	1.56	12-28
USDA2	150[c]	513.3	0.141	146.7	0.44	14-26	602.1	0.149	152.7	1.00	14-26
Purdue	150[c]	580.2	0.185	83.4	0.95	13-25	644.2	0.179	91.5	0.54	12-22
T1	100[d]	483.8	0.15	103.9	0.62	12-25	481.5	0.155	77.6	0.64	12-24
T2	100[d]	421.5	0.139	84.2	0.89	12-26	434.3	0.140	96.04	0.64	14-27
T3	100[d]	383.7	0.132	107.1	1.13	11-26	569.4	0.160	92.52	0.98	11-25
T4	100[d]	614.3	0.160	113.7	0.63	11-26	805.1	0.178	96.30	0.41	11-25
Y. Dent[e]	30	358.5	0.143	76.4	0.31	13-25	610.7	0.156	91.7	0.24	11-25
White[e]	30	410.2	0.137	104.8	0.48	13-24	485.3	0.146	95.8	0.43	12-24
Waxy[e]	30	314.0	0.115	117.5	0.42	12-24	423.3	0.130	103.3	0.15	11-24
Average SEE[f]					0.90					0.82	

[a] N is the number of sensor readings used for the model.
[b] Nominal moisture range of model.
[c] Three boxes (six sensors) used for each MC level.
[d] Two boxes (four sensors) used for each MC level.
[e] Modeled using data from Bartosik and Maier (2007) (table 2 and 3).
[f] Averages excluding Bartosik and Maier (2007) data.

Table 2. Standard errors determined from sensor data using Modified Chung-Pfost models developed for 4-point (4-P) and 2-point (2-P) models.

Grain ID	Adsorption				Desorption			
	4-P SEE	2-P SEE	2-P Prediction of 4-P Data SEP	MCdb [a] Range	4-P SEE	2-P SEE	2-P Prediction of 4-P Data SEP	MCdb [a] Range
USDA1	0.23	0.16	0.27	12-22	0.32	0.30	0.34	12-22
USDA2	0.32	0.31	0.36	14-19	0. 54	0.76	0.56	14-22
Purdue	0.48	0.55	0.50	12-21	0.51	0.61	0.52	11-19.5
T1	0.44	0.44	0.50	12-24	0.23	0.15	0.25	12-25
T2	0.41	0.38	0.43	11-21	0.23	0.22	0.24	12-20
T3	0.30	0.22	0.36	11-21	0.35	0.19	0.48	11-21
T4	0.39	0.29	0.42	11-21	0.36	0.36	0.37	11-21
Yellow Dent[b]	0.17	0.20	0.17	11-21	0.05	0.04	0.06	11-20
White[b]	0.15	0.07	0.17	11-21	0.17	0.11	0.21	11-20
Waxy[b]	0.15	0.05	0.17	11-21	0.09	0.04	0.10	11-20
Average SE[c]	0.37	0.34	0.41		0.33	0.37	0.39	

[a] Nominal moisture range of model.
[b] Modeled using Bartosik and Maier (2007) data (table 2 and 3).
[c] Averages excluding Bartosik and Maier (2007) data.

Table 3. Modified Chung-Pfost model parameters developed from 4-point and 2-point models.

Grain ID	N[a]	Model	Adsorption				Desorption			
			A	B	C	MCdb[b] Range	A	B	C	MCdb[b] Range
USDA1	48	4-point	677.11	0.173	88.90	12-24	856.50	0.177	103.18	12-28
	24	2-point	719.46	0.170	97.85		932.67	0.179	107.86	
USDA2	120	4-point	404.10	0.154	89.52	14-19	941.30	0.204	93.35	14-22
	60	2-point	443.41	0.156	95.87		974.50	0.204	96.59	
Purdue	120	4-point	698.36	0.179	116.40	12-21	612.89	0.180	85.70	11-19.5
	60	2-point	755.60	0.177	127.24		740.45	0.182	101.19	
T1	80	4-point	510.26	0.161	94.08	12-24	513.58	0.171	64.45	12-25
	40	2-point	582.12	0.159	107.34		557.09	0.170	73.38	
T2	80	4-point	533.07	0.157	93.21	11-21	445.29	0.157	64.58	12-20
	40	2-point	605.69	0.155	108.99		459.27	0.156	67.59	
T3	80	4-point	489.86	0.157	98.93	11-21	519.16	0.168	71.99	11-21
	40	2-point	597.46	0.157	118.25		456.96	0.162	65.22	
T4	80	4-point	580.04	0.168	93.25	11-21	754.91	0.182	82.68	11-21
	40	2-point	683.11	0.168	109.04		843.80	0.180	97.6	
Yellow dent[c]	24	4-point	357.39	0.151	69.99	11-21	633.89	0.162	86.73	11-20
	12	2-point	351.51	0.150	65.66		630.09	0.161	86.30	
White[c]	24	4-point	434.43	0.149	92.81	11-21	470.47	0.149	88.66	11-20
	12	2-point	438.40	0.150	91.68		473.89	0.150	86.82	
Waxy[c]	24	4-point	332.2	0.127	102.51	11-21	432.05	0.137	93.98	11-20
	12	2-point	316.25	0.126	98.85		434.33	0.136	94.48	

[a] N is the number of sensor readings used for the model.
[b] Nominal moisture range of model.
[c] Modeled using Bartosik and Maier (2007) data (table 2 and 3).

readings. The USDA1 model had an unusually large SEE compared to others and may be the result of difficulty in fitting across a broader moisture range. This sample was also taken from corn which had been cycled in and out of a 30-m elevator bin, more than 10 times, and had a relatively large amount of fines and broken kernels. The percentage of broken kernels and fine material by weight was 5.2% and 0.49%. These fractions were determined by sieving through a 12/64-in. round screen for broken kernels and 6/64-in. screen for fines. The average SEP values for adsorption and desorption when predicting 4-point data with the 2-point model were 0.41 and 0.39, respectively. This compares well with the overall SEP value of 0.5 for a recently developed *in situ* grain moisture sensor (Casada and Armstrong, 2009).

EMC Model Prediction Residuals

The prediction residuals for the USDA2 sample (fig. 2 data) are shown in figure 3 and were determined from the 5-point desorption model, which spanned the nominal moisture range of 14% to 26% MCdb. Residuals were calculated as the differences between predicted and measurd MC. Residuals were sorted by MCdb and show a pattern indicating the Chung-Pfost model does not fit this data particularly well. Residuals should ideally be randomly scattered. The trend of under- or over-predicting across a moisture range was observed, to varying degrees, for the other models.

Modeling of the 4-point data, which excluded the highest MC data, resulted in much improved SEE over the 5-point model (0.54 vs. 1.00) and much lower residuals for the lower moisture levels but a small area of high, patterned residuals still persisted at moisture levels at or near 22% MCdb (fig. 4). This trend was sometimes observed for other 4-point models and indicates that the SEE magnitude was largely influenced by the residuals at higher moisture levels for the 4-point model. Residuals obtained when the 2-point model was used to predict the same range as the 4-point model are shown in figure 5. The resulting SEP was 0.56. The upper moisture range (20%-22% dry basis, 16.7%-18% wet basis) of the 4-point model was specifically targeted for moisture levels where accurate moisture levels for corn become more important in terms of storability and marketing. The maximum SEE and SEP for 4- and 2-point models predicting 4-point data were 0.48 and 0.56, respectively.

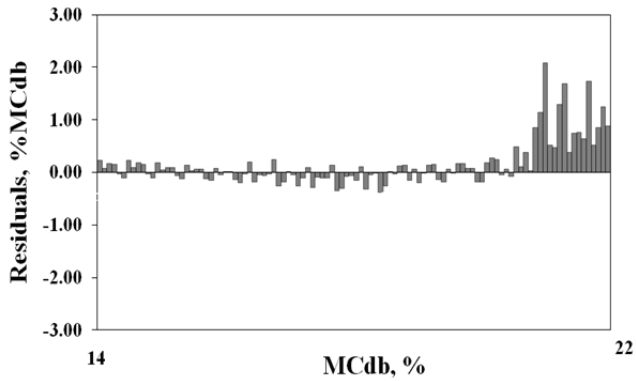

Figure 4. Prediction residuals for the USDA2 sample using the 4-point desorption model data over the MCdb range of 14% to 22% (SEE = 0.54).

Similar observations to the above were observed for adsorption models. The pattern of the SEE values show this because the 4- and 2-point models have a similar decrease in magnitude relative to 5-point models and the SEE was strongly influenced by the residuals at higher moistures.

Residuals for all the 5-, 4-, and 2-point desorption models are shown in figures 6-8 excluding the Bartosik and Maier (2007) data. In general the 5-point model residuals (fig. 6) are large whenever ERH values are approach 90% and higher. Residuals are affected in the region above 90% RH by two factors: (1) sensor accuracy decreases at high RH and (2) the increasing slope of the EMC/ERH curve make MC prediction very sensitive to RH measurement. These conditions will compound the error and data in this region will likely affect the development of an accurate model for lower moisture regions. Consequently, prediction at lower ERH will generally suffer due to the model being fit to noisy data at high ERH. Limiting the modeling moisture range or ERH by a small amount can improve the model significantly for the slightly limited range. The residuals for the 4-point and 2-point models are nearly identical and indicate that the judicious selection of two moisture levels for modeling can result in good predictions over common storage moistures. The upper ERH should be targeted to be between 85% and 90% to accommodate a high MC but to avoid the region of large sensor error; the

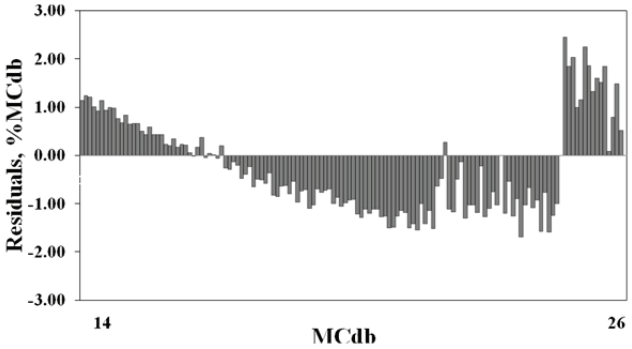

Figure 3. Prediction residuals for the USDA2 sample using the 5-point desporption model data over the MCdb range of 14% to 26% (SEE = 1.00).

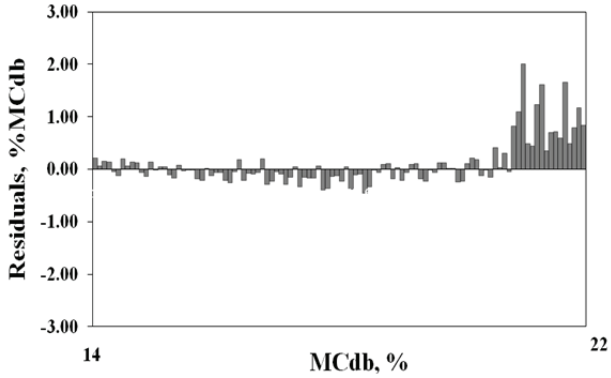

Figure 5. Prediction residuals for the USDA2 sample using the 2-point desorption model to predict the same moisture range used in the 4-point model, 14% to 22% MCdb (SEP = 0.56).

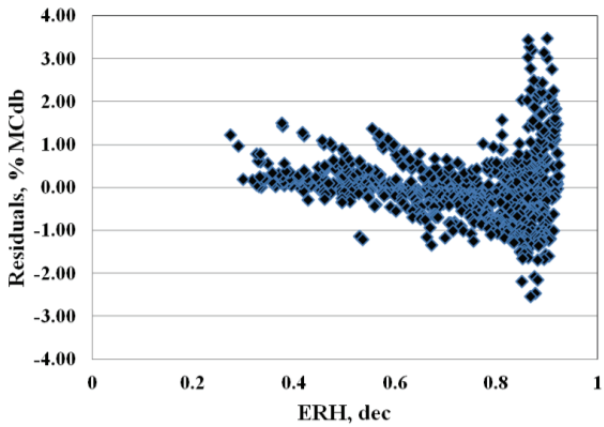

Figure 6. Prediction residuals vs. ERH for all samples using 5-point modeling desorption data. The calculated SEE using all residuals was 0.85.

lower range is less affected and an ERH of 35% to 50% seems acceptable. This equates to limiting the upper model range moisture to approximately 21% MCdb (17.4% MCwb); the lower model moisture can extend to 10% MCdb (9% MCwb).

The upper and lower bounds prediction from any of the yellow dent, 2-point model predictions are shown in figure 9 for desorption and adsorption at 20°C. The average MC difference across the RH range is approximately 1.5% and 1.4% for adsorption and desorption, respectively. The lower predictions, for both adsorption and desorption, were comprised mainly from data of the USDA2 model, while the upper points for desorption and adsorption were mainly from the Yellow Dent and T2 models, respectively. The upper and lower ranges will also vary by the SEE from the model each point was derived. This basically shows that without developing a grain-specific EMC relationship, random selection of an EMC relationship to represent a grain could result in significant moisture measurement error. ASAE Standard D245.6 for shelled corn, derived from Chen and Morey (1989b), is also shown (A = 374.34, B = 0.18662, C = 31.696). These predictions lie well within the limits of the desorption extremes.

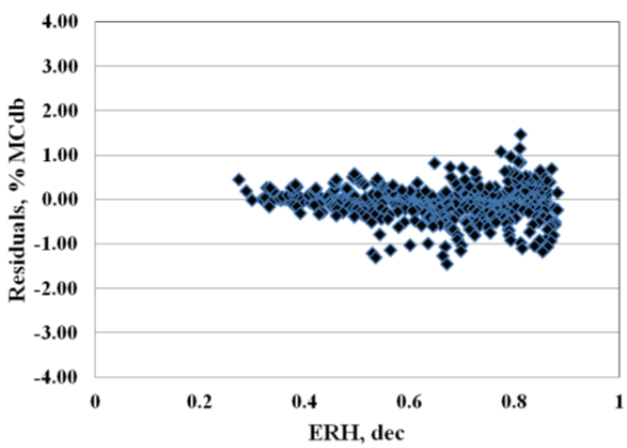

Figure 7. Prediction residuals vs. ERH for all samples using 4-point modeling desorption data. The calculated SEE using all residuals was 0.36.

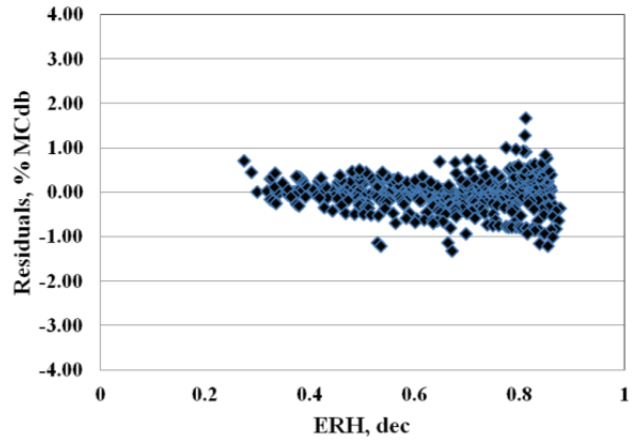

Figure 8. Prediction residuals versus ERH for all samples using 2-point modeling desorption data. The calculated SEE using all residuals was 0.35.

How well an EMC sensor will perform in practice will depend on more than developing an accurate EMC/ERH relationship. Long-term sensor stability could be an issue. Although the sensor is relatively inexpensive, identifying a sensor that is not working well may be a challenge in the field. Large bins may also contain multiple sources of grain which exhibit different EMC/ERH behavior. Another potential for error is not knowing whether adsorption or desorption is occurring. For controlled aeration or in-bin drying, this can be determined by the monitoring system but during static storage it may be difficult to decide which is most appropriate, i.e., temperature fluctuations and convection currents may cause a mixture of moisture transfer modes over time. It is also unknown if the method of conditioning of samples for model development may affect EMC relationships, i.e., does re-wetting have any effect compared to obtaining wet field samples or what are appropriate equilibration times. Bartosik and Maier (2007) outline these concerns as well. In somewhat related work, Wilke et al. (2001) found the use of high moisture, frozen samples, and re-wetting frozen samples gave similar results for storability tests.

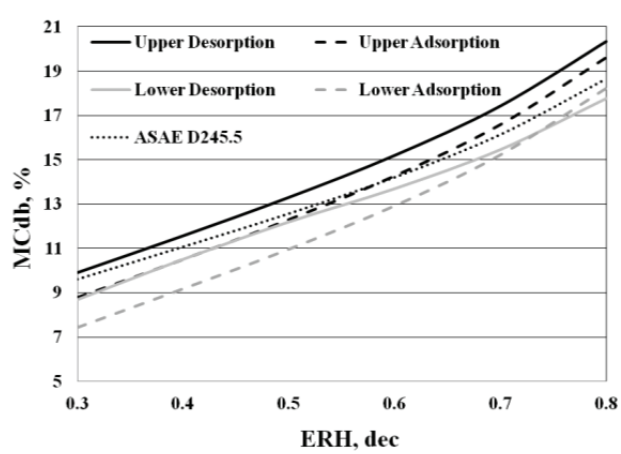

Figure 9. Envelope of maximum and minimum EMC predictions for desorption and adsorption from all models at 20°C.

Conclusions

Modeling EMC/ERH relationships over a limited range of moisture resulted in improved prediction accuracy for specific corn lots. The appropriate upper limit of moisture content was found to be moisture levels equivalent to an ERH of 85% to <90%. Although this excludes high moisture conditions, the remaining upper range still covers moisture levels that are most common for stored corn.

This work has also revealed that two samples carefully conditioned to moistures levels at equivalent ERH conditions of 85% to less than 90% and 35% to 50% can be used to develop 2-point equilibrium moisture models with standard errors similar to 4-point models. This facilitates the development of models for specific corn lots by simplifying the sample conditioning requirements. Additional research should include methods that would easily match the behavior of an unknown grain with a library of existing EMC/ERH relationships. The procedures and conclusions from this research should also be applicable to other grain or seed types.

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