

# **A COMPARISON OF CONVENTIONAL AND SENSOR-BASED LIME REQUIREMENT MAPS**

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## **ABSTRACT**

Successful variable-rate applications of agricultural inputs such as lime rely on the quality of the input data. Systematic soil sampling is the most common method used for creating variable rate prescription maps. The low density of economically feasible sampling has been primarily responsible for the typical inaccuracy of lime prescription maps. To increase sampling density, on-the-go sensing technology was developed for the mapping of soil pH and other relevant attributes. In this study, two fields in eastern Nebraska were mapped using both on-the-go mapping and systematic grid sampling approaches. Ten random validation locations in each field were used to compare the prescribed liming rate with lime requirement based on the traditional buffer pH test. The data collected were used to compare three soil acidity management scenarios: 1) uniform rate liming; 2) variable rate liming based on systematic grid sampling, and 3) variable rate liming based on sensor-based mapping. In general, sensor-based maps were better predictors of soil pH, buffer pH and lime requirement than field average or grid-based maps.

**Keywords:** soil pH, buffer pH, liming, on-the-go soil sensing

## **INTRODUCTION**

Sustainability and profitability of agricultural production are major challenges faced by farmers today. Due to growing global demand for agricultural produce, rising fertilizer prices, and mounting environmental concerns, farmers must be able to optimize their production through informed decision-making (Gebbers and

Adamchuk, 2010). Precision agriculture offers an opportunity to reduce production costs while increasing yield and/or protecting the environment by treating agricultural land according to local needs. Variable rate liming is one of the most promising precision agriculture technologies (Bongiovanni and Lowenberg-DeBoer, 2000). However, the quality of variable rate lime prescription maps remains one of the main considerations when it comes to non-uniform treatments of fields with spatially variable soil acidity (Bianchini and Mallarino, 2002; Viscarra Rossel and Walter, 2004; Brouder et al., 2005).

The most widespread practice used to prescribe variable rate liming has been grid sampling. Typically, one sample analyzed by a soil testing laboratory represents at least 1 ha of land. As one sample per hectare can be insensitive to short-range soil variability, researchers have explored opportunities to economically map soil pH at a denser scale. For example, on-the-go sensing using the Veris<sup>®</sup> Mobile Sensing Platform (MSP, Veris Technologies, Inc., Salina, KS) enables soil pH to be measured at scales of 20-30 samples/ha along with apparent soil electrical conductivity (EC<sub>a</sub>). Adamchuk et al. (2007) has shown that soil pH maps produced from data collected by on-the-go sensing are more accurate than those obtained using traditional grid sampling methods. However, this does not necessarily imply that using sensor-based data will generate superior lime recommendation maps. That question is addressed in this study.

Acidity in the soil can be thought of as having two forms: active and reserve. The active acidity consists of free-moving hydrogen ions, which quickly bond with any available bases. Reserve acidity consists of hydrogen ions which are bound only loosely. When active acidity is neutralized by reacting with a small amount of base, these loosely-bound hydrogen ions break their bonds and become active, preserving an acidic equilibrium. Since a simple (water) pH measurement relates only to active acidity, more information is needed to determine a soil's lime requirement (Van Lierop, 1990).

Lime requirement (LR) is the amount of lime to be added to a soil to neutralize the active acidity as well as a significant portion of the reserve acidity. The reserve acidity can be influenced by the presence of organic matter, exchangeable aluminum, clay content, weathering, parent material, metallic oxides, etc. (Carter, 1993). While the active soil pH is easily measurable on-the-go, due to the multivariate nature of reserve acidity, its overall nature must be tested for each specific situation. Conventionally, when grid-based soil samples are analyzed, a buffer pH test is performed. A soil's buffer pH is determined by adding measured quantities of a base to the soil solution (e.g., Woodruff, 1948).

The LR derived from a buffer pH test can also vary due to cultivation depth and with the nature of the liming material applied. Therefore, it is important to adjust LR according to the depth of sampling and tillage practice. Other properties to consider are the neutralizing capacity, the calcium carbonate equivalent (CCE), and the physical state of the limestone (Nathan et al., 2006; Ferguson, 2006). For example, the University of Nebraska-Lincoln lime requirement algorithm (Ferguson et al. 2006; Mamo et al., 2009) can be expressed as:

$$LR = \begin{cases} 0 & \text{if } BpH > 7.0 \\ (7.0 - BpH) \cdot 11.2 & \text{if } 6.3 < BpH < 7.0 \\ 7.85 & \text{if } BpH \leq 6.3 \end{cases} \quad (1)$$

where  $LR$  is 60% CCE (aglime) lime requirement (Mg/ha) and  $BpH$  is Woodruff buffer pH (Woodruff, 1948).

The objectives of this study are: 1) to generate lime requirement maps using different mapping approaches (average application rate, 1-ha grid sampling, and on-the-go sensor mapping); and 2) to compare these maps in terms of the accuracy of soil pH, buffer pH, and lime requirement predictions.

## MATERIALS AND METHODS

### Site Descriptions and Data Collection

Strnad field (47.6 ha), in Nance County, Nebraska, consists mainly of gently sloping Moody silty clay loam (fine-silty, mixed, superactive, mesic Udic Haplustolls), an excellent farming soil with a typical topsoil pH between 5.6 and 7.3. In the northern and southwest parts of the field one finds highly sloped, highly eroded Crofton silt loam (fine-silty, mixed, superactive, calcareous, mesic Udic Ustorthents), with a typical pH in the range of 7.4 to 8.4 near the surface. Toward the northeast, the field descends to meet the southern branch of Skeedee Creek, along which Crofton silt loam is the primary soil. In the transition areas, severely eroded Nora silt loam (fine-silty, mixed, superactive, mesic Udic Haplustolls) with moderate slopes is found. Nora silt loam typically exhibits a soil pH between 5.6 and 7.3 in the upper 15 cm. Though these eroded soils play an important role in drainage patterns in the field, they are minimally represented in the study area.



Fig. 1. Maps of Strnad field's soil series (a) and shallow (0-30 cm)  $EC_a$  (b).

Just south of the Platte River in Saunders County, Williams field (20.2 ha) is chiefly composed of three moderately eroded soil classes: Pohocco silty clay loam (fine-silty, mixed, superactive, mesic Typic Eutrudepts) on the western half, with Yutan eroded Judson complex and Yutan eroded Aksarben silty clay loams (fine-silty, mixed, superactive, mesic Mollic Hapludalfs) on the eastern half. Each of these soils is susceptible to erosion. The typical pH of Yutan soils is 6.0 in the upper 20 cm of soil, while the pH of the Pohocco loam is typically around 7.2.

In this study, traditional grid sampling was represented by collecting one composite sample (consisting of 5-6 20-cm deep cores obtained with a manual probe) in each 1-ha square grid cell from around the center of the grid within a

3 m x 3m area. All samples collected manually were analyzed by Ward Laboratories, Inc. (Kearney, NE) for a variety of soil attributes, including soil pH (1:1 soil-water solution) and Woodruff buffer pH.

In both fields, sensor data collection was performed using Veris<sup>®</sup> MSP, which employs antimony ion-sensitive electrodes and measures active acidity. Soil pH was measured 10-15 cm deep with an average of 10 s between samples, while mapping at 4-8 km/hr travel speed using a 15-m width between passes. In addition, EC<sub>a</sub> measurements relating to the soil's ability to conduct electrical charge were obtained. In many instances, EC<sub>a</sub> involves soil texture, moisture, and metallic ion content, among other properties, and can be used to distinguish soil classes within a field (Mulla and McBratney, 2000). Soil pH and EC<sub>a</sub> maps combined are therefore expected to be useful in predicting buffer pH, which is directly related to the lime requirement. The Manifold<sup>®</sup> System (Manifold Net Ltd, Carson City, NV) software package was used to process spatial data.

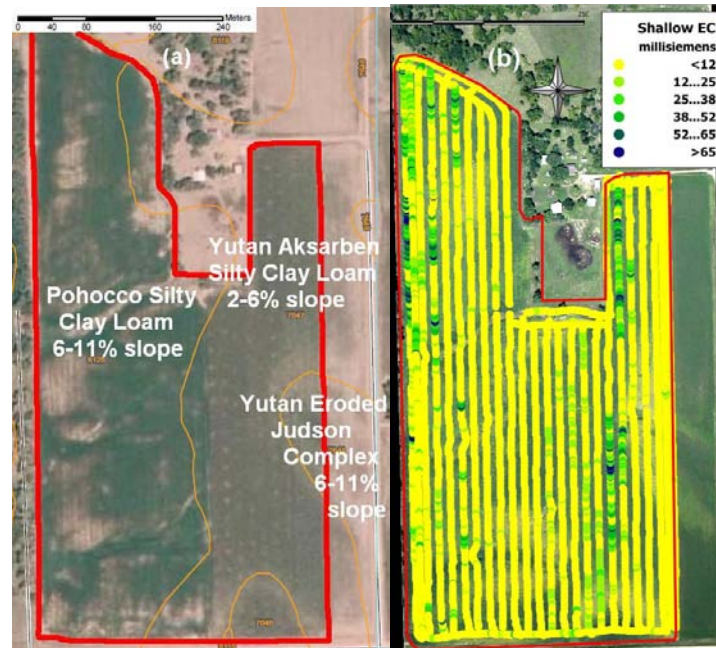


Fig. 2. Maps of Williams field's soil classes (a), and shallow (0-30 cm) EC<sub>a</sub> (b).

In addition to 1-ha center-point square grid sampling, additional samples were collected for sensor calibration (10 samples) as well as for validation purposes, totaling 24 from Strnad field and 25 from Williams field. While locations for calibration samples were manually established following Adamchuk et al. (2008), locations for validation samples were established randomly. Table 1 summarizes the number of independent measurements obtained in each field.

**Table 1. Number of sampling and measurement locations.**

Sampling/measuring	Strnad field	Williams field
Grid-based sampling (1-ha)	50	24
Calibration samples	10	10
Validation samples	14	15
On-the-go soil pH measurements	1698	610
On-the-go EC <sub>a</sub> measurements	19717	7024

### Data Processing

A lime prescription map shows a surface array of lime requirement values predicted in each field location. This process typically involves interpolation (Brouder et al., 2005), which means that lime requirement values obtained with a non-continuous function (e.g., equation 1) cannot be used. One way to address the issue is to interpolate the buffer pH instead of the lime requirement and then apply equation 1. Unfortunately, commercial laboratories do not measure the buffer pH if the soil pH is found to be greater than 6.5, as no lime is needed. Therefore, to predict the buffer pH for neutral and alkaline soils ( $pH > 6.5$ ), a continuation of the linear relationship between soil and buffer pH was assumed:

$$BpH = a_0 + a_1 \cdot pH \quad (2)$$

where  $pH$  is soil pH in a 1:1 soil-water solution;  $a_0$  and  $a_1$  are regression parameters.

In addition to this “no-constraints” model (equation 2), it was assumed that 7.0  $BpH$  (a critical value for equation 1) corresponds to  $pH$  of 6.5 (one constraint):

$$BpH = 7.0 + a^*(pH - 6.5) \quad (3)$$

Also, another constraint was added to assume that when  $pH$  is equal to 8.0,  $BpH = 8.0$  as well:

$$BpH = 2.7 + 0.67 pH \quad (4)$$

Once  $BpH$  was defined for every sample analyzed in the laboratory,  $Lab pH$  and  $Lab BpH$  values corresponding to grid sampling locations were interpolated to the extent of all field boundaries, using ordinary kriging interpolation with all points involved and a spherical semivariogram model to obtain a 5 x 5 m pixel size surface. Similarly,  $Sensor pH$  and  $EC_a$  measurements were interpolated with only 10 neighbor points involved (Manifold software default).

The four surfaces were used to find interpolated values corresponding to calibration and validation sampling locations. The ten calibration samples for each field were used to define the relationships between  $Sensor pH$  and  $Lab pH$  (equation 5) as well as between  $Sensor pH$  integrated with  $EC_a$  and  $Lab BpH$  (equation 6).

$$Lab pH = b_0 + b_1 \cdot Sensor pH \quad (5)$$

$$Lab\ BpH = c_0 + c_1 \cdot Sensor\ pH + c_2 \cdot EC_a + c_3 \cdot Sensor\ pH \cdot EC_a \quad (6)$$

For each field, partial cases were considered to include: 1)  $b_1 = 1$  – data shift; 2)  $b_0 = 0$  – data scale; 3)  $b_0 = 0$  and  $b_1 = 1$  – original data; 4)  $c_1 = 1$  and  $c_2 = c_3 = 0$  – data shift; 5)  $c_2 = c_3 = 0$  – linear regression without  $EC_a$ ; and 6)  $c_3 = 0$  – no interaction term. An appropriate model was selected as the one providing the lowest root mean squared error (RMSE) with the fewest parameters. Thus, when regression parameters were not significantly different from either 1 (multiplier of a significant variable) or 0 (intercept or multiplier of a non-significant variable) at  $\alpha = 0.05$ , they were omitted from further regression analysis.

Once the best site-specific model for predicting *Lab pH* and *Lab BpH* using on-the-go sensor data was defined, interpolated surfaces of sensor data were transformed to obtain the corrected *Sensor pH* (predicted *Lab pH* and *Lab BpH*) maps. Later, all *BpH* maps were translated into *LR* maps using equation 1.

Additionally, field average estimates were calculated by averaging all grid pH points for pH, all grid BpH points for BpH, and applying equation 1 to the averaged BpH value to obtain LR. For Williams field, the field average estimate resulted in zero lime requirement. Therefore, the field was split in two halves (eastern and western) and the average liming prescription was calculated for each half separately, as only the eastern half had acidic and slightly acidic soils.

Having developed full *Lab pH*, *Lab BpH*, and *LR* maps from each of the three main sampling schemes, validation locations were used to compare corresponding values from 1) field average estimate; 2) interpolated grid-based map; and 3) sensor-based map with laboratory values.

## RESULTS AND DISCUSSION

*Lab pH* and *Lab BpH* were linearly related with  $R^2 = 0.80$  for Strnad field and  $R^2 = 0.36$  for Williams field using all samples with *Lab pH* of 6.5 and less analyzed in the laboratory (Fig. 3). This relationship yields  $R^2 = 0.97$  if only calibration samples are used in both fields. Based on the RMSE values (Table 2), the one-constraint model (equation 3) appeared to be the most appropriate to predict *BpH* values for *Lab pH* > 6.5. Following equation 3,  $a^*$  for Strnad field was 0.78, while  $a^*$  for Williams field was 0.74. This way, equation 1 can be used despite the lab practice of not measuring *BpH* for soils with  $pH > 6.5$ .

The raw on-the-go *Sensor pH* and *Lab pH* measurements for ten calibration samples (Fig. 4) were correlated with  $R^2 = 0.90$  for Strnad field and  $R^2 = 0.91$  for Williams field. A 0.27 unit increase of soil pH was used for site-specific correction of *Sensor pH* data for Strnad field (Table 3) as the slope of simple linear regression was not significantly different from 1. In Williams field, on the other hand, the different rate of sensor responses to changes in soil pH in the alkaline range made complete linear regression justifiable ( $b_0 = -5.3$  and  $b_1 = 1.82$ ). It appears that for both fields, the sensor-based approach showed a more detailed delineation of acidic and alkaline areas (Fig. 5, Fig. 6). However, general spatial trends of soil pH remained similar.

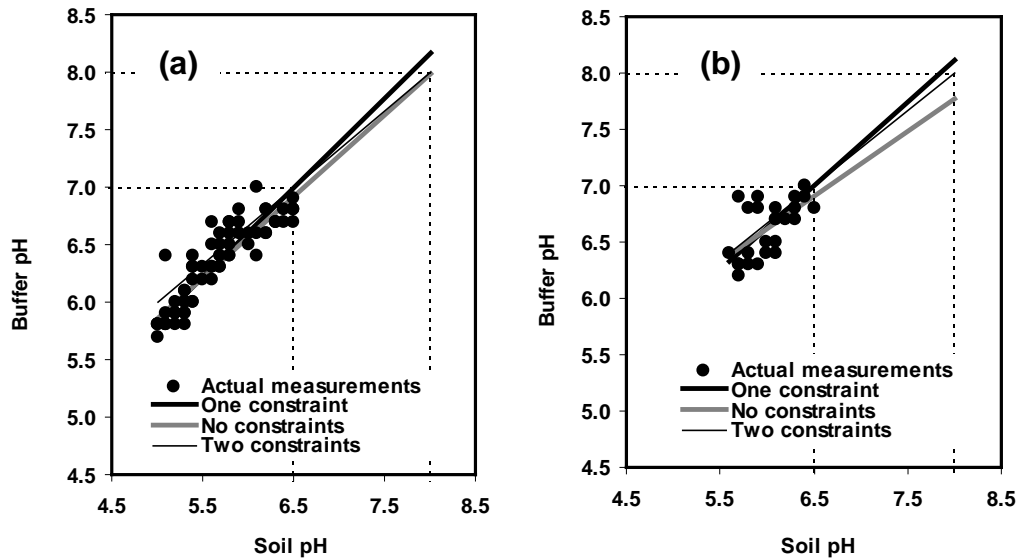


Fig. 3. Relationships between pH and BpH for Strnad (a) and Williams (b) fields.

Table 2. RMSE values for three different alkaline soil BpH prediction models.

Model	Strnad Field	Williams Field
Equation 2 (no constraints)	0.16	0.19
Equation 3 (one constraint)	<b>0.16*</b>	<b>0.20</b>
Equation 4 (two constraints)	0.20	0.20

\* Bold values indicate the model selected.

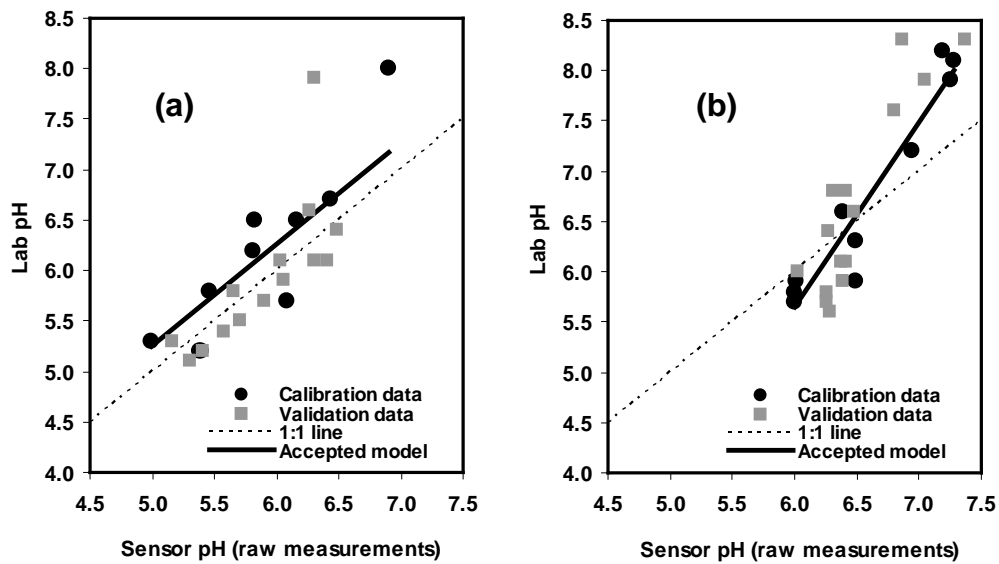
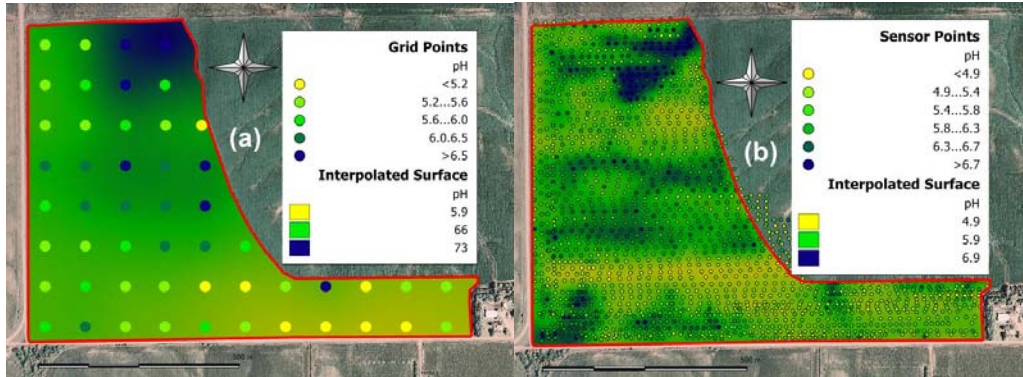


Fig. 4. Relationships between Sensor pH and Lab pH for Strnad (a) and Williams (b) fields.

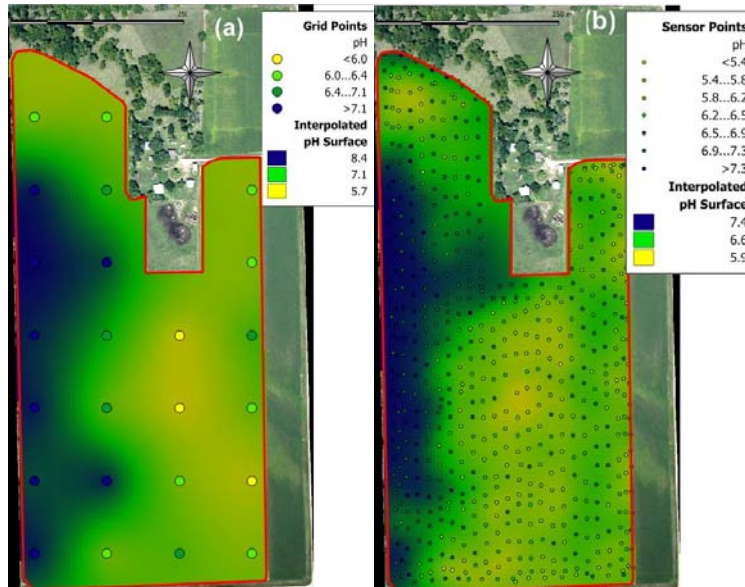
**Table 3. RMSE values for four different Lab pH prediction models.**

Model (equation 5)	Strnad Field	Williams Field
$b_0 \neq 0$ and $b_1 \neq 1$ (linear regression)	0.36	<b>0.29*</b>
$b_0 \neq 0$ and $b_1 = 1$ (data shift)	<b>0.42</b>	0.50
$b_0 = 0$ and $b_1 \neq 1$ (data scale)	0.40	0.49
$b_0 = 0$ and $b_1 = 1$ (raw data)	0.49	0.52

\* Bold values indicate the model selected.



**Fig. 5. Point and interpolated maps of soil pH for Strnad field based on 1-ha grid sampling (a) and on-the-go mapping (b).**

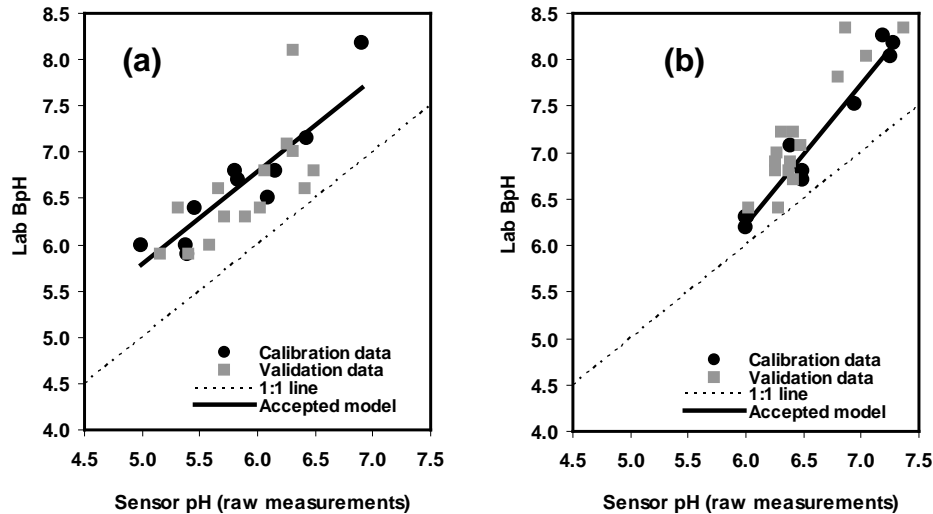


**Fig. 6. Point and interpolated maps of soil pH for Williams field based on 1-ha grid sampling (a) and on-the-go mapping (b).**

The raw on-the-go *Sensor pH* and *Lab BpH* measurements (Fig. 7) were correlated with  $R^2 = 0.85$  for Strnad field and  $R^2 = 0.96$  for Williams field. A simple 0.80 unit increase of *Sensor pH* has been used to make site-specific prediction of *Lab BpH* in Strnad field (data shift in Table 4). As was the case with *Lab pH* in Williams field, the relationship between *Sensor pH* and *Lab BpH* did not produce a slope equal to 1 ( $c_0 = -2.8$  and  $c_1 = 1.50$ ). Using only the 10 calibration samples, *Lab pH* and *Lab BpH* were highly correlated for both fields ( $R^2 = 0.97$ ), and addition of  $EC_a$  measurements in the regression model was not



beneficial. Maps of *Lab BpH* obtained from interpolated grid-based measurements, corrected *Sensor pH* measurements, and an average of grid-based measurements were converted into LR maps using equation 1 (Figs. 8 and 9). These maps can be used for an actual variable rate application of lime. Once again, overall spatial patterns were shown to be similar in both fields. However, both fields have areas of discrepancy between the two variable rate liming maps (Fig. 10).



**Fig. 7. Relationships between Sensor pH and Lab BpH for Strnad (a) and Williams (b) fields.**

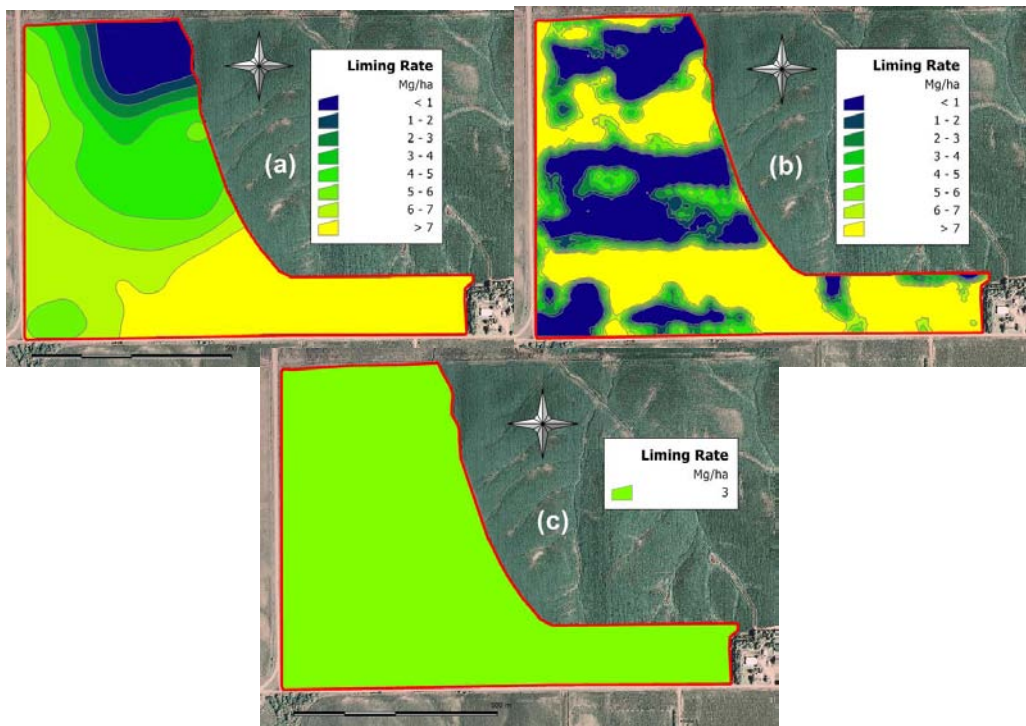
**Table 4. RMSE values for four different Lab BpH prediction models.**

Model (equation 6)	Strnad Field	Williams Field
$c_0 \neq 0, c_1 \neq 1, c_2 = 0, \text{ and } c_3 = 0$ (regression)	0.24	<b>0.16*</b>
$c_0 \neq 0, c_1 = 1, c_2 = 0, \text{ and } c_3 = 0$ (data shift)	<b>0.25</b>	0.30
$c_0 \neq 0, c_1 \neq 1, c_2 \neq 0, \text{ and } c_3 = 0$ (no interaction)	0.27	0.16
$c_0 \neq 0, c_1 \neq 1, c_2 \neq 0, \text{ and } c_3 \neq 0$ (full regression)	0.22	0.16
$c_0 = 0, c_1 = 1, c_2 = 0, \text{ and } c_3 = 0$ (raw data)	0.84	0.61

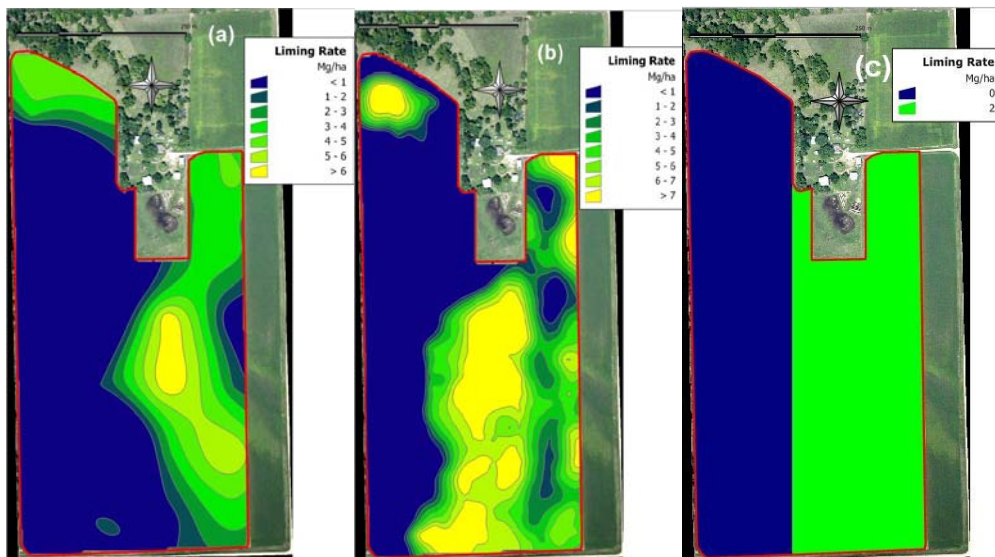
\* Bold values indicate the model selected.

From the visual relationships between corresponding values for both calibration and validation datasets (Figs. 11 through 16) as well as  $R^2$  values for linear regressions between corresponding laboratory measurements and map predictions of *Lab pH*, *Lab BpH*, and *LR* (Table 5), sensor-based maps overall were better predictors of *Lab pH*, *Lab BpH*, and *LR* than either grid-based interpolated maps or field average maps. RMSE values (the root of the mean squared difference between corresponding map predictions and measurements) summarized in Table 6 also indicate reduction in prediction errors when using sensor-based estimates.

In addition to the overall comparison, two points in each field (A and B in Strnad field, C and D in Williams field) were identified in the areas with greater discrepancy between grid-based and sensor-based maps (Figs. 11-16). In each case, the spatial variability of soil pH resulted in grid-based map predictions which were less accurate than maps based on sensor data.



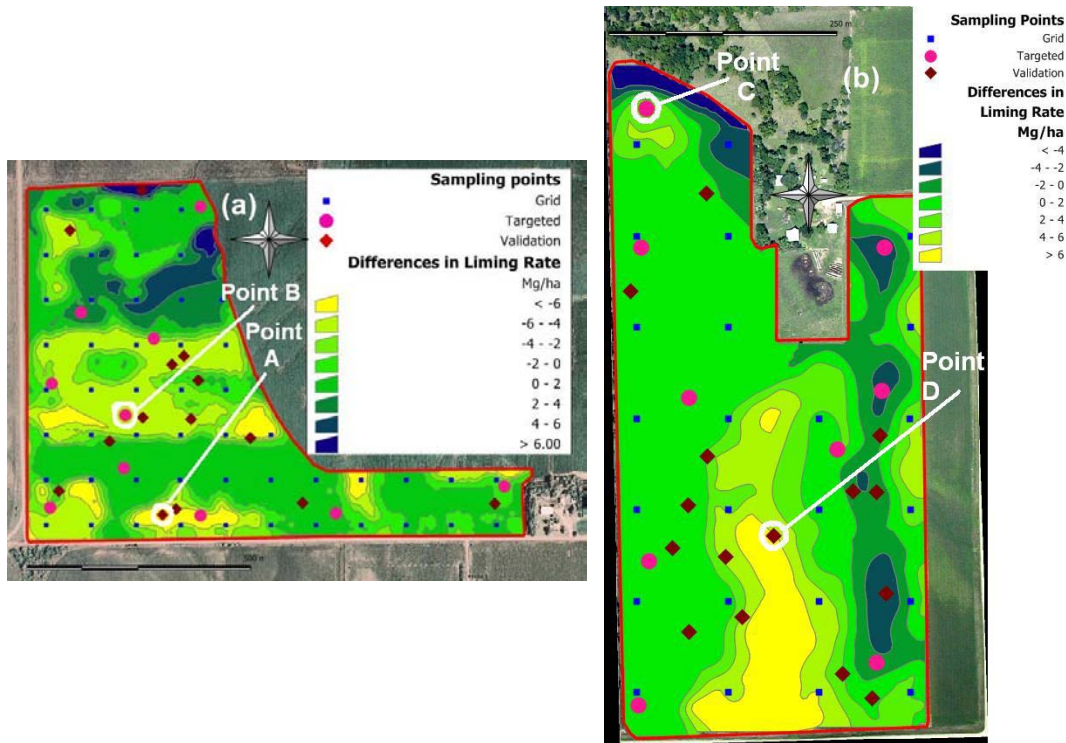
**Fig. 8.** Contour maps of LR for Strnad field based on 1-ha grid sampling (a), on-the-go mapping (b), and field average (c).



**Fig. 9.** Contour maps of LR for Williams field based on 1-ha grid sampling (a), on-the-go mapping (b), and field average (c).

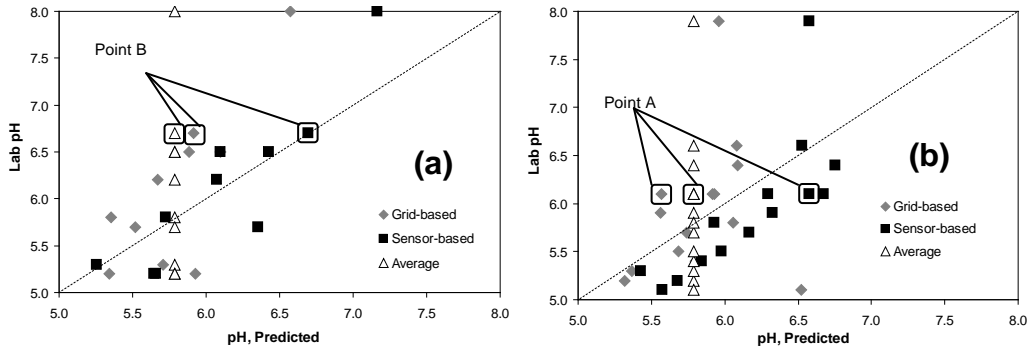
Each of the fields presented in this study has a relatively strong spatial structure. As a result, even a coarse (1-ha) grid sampling was sufficient to reveal the overall field pattern. In addition, the close association between soil pH and buffer pH suggests that LR rates could be defined using either measurement.

Therefore, there was no benefit derived from adding  $EC_a$  measurements to the regression analysis predicting buffer pH using sensor data. Although LR RMSE values were lower for sensor-based data, they were relatively high and similar in order to those obtained for either grid-based or field average data (Table 6). Most of the uncertainties can be attributed to systematic differences between Sensor pH and Lab pH/BpH and, to an even greater extent, are the result of the spatial soil variability at short ranges, as corresponding sensor measurements and grid soil sampling may have occurred more than 10 m apart.

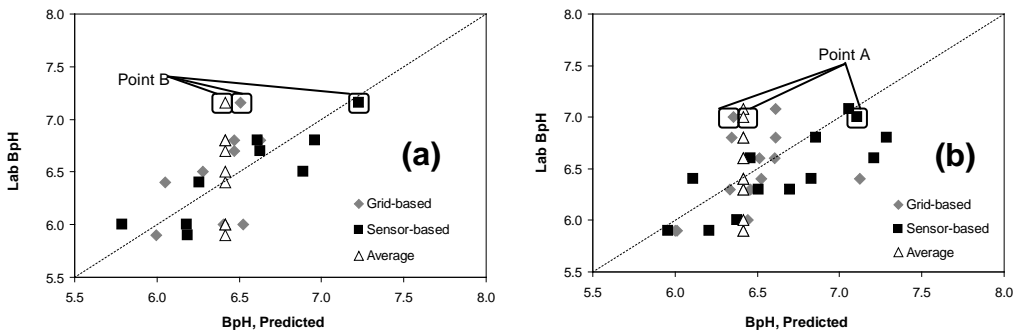


**Fig. 10. Contour maps of the difference between LR maps based on 1-ha grid sampling and on-the-go sensing for Strnad (a) and Williams (b) fields. Points A, B, C, and D are examples of sampled locations with substantial disagreement between grid-based and sensor based maps.**

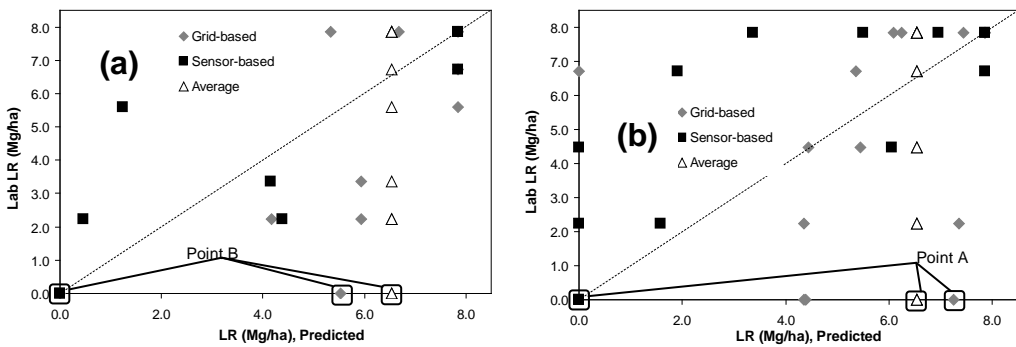
In addition, it is important to note that the LR recommendation used in this study relies on the prescription rate varying in a relatively short range of BpH values (6.3 to 7.0). This means that either direct estimation or prediction errors typically observed with any mapping strategy result in a significant LR estimation error (1.1 Mg/ha per 0.1 pH). In addition, the fixed application rate over the 18-24 m swath of a lime applicator with equipment application error creates an additional level of uncertainty. That is why a variable rate liming prescription mechanism is expected to rely on a smoothing factor to allow a larger array of unbiased measurements to define LR. As shown in this study, with a significantly greater number of such measurements using on-the-go sensing technology, it is feasible to bring the level of LR prediction uncertainty to a spatial scale less than or equal to the width of fixed rate application. Dealing with both types of uncertainties is a logical next step in variable rate liming research.



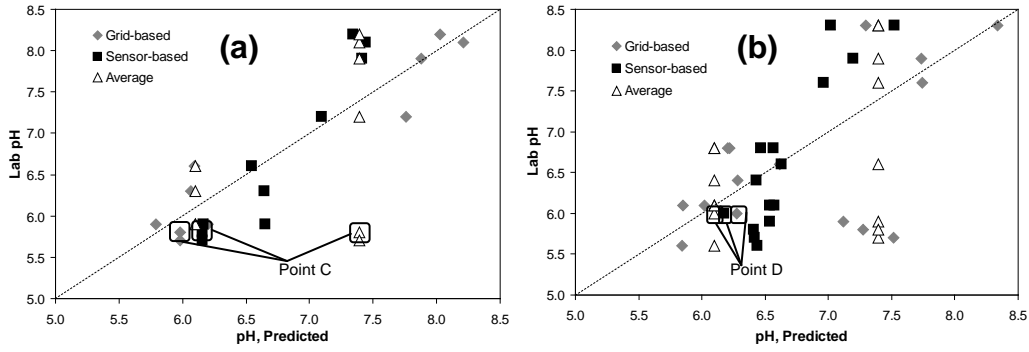
**Fig. 11. Relationships between measured *Lab pH* and predictions obtained using three different methods (grid-based sampling, on-the-go sensing, and field average) for calibration (a) and validation (b) datasets (Strnad field).**



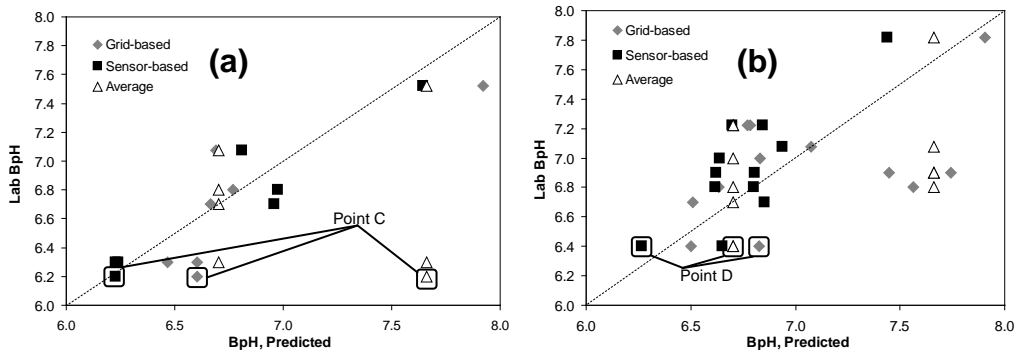
**Fig. 12. Relationships between measured *Lab BpH* and predictions obtained using three different methods (grid-based sampling, on-the-go sensing, and field average) for calibration (a) and validation (b) datasets (Strnad field).**



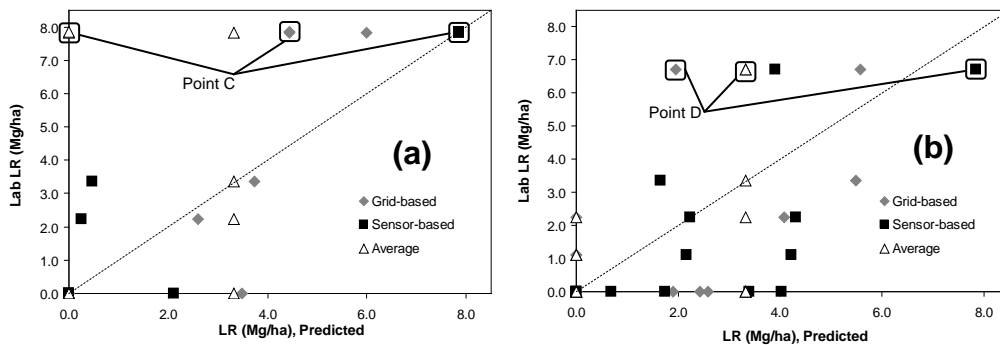
**Fig. 13. Relationships between measured *LR* and predictions obtained using three different methods (grid-based sampling, on-the-go sensing, and field average) for calibration (a) and validation (b) datasets (Strnad field).**



**Fig. 14. Relationships between measured *Lab pH* and predictions obtained using three different methods (grid-based sampling, on-the-go sensing, and field average) for calibration (a) and validation (b) datasets (Williams field).**



**Fig. 15. Relationships between measured *Lab BpH* and predictions obtained using three different methods (grid-based sampling, on-the-go sensing, and field average) for calibration (a) and validation (b) datasets (Williams field).**



**Fig. 16. Relationships between measured *Lab LR* and predictions obtained using three different methods (grid-based sampling, on-the-go sensing, and field average) for calibration (a) and validation (b) datasets (Williams field).**

**Table 5. Summary of R<sup>2</sup> values for the relationships shown in Figs. 11 -16.**

Map	Dataset	Strnad field		Williams field	
		Grid	Sensor	Grid	Sensor
Lab pH	Calibration	0.62*	0.81*	0.91*	0.91*
	Validation	0.05	0.58*	0.37	0.79*
Lab BpH	Calibration	0.65*	0.85*	0.90*	0.96*
	Validation	0.15	0.50*	0.54*	0.84*
LR	Calibration	0.45	0.75*	0.73*	0.87*
	Validation	0.03	0.64*	0.36	0.46

\* - significant relationships with R<sup>2</sup> > 0.5.

**Table 6. Summary of RMSE values for the relationships shown in Figs. 11 -16.**

Map	Dataset	Strnad field			Williams field		
		Grid	Sensor	Average	Grid	Sensor	Average
Lab pH	Calibration	0.67	0.42	0.89	0.30	0.50	0.85
	Validation	0.70	0.52	0.71	0.77	0.62	0.88
Lab BpH	Calibration	0.47	0.25	0.68	0.25	0.16	0.71
	Validation	0.53	0.41	0.58	0.44	0.33	0.53
LR, Mg/ha	Calibration	2.62	1.69	3.72	1.98	1.30	3.95
	Validation	3.54	2.37	3.61	1.92	1.97	2.08

## CONCLUSIONS

In this study, the quality of soil pH, buffer pH, and lime requirement maps was compared for three mapping methods: grid-based sampling, on-the-go sensing, and field average. In two Nebraska production fields, it was shown that lime application maps based on sensor data with ten calibration points provided better delineation of acidic soil areas that needed lime than grid sampling or field average methods. After following the overall statistics as well as individual field locations, it appeared that agreement between actual laboratory measurements and corresponding map values was improved when spatial structure was recognized using a greater number of measurements, such as when using an on-the-go soil sensing approach. When defining a site-specific relationship between corresponding *Sensor pH* and *Lab pH/BpH* measurements, it is not always necessary to adjust each parameter of a corresponding regression model because the slope of response and/or the average of all corresponding measurements may not differ significantly. A more involved analysis will be performed to investigate the combined effect of LR prediction uncertainties and variable rate application errors.

## ACKNOWLEDGEMENT

This publication is a contribution of the University of Nebraska Agricultural Research Division, supported in part by the Hatch Act. Funding was also provided through the Nebraska Soybean Board. Thanks to Mark Strnad and Bradley Williams for the use of their fields.

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