

Predicting Soil pH and Buffer pH In Situ with a Real-Time Sensor

S. A. Staggenborg,* M. Carignano, and L. Haag

ABSTRACT

Measuring soil pH is an important step in assessing the chemical status of a soil and in remediating high and low soil pH situations. Soil pH measurements on a spatial scale are limited by labor and lab analysis costs. A pH sensor mounted on a mobile sensing platform may be able to reduce these costs while providing a high-resolution soil pH map. The objective of this research was to evaluate a pH sensor mounted on a mobile platform on two fields in Kansas, one with a uniform soil and one with six different soil complexes. Real-time measurements were taken at a density of 17 points ha⁻¹ and compared with soil samples collected at depths of 0 to 7.5 and 7.5 to 15 cm. The real-time sensors predicted soil pH most accurately at the 0- to 7.5-cm depth (R^2 from 0.75 to 0.83) and less accurately for the other depth and combined depth (R^2 from 0.53 to 0.79). The inclusion of soil electrical conductivity (EC) improved pH predictions in the field with six different soil types, but not the uniform field. Buffer pH predictions were less accurate than pH predictions (R^2 from 0.04 to 0.43) across locations and depths. However, if a relationship between lab pH to buffer pH was developed and used to predict buffer pH from real-time pH, the accuracy improved (R^2 from 0.75 to 0.95), suggesting that real-time pH measurements may be capable of predicting buffer pH and lime requirements in real time. These results suggest that real-time pH sensors on a mobile platform can be used to measure spatial pH and buffer pH and provide subsequent variable-rate lime recommendations.

SOIL pH IS CREDITED with being both an indication of a soil's condition and a causal agent in many soil reactions (McLean, 1982). In fact, the availability of most plant essential elements is influenced by soil pH, thus making it a yield-limiting factor and a management concern for decades. Low soil pH results in increased availability of aluminum (Havlin and Beaton, 1998) which has been reported to affect root growth (Doss and Lund, 1975; Yang et al., 1996), seedling dry matter production (Fageria and Baligar, 1999; Tsakelidou, 2000), nutrient availability (Havlin and Beaton, 1998), and soybean cyst nematode [*Heterodera glycines* Ichinohe] reproduction rates (Anand et al., 1995). These conditions can influence yields in crops such as wheat (*Triticum aestivum* L.) (Whitney and Lamond, 1993; Patiram and Prasad, 1990), soybean [*Glycine max* (L.) Merr.] (Adams et al., 1982; Bell, 1996), corn (*Zea mays* L.) (Adeoye and Singh, 1985; Fox, 1979; Hensler et al., 1970), cotton (*Gossypium hirsutum* L.) (Doss and Lund, 1975; Pearson et al., 1970), grain sorghum [*Sorghum bicolor* (L.) Moench] (Adeoye and Singh, 1985; Duncan, 1991; Walker et al., 1975), and alfalfa (*Medicago sativa* L.) (Dionne et al., 1989; Mahler, 1983; Rechcigl et al., 1986; Van Lierop et al., 1980).

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Neutralizing soil pH at the farm level is hampered by the cost of procuring, transporting, and applying neutralizing materials such as lime. Lime is typically not expensive to purchase from quarries or other sources, yet these sources are not often near the target field (Warmann, 1995). Because large amounts of neutralizing materials are often needed, transport costs often bring into question the economics of liming decisions (Warmann, 1995). Soil pH management is further complicated by the fact that it is often spatially oriented because of spatial differences in soil type, buffering capacities, and yield (Lauzon et al., 2005; Zacharias et al., 1997). The spatial variability of soil pH, coupled with high input costs, has made spatial lime applications one of the most economical applications of site-specific management (Bongiovanni and Lowenberg-DeBoer, 1999). Adamchuk et al. (2004) illustrated that variable-rate lime applications based on automated soil pH sampling had a \$6.13 ha⁻¹ advantage compared with variable rate lime applications based on 1-ha grid samples.

Spatial lime applications have largely been guided by point or grid soil-sampling results. This method of assessing spatial soil variability is hampered by high labor costs. The use of such data also is inherently prone to errors depending on the interpolation method used. Staggenborg et al. (2001) illustrated that inverse-distance and kriging interpolation methods may actually introduce more error than using the grid mean when using soil samples are taken at 1-ha resolution. Laslett and McBratney (1990) reported that the best method of creating a pH surface map was universal kriging when the parameter estimates were predicted using restricted maximum likelihood method.

Real-time sensors offer two distinct advantages for site-specific pH management, immediate data availability, and reduced labor costs. However, when sensors are mounted on a mobile platform, two issues must be addressed. They are (i) obtaining soil-to-sensor contact and (ii) finding a sensor rugged enough to perform in an off-road environment. Viscarra Rossel and McBratney (1997) evaluated a series of pH sensors under the criterion needed for on-the-go or real-time sensing. They addressed the issues of sensor durability and a tine-mounted sensor to achieve soil-to-sensor contact. Adamchuk et al. (1999) proposed a method of removing a soil core so that the soil could be placed in direct contact with the sensor, a pH sensor in their case.

The recent development of a soil sampling system to remove cores rapidly and place them in contact with a pH sensor while in motion will expand the possibilities for real-time soil sensing (Lund et al., 2005). This system utilizes a soil sampling shoe that can collect a soil sam-

Abbreviations: EC, electrical conductivity; MSP, mobile sensor platform; RMSE, root mean square error.

ple while in motion, reducing sample collection time dramatically as soil sampling and pH measurement can be achieved while in motion. It is possible that this continuous movement may influence sensor-to-soil contact and sensor performance, thus affecting pH sensor performance. The objective of this study was to compare soil pH and buffer pH measured from soil cores collected from traditional sampling methods and lab analysis with soil pH measured in real time using a mobile platform equipped with a pH sensor.

MATERIALS AND METHODS

Two fields near Manhattan, KS, were selected for this experiment. The first area sampled was a 4.6-ha subset of a larger

production and research field that is part of the Ashland Research Site near Manhattan, KS (39°7' N, 96°38' W). The Ashland field is comprised of a Wymore silty clay loam soil (fine, smectitic, mesic Aquertic Argiudolls) with a relatively level area at the south end and a sloping area at the north end (Fig. 1). The second area sampled was an 11.6-ha production field near Ogden, KS (96°42' N, 39°7' W). This field represents the transition area near a stream to an upland plateau. As a result, the field is comprised of six soil complexes (Fig. 1). These soil types include a Kenesaw silt loam (coarse-silty, mixed, superactive, mesic Typic Haplustolls) with 2 to 5% slope, Reading silt loam (fine-silty, mixed, superactive, mesic Pachic Argiudolls), a channeled Ivan silty clay loam (fine-silty, mixed, superactive, mesic Cumulic Hapludolls), and two soil complexes, an Ivan-Kenebec silt loam complex (fine-silty, mixed, superactive, mesic Cumulic Hapludolls) and a Bismarckgrove-Kimo complex

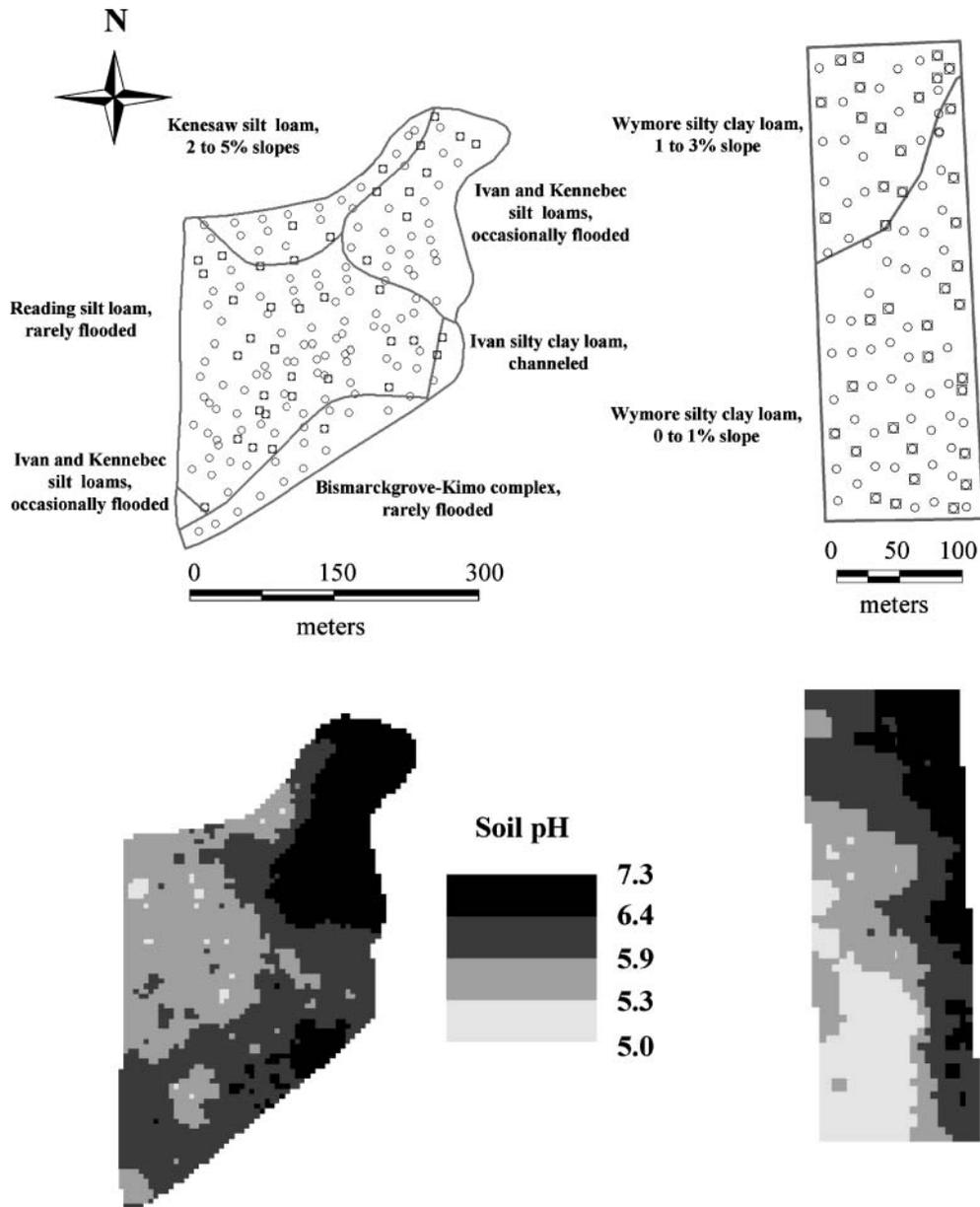


Fig. 1. Two fields sampled by mobile sensor platform (MSP) and lab measurements of pH and buffer pH. Sample locations are represented by (○) for MSP measurements and (□) for soil core (lab) sample locations. Ogden is on the left and Ashland is on the right. The lower figures represent soil pH as interpolated with inverse distance weighting, $P = 1, n = 8$.

(fine-silty, mixed, superactive, mesic Fluventic Hapludolls–clayey over loamy, smectitic, mesic Fluvaquentic Hapludolls). Both sites had not been disturbed since the previous fall crop harvest, with Ashland having soybean residue and Ogden having corn residue on the soil surface.

Soil pH in both fields was measured using a mobile sensor platform equipped with dual pH sensors (Model MSP, Veris Technologies, Salina, KS) on 18 Apr. 2005. The MSP system automatically retrieves a sample and presses it against an ion-selective electrode for analysis as the system is traveling through the field. Sampling depth was ≈ 10 cm. A wash system on the MSP washes the electrodes after each reading and provides water for the pH measurement (Christy et al., 2004). Before the measurements, the sensor was calibrated with standard buffer solutions (pH 4 and pH 7). The distance between passes was 20 m in the Ogden field and 15 m in the Ashland field. These transects resulted in 168 samples being taken from the Ogden field, a sample density of 21 samples ha^{-1} , and 100 samples were taken from the Ashland field, a sample density of 14.5 samples ha^{-1} . Soil EC was measured simultaneously to depths of ≈ 0.3 (EC_s) and 0.9 m (EC_d) (Model 3100, Veris Technologies, Salina, KS).

Soil pH maps were created using GIS software (ArcView 3.2, ESRI, Redlands, CA). To verify the reliability of the MSP pH data, soil sampling locations were identified for each field, with 40 sample points from Ashland and 38 samples points from Ogden selected. Points were selected to span the range of pH values from each field, about 4.5 to 7.6. These sampling sites were located and sampled 7 d after the MSP sampling using a pocket PC (Compaq Ipaq, Model 3680, Hewlett-Packard, Palo Alto, CA) equipped with field software (Farmworks Farm Site Mate, v. 8.22, Farm Works Software, Hamilton, IN) and a wide area augmentation system correction enabled GPS unit (Model 17N, Garmin International, Olathe, KS). Soil cores were collected from the 15-cm depth by removing 10 cores per composite sample in a diameter no farther than 1 m from the MSP sampled site. Samples were split into depths of 0 to 7.5 and 7.5 to 15 cm at sampling time.

All soil testing was completed by the Kansas State Soil Testing Lab. Soil pH was determined at a 1:1 soil–water ratio using an ion selective electrode (Watson and Brown, 1998). Buffer pH was determined using SMP buffer tests as described by Watson and Brown (1998). Soil organic matter content was determined by the Walkley-Black procedure (Combs and Nathan, 1998) and soil cation exchange capacity (CEC) was determined by the ammonium ion replacement method as described by Chapman (1965).

Laboratory results were compared with the MSP value closest to the core sampling site. Data were subjected to *t* tests, correlation analyses, and regression analyses to determine the relationship between MSP pH and the soil properties measured from the manually collected soil samples. Root mean square errors (RMSEs) were calculated for each relationship as a means of determining the error rate of the predictions. These analyses were completed for each location, as well as across locations. When the data from both locations were combined for an overall analysis, a binary value was used to normalize the data from both locations.

Since EC has been reported to vary with soil texture (Corwin and Lesch, 2003; and Kitchen et al., 1999), it seemed intuitive to determine if soil pH measurements from the MSP could be improved by including the EC values in the regression analysis as covariates. When evaluating the impact of EC_s and EC_d in such regression analyses, an *F* test was calculated using Eq. [1] as described in Ott (1990).

$$F_{(df_1, df_2)} = \frac{\text{SSE}_{\text{drop}}}{\text{MSE}_1} \quad [1]$$

SSE_{drop} is the reduction in error sum of squares compared with the base equation of ($Y = \text{intercept} + \text{MSP pH}$) and MSE_1 is the mean square error from the base equation. Significant *F* test results suggest that the inclusion of the additional variable, EC in this case, improves the model fit.

RESULTS AND DISCUSSION

Soil pH

When MSP pH and lab pH from 0 to 7.5 cm are compared, the ranges in soil pH and standard deviations are similar for both locations (Table 1). However, mean MSP pH was higher than the lab pH at Ogden ($P < 0.01$) and was not different at Ashland ($P = 0.25$) (Table 1). Mean MSP pH was higher than the lab pH measured from 7.5 to 15 cm at both locations ($P < 0.05$).

Correlation analyses indicated that lab pH was correlated to MSP pH at all locations and depths (Table 2). These correlations exist for the combined location data as well. Relationships between lab pH and MSP pH were different for each location (Fig. 2 and Table 3). At Ashland, the linear equation indicated that the lab pH and MSP pH values agreed across the range measured at all three depths (Fig. 2 and Table 3). The absolute error ranged from 0.34 to 0.45 pH, with RMSEs of 0.25, 0.31, and 0.24 pH for depths of 0 to 7.5, 7.5 to 15, and 0 to 15 cm, respectively. It might be of concern that the relationship has a bias toward overestimating at lower soil pH (below 5.0) and underestimating in situations with high soil pH situations (above 7.0). This is not likely to be of concern because the predicted values would still be such that low pH soils could be identified with the MSP.

At Ogden, the linear relationship between lab and MSP pH illustrates a bias toward underestimation of pH by the MSP (Fig. 2 and Table 3). Upon inspection, it is clear that 19 data points exist from which lab pH was

Table 1. Laboratory measured mean, range, and standard deviation for soil pH, buffer pH, organic matter (OM), and cation exchange capacity (CEC) measured from samples at two depths from two fields located near Manhattan, KS (Ashland, $n = 38$; Ogden, $n = 40$). Mobile sensor platform (MSP) measured mean, range, and standard deviation for soil pH, and deep and shallow electrical conductivity for the same two fields (Ashland, $n = 100$; Ogden, $n = 138$).

	Ashland			Ogden		
	Mean	Range	SD	Mean	Range	SD
Laboratory						
0 to 7.5 cm depth						
pH	6.12	5.5–7.2	0.53	5.39	4.3–7.5	0.93
buffer pH	6.66	6.5–6.9	0.10	6.72	6.3–7.5	0.32
CEC, meq 100 g ⁻¹	21.76	17.7–29.2	3.09	17.74	7.6–25.7	3.96
OM, %	2.74	0.4–3.0	0.17	2.30	1.5–3.1	0.38
7.5 to 15 cm depth						
pH	6.01	5.2–6.9	0.47	5.07	4.3–7.5	0.84
buffer pH	6.70	6.4–7.0	0.15	6.38	6.0–7.0	0.22
CEC, meq 100 g ⁻¹	21.86	17.6–27.8	2.50	19.09	8.2–25.2	3.65
OM, %	2.41	1.9–2.8	0.21	1.87	0.9–2.6	0.35
MSP						
pH	6.20	4.9–7.7	0.75	6.01	4.5–7.5	0.84
Shallow EC, mS s ⁻¹	13.33	17.9–28.3	2.48	9.08	1.9–15.8	3.39
Deep EC, mS s ⁻¹	42.57	25.0–51.9	5.64	25.05	5.6–42.8	8.80

Table 2. Correlation coefficients for mobile sensor platform (MSP) pH measured, soil EC and lab measurements of soil pH, soil buffer pH, soil organic matter (OM) and cation exchange capacity (CEC) for two fields in Kansas and the entire dataset.

Variable	Correlation with MSP measured pH (<i>r</i>)		
	Ashland	Ogden	Combined
Samples from 0 to 7.5 cm			
pH	0.88**	0.75**	0.74**
Buffer pH	0.19	0.74**	0.66**
OM, g g ⁻¹	-0.29	-0.13	-0.06
CEC	0.15	0.42**	0.33**
Samples from 7.5 to 15 cm			
pH	0.77**	0.69**	0.63**
Buffer pH	0.63**	0.53**	0.49**
OM, g g ⁻¹	-0.12	-0.11	0.01
CEC	-0.03	0.15	0.12
Samples from 0 to 15 cm			
pH	0.87**	0.73**	0.70**
Buffer pH	0.62**	0.73**	0.67**
OM, g g ⁻¹	-0.23	-0.13	-0.04
CEC	0.08	0.31*	0.24*
Other variables			
EC _{shallow} , mS s ⁻¹	0.37*	0.42**	0.39**
EC _{deep} , mS s ⁻¹	0.39*	0.25	0.27**

* Indicates correlation significance at the 0.05 level.

** Indicates correlation significance at the 0.01 level.

substantially lower than the MSP pH (points in oval, Fig. 2). If the differences between these points are examined in comparison with the rest of the data from Ogden, the MSP pH values at these locations were 1.12 pH higher than the lab pH values. If these points are excluded from the data set, the linear equation for the remaining 22 points represents predicted values similar to those found at Ashland. (Lab pH = 0.38 + 0.8 MSP pH, $r^2 = 0.83$ for the 0- to 7.5-cm depth). The most probable explanation for the lower lab pH values for these data points is that ≈ 3 wk before the MSP measurements and 4 wk before the hand sampling, anhydrous ammonia (NH₃) was applied to the field at a depth of ≈ 5 to 10 cm at rates that would supply ≈ 150 kg N ha⁻¹. When the soil samples were removed for the lab sample, 10 cores in a 1-m radius were taken. This alone significantly increases the probability that a sample might have been removed from a zone of low pH that was created by the anhydrous application. Robbins and Voss (1989) reported that the acid soil zones around such an application extending in a circular pattern with diameters from 12 to 18 cm. So samples could be affected even if attempts were made to avoid sampling directly in the ammonia application zone.

When the data from both locations were combined, the relationship was obviously influenced by the aberrant points from the Ogden field (Fig. 2 and Table 3). The resulting linear equations continue to illustrate the bias toward underestimation across the range of pH values measured for all three depths. If these same 19 points are excluded from the combined analysis, the resulting linear equations are

$$\text{Lab pH} = 1.04 + 0.81 \text{ MSP pH} \quad (r^2 = 0.83)$$

for the 0- to 7.5-cm depth, [2]

$$\text{Lab pH} = 1.49 + 0.70 \text{ MSP pH} \quad (r^2 = 0.68)$$

for the 7.5- to 15-cm depth, [3]

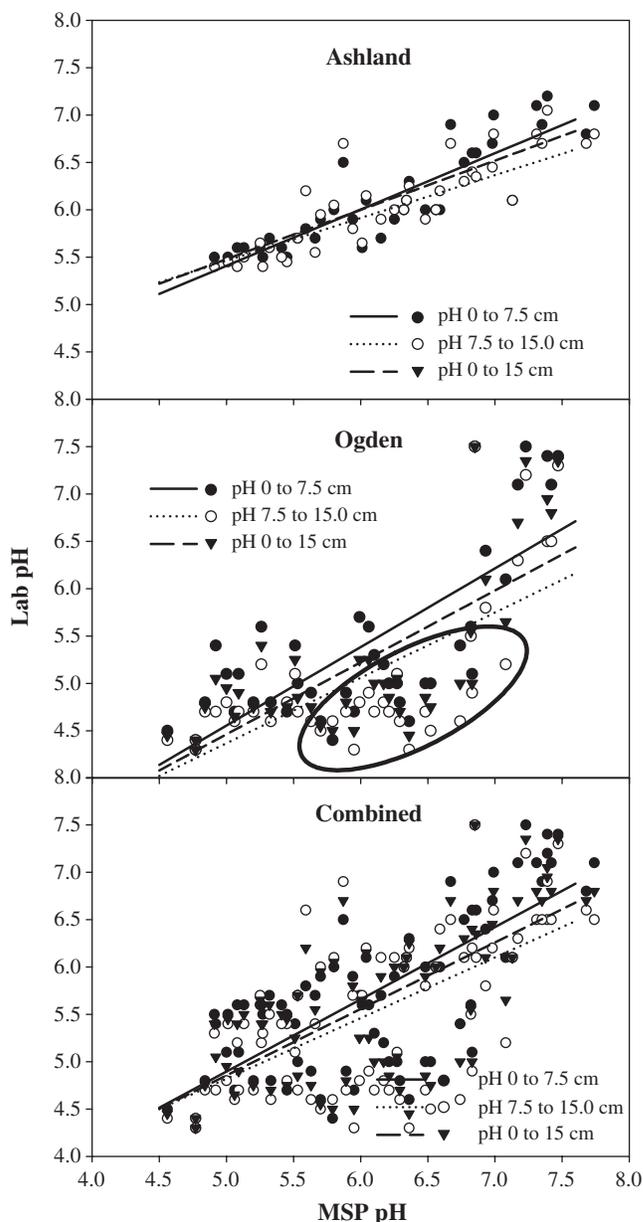


Fig. 2. Lab pH as function of mobile sensor platform (MSP) pH at two locations near Manhattan, KS, and the combined data set for both locations.

$$\text{Lab pH} = 1.27 + 0.76 \text{ MSP pH} \quad (r^2 = 0.79)$$

for the 0- to 15-cm depth. [4]

These results illustrate that the MSP system is capable of measuring soil pH with results similar to those expected from traditional soil sampling. The greatest advantage of the MSP is sampling density and reduced labor costs associated with collecting soil samples at this density. A seeming limitation of the MSP system may be sampling depth since it is limited based on the core removal method when compared with a soil coring tool. The MSP will allow land managers to collect spatial soil pH layers frequently to evaluate the need for, or the effects of, soil pH remediation methods. Obviously, the

Table 3. Regression analysis for lab pH as predicted from mobile sensor platform (MSP) pH measured in fields near Ashland and Ogden, KS, and for the combined dataset.

Location	Depth	Linear Equation	r^2
Ashland	0–7.5 cm	$\text{pH} = 2.44 + 0.59 \text{ MSP pH}^*$	0.78
	7.5–15 cm	$\text{pH} = 3.20^* + 0.45 \text{ MSP pH}^*$	0.59
	0–15 cm	$\text{pH} = 2.82^* + 0.52 \text{ MSP pH}^*$	0.75
Ogden	0–7.5 cm	$\text{pH} = 0.40 + 0.83 \text{ MSP pH}^*$	0.56
	7.5–15 cm	$\text{pH} = 0.92^* + 0.69 \text{ MSP pH}^*$	0.47
	0–15 cm	$\text{pH} = 0.66^* + 0.76 \text{ MSP pH}^*$	0.53
Combined	0–7.5 cm	$\text{pH} = 1.08^* + 0.76 \text{ MSP pH}^*$	0.54
	7.5–15 cm	$\text{pH} = 1.62^* + 0.64 \text{ MSP pH}^*$	0.40
	0–15 cm	$\text{pH} = 1.35^* + 0.70 \text{ MSP pH}^*$	0.49

* Indicates that either the intercept is significantly different than 0 or the slope is significantly different than 1.0, both at the 0.05 level.

cost of the system is higher than manual sampling systems and this will need to be considered in any decisions to adopt this technology.

Buffer pH

Buffer pH measured from 0 to 7.5, 7.5 to 15, and 0 to 15 cm was correlated to MSP pH at Ogden and the combined data set (Table 2). Buffer pH measured from 0 to 7.5 cm at Ashland was not correlated to MSP pH, whereas the other two depths were. The low correlation at the surface was the result of the narrow range of buffer pH measured (Table 1).

As expected, the relationship between MSP pH and lab measured buffer pH was more variable and did not follow the 1:1 relationship that pH did (Fig. 3 and Table 4). The narrow range of buffer pH at Ashland resulted in steep relationships for buffer pH and MSP pH measured from 7.5 to 15 cm and 0 to 15 cm, whereas at Ogden and in the combined data set the MSP pH and buffer pH relationships contain intercepts that approach zero and slopes that approach one (Fig. 3 and Table 4). As observed at Ashland, the MSP at Ogden captured less of the variability in buffer pH than in pH.

These results suggest that before MSP pH data can be used to make lime recommendations, localized calibrations will be necessary to attempt to relate soil pH to buffer pH and/or subsequent lime requirements. If current soil pH, buffer pH, and lime requirement approaches are considered, one might propose developing a soil pH to buffer pH relationship using lab data and then use this relationship to convert MSP pH to lime requirements in real time or near real time. Creating a pH to buffer pH relationship from the lab data at each location results in two similar relationships (Fig. 4A) with pH accounting for less variability in buffer pH at Ashland than at Ogden. But the two data sets seem to represent similar populations. Using either the individual location pH to buffer pH relationship or the entire dataset, one can now construct a predicted buffer pH for each measured by the MSP (Fig. 4B). In either method, the predicted buffer pH is similar to the measured buffer pH, with r^2 of 0.95 when the entire dataset relationship is used.

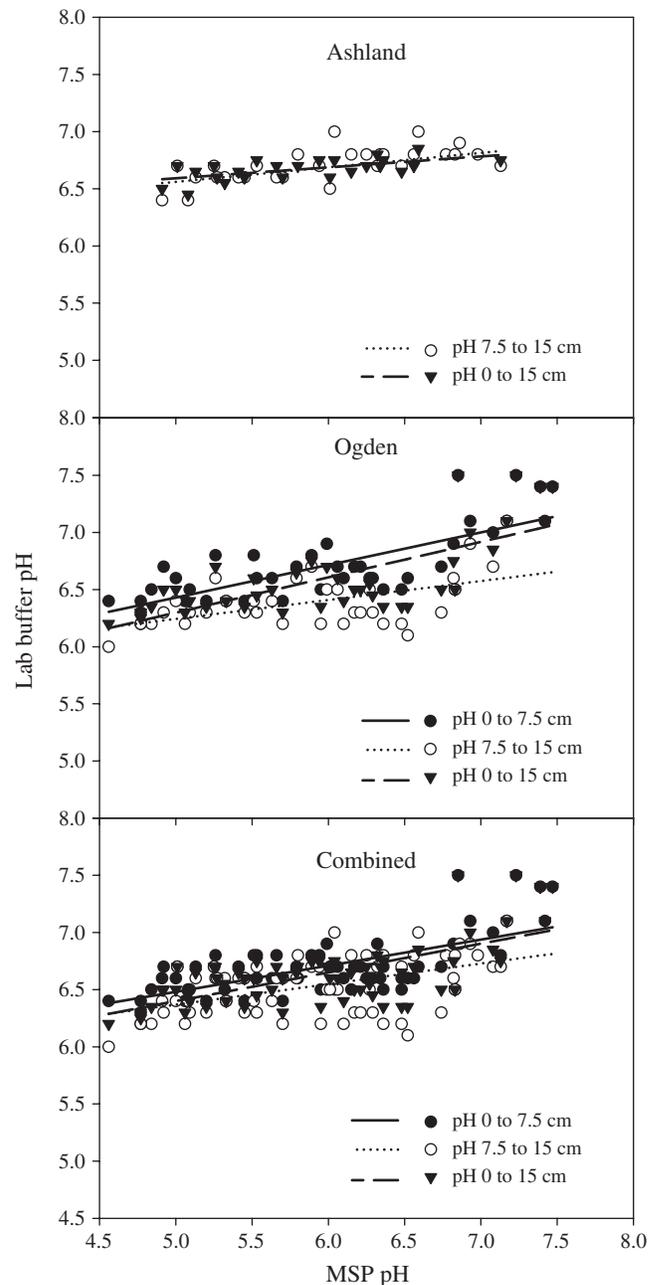


Fig. 3. Lab buffer pH as a function of mobile sensor platform (MSP) pH at two locations near Manhattan, KS, and the combined dataset from both locations.

The above approach would, however, propagate any errors in either of the steps (pH to buffer pH and buffer pH to lime requirement). A better approach would be to develop a soil pH to lime requirement relationship. An approach similar to that used by Viscarra Rossel and McBratney (1999, 2000) would be appropriate. Using soil- CaCO_3 incubation data from 22 soils from New South Wales, Australia, they develop single and two factor empirical response surface models for directly determining lime requirements from soil pH and buffer pH. These approaches improve lime requirement predictions compared with standard regression lime re-

Table 4. Regression analysis result for buffer pH as a function of mobile sensor platform (MSP) pH in fields near Ashland and Ogden, KS, and in the combined dataset.

Location	Depth	Linear equation	r^2
Ashland	0–7.5 cm	Buffer pH = 6.45* + 0.03 MSP pH	0.04
	7.5–15 cm	Buffer pH = 5.93* + 0.13 MSP pH*	0.47
	0–15 cm	Buffer pH = 6.11* + 0.09 MSP pH*	0.38
Ogden	0–7.5 cm	Buffer pH = 5.01* + 0.28 MSP pH*	0.55
	7.5–15 cm	Buffer pH = 5.42* + 0.17 MSP pH*	0.28
	0–15 cm	Buffer pH = 4.75* + 0.31 MSP pH*	0.37
Combined	0–7.5 cm	Buffer pH = 5.34* + 0.23 MSP pH*	0.44
	7.5–15 cm	Buffer pH = 5.47* + 0.18 MSP pH*	0.24
	0–15 cm	Buffer pH = 5.14* + 0.25 MSP pH*	0.46

* Indicates that either the intercept is significantly different than 0 or the slope is significantly different than 1.0, both at the 0.05 level.

quirement methods that are often used by soil test labs. Once such a model has been developed, MSP pH can be used to measure soil pH and produce lime requirements in real time.

The approach suggested above and by Viscarra Rossel and McBratney (2000) is beyond the scope of the data collected in this experiment as only two fields from a

narrow geographic region are represented. It may be necessary to develop regional pH–lime requirement relationships. It may also be necessary, within an area, to develop these relationships on the basis of soil types because soil buffering capacity will change with soil texture and subsequent soil chemical properties.

Inclusion of Soil Electrical Conductivity

Another variable that may be useful in developing pH relationships is soil EC. Since the MSP has the ability to measure soil pH and EC simultaneously, it may be possible to capitalize on this data set to improve the prediction of soil buffer pH. Soil EC has been reported to be influenced by soil texture (Corwin and Lesch, 2003; Williams and Hoey, 1987; Cook et al., 1992; Kitchen et al., 1999), soil bulk density (Doolittle et al., 1994), soil salinity (Williams and Baker, 1982; Rhoades et al., 1989), and soil moisture content (Corwin and Lesch, 2003; Sheets and Hendrickx, 1995). These results suggest that EC may be used as a proxy for soil type and thus improve the MSP predictive ability for buffer pH.

At Ashland, EC did not improve the relationship between lab pH and MSP pH, as measured by reductions in the mean square error for any of the depths (Table 5). At Ogden, however, including the polynomial response of either EC_s or EC_d improved the model for lab pH as a function of MSP pH at all three depths (Table 5). At both locations, the inclusion of EC did not improve the relationship between buffer pH. These results are not unexpected because the soil types at each location are drastically different in their composition. At Ashland, the soil type is the same throughout the sampling area, with only slope affecting the soil designation based on the soil survey (Fig. 1). At Ogden, however, the soil survey for the field consists of six different polygons with unique soil designations. These designations include silt loams and clay loam soils. As these soil types changed, it is likely that the soil EC changed, along with a systematic bias in the pH, as indicated by the inclusion of each in the final model.

CONCLUSIONS

Measuring soil pH with a MSP resulted in predictions of lab pH that were within 6% at one location and 13% at a second location. The direct prediction of buffer pH was less accurate, with R^2 ranging from 0.03 to 0.55. This suggests that if MSP values are to be used to develop real-time lime recommendations, a method to predict buffer pH or lime requirements directly from MSP pH will need to be developed. The inclusion of EC (shallow or deep) improved the MSP-predicted pH for the field that contained numerous soil types. In the field with a more uniform soil, the inclusion of EC did not affect predicted pH accuracy. The errors in the MSP approach compared with lab pH are offset by the increased data density, timeliness of the data, and reduced labor costs to collect the data.

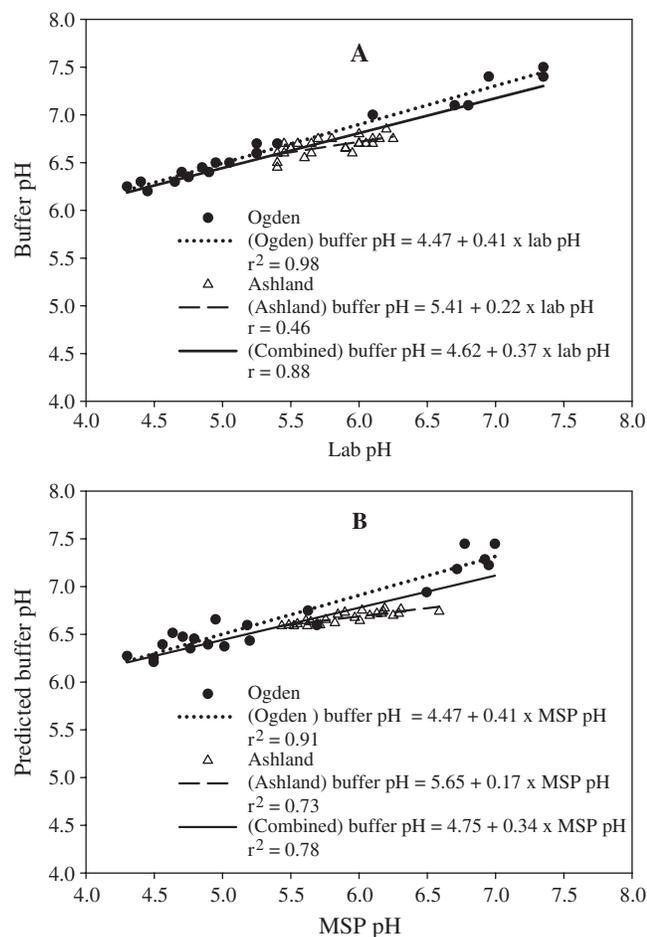


Fig. 4. (A) Buffer pH and soil pH from soil samples collected from two fields near Manhattan, KS, and the combined dataset. (B) Buffer pH predicted from mobile sensor platform (MSP) pH and the relationships in (A).

Table 5. Partial regression analysis drop in mean square errors and R^2 for regression containing mobile sensor platform (MSP) pH, EC_s (soil electrical conductivity shallow), and EC_d (soil electrical conductivity deep) from the Ashland and Ogden fields.

Variable (Y)†	Equation	Ashland		Ogden	
		MSE reduction	R^2	MSE reduction	R^2
pH ₀₇₅	Y = intercept + MSP pH	–	0.78	–	0.56
	Y = intercept + MSP pH + EC _s	0.02	0.78	0.73	0.58
	Y = intercept + MSP pH + EC _s + EC _s ²	0.09	0.79	0.28	0.56
	Y = intercept + MSP pH + EC _d	0.05	0.79	3.37*	0.65
	Y = intercept + MSP pH + EC _d + EC _d ²	0.10	0.79	2.87*	0.64
pH ₇₅₁₅	Y = intercept + MSP pH	–	0.59	–	0.47
	Y = intercept + MSP pH + EC _s	0.17	0.60	0.32	0.48
	Y = intercept + MSP pH + EC _s + EC _s ²	0.16	0.59	0.21	0.48
	Y = intercept + MSP pH + EC _d	0.17	0.61	2.28*	0.55
	Y = intercept + MSP pH + EC _d + EC _d ²	0.01	0.59	1.75*	0.53
pH ₀₁₅	Y = intercept + MSP pH	–	0.75	–	0.53
	Y = intercept + MSP pH + EC _s	0.02	0.76	0.51	0.54
	Y = intercept + MSP pH + EC _s + EC _s ²	0.01	0.75	0.25	0.54
	Y = intercept + MSP pH + EC _d	0.03	0.76	2.80*	0.62
	Y = intercept + MSP pH + EC _d + EC _d ²	0.01	0.75	2.28*	0.60
Buffer pH ₀₇₅	Y = intercept + MSP pH	–	0.04	–	0.39
	Y = intercept + MSP pH + EC _s	0.02	0.08	0.01	0.40
	Y = intercept + MSP pH + EC _s + EC _s ²	0.01	0.06	0.04	0.42
	Y = intercept + MSP pH + EC _d	0.02	0.09	0.06	0.44
	Y = intercept + MSP pH + EC _d + EC _d ²	0.01	0.07	0.09	0.46
Buffer pH ₇₅₁₅	Y = intercept + MSP pH	–	0.38	–	0.28
	Y = intercept + MSP pH + EC _s	0.01	0.38	0.01	0.28
	Y = intercept + MSP pH + EC _s + EC _s ²	0.01	0.40	0.02	0.30
	Y = intercept + MSP pH + EC _d	0.01	0.41	0.03	0.29
	Y = intercept + MSP pH + EC _d + EC _d ²	0.01	0.41	0.01	0.30
Buffer pH ₀₁₅	Y = intercept + MSP pH	–	0.38	–	0.37
	Y = intercept + MSP pH + EC _s	0.01	0.40	0.01	0.37
	Y = intercept + MSP pH + EC _s + EC _s ²	0.01	0.43	0.03	0.39
	Y = intercept + MSP pH + EC _d	0.01	0.43	0.04	0.39
	Y = intercept + MSP pH + EC _d + EC _d ²	0.01	0.44	0.06	0.40

* Indicates significant *F* test to test differences between the respective regression and the base regression of $Y = \text{intercept} + \text{MSP pH}$.

† pH₀₇₅, soil pH of sample taken from 0 to 7.5 cm; pH₇₅₁₅, pH from soil taken from 7.5 to 15 cm; pH₀₁₅, average soil pH of pH₇₅ and pH₇₅₁₅; Buffer pH₀₇₅, buffer soil pH of sample taken from 0 to 7.5 cm; Buffer pH₇₅₁₅, buffer pH from soil taken from 7.5 to 15 cm; Buffer pH₀₁₅ = average soil buffer pH of pH₇₅ and pH₇₅₁₅.

REFERENCES

- Adamchuk, V.I., M.T. Morgan, and D.R. Ess. 1999. An automated sampling system for measuring soil pH. *Trans. ASAE* 42(4):885–891.
- Adamchuk, V.I., M.T. Morgan, and J.M. Lowenberg-DeBoer. 2004. A model for agro-economic analysis of soil pH mapping. *Precis. Agric.* 5:111–129.
- Adams, J.F., F. Adams, and J.W. Odom. 1982. Interaction of phosphorus and soil pH on soybean yield and soil solution composition of two phosphorus-sufficient Ultisols. *Soil Sci. Soc. Am. J.* 46:323–328.
- Adeoye, K.B., and L. Singh. 1985. The effect of bulk application of lime under two tillage depths on soil pH and crop yield. *Plant Soil* 85:295–297.
- Anand, S.C., K.W. Watson, and S.B. Sharma. 1995. Effect of soil temperature and pH on resistance of soybean to *Heterodera glycines*. *J. Nematol.* 27:478–482.
- Bell, P.F. 1996. Predicting liming needs of soybean using soil pH, aluminum and manganese soil tests. *Commun. Soil Sci. Plant Anal.* 27:2749–2764.
- Bongiovanni, R., and J. Lowenberg-DeBoer. 1999. Economics of variable rate lime in Indiana. p. 1653–1666. *In* P. Robert (ed.) *Precision agriculture: Proc. of the 4th Int. Conf.*, St. Paul, MN, 19–22 July 1998. ASA, CSSA, and SSSA, Madison, WI.
- Chapman, H.D. 1965. Cation exchange capacity. p. 891–901. *In* C.A. Black et al. (ed.) *Methods of soil analysis*. Agron. Monogr. 9. ASA, Madison, WI.
- Christy, C., K. Collings, P. Drummond, and E. Lund. 2004. A mobile sensor platform for measurement of soil pH and buffering. Paper 041042. ASAE, St. Joseph, MI.
- Combs, S.M., and M.V. Nathan. 1998. Soil organic matter. p. 53–58. *In* Recommended chemical soil test procedures for the north central region. North Central Regional Res. Publ. 221 (revised). Missouri Agric. Exp. Stn., Columbia.
- Cook, P.G., G.R. Walker, G. Buselli, I. Potts, and A.R. Dodds. 1992. The application of electromagnetic techniques to groundwater recharge investigations. *J. Hydrol. (Amsterdam)* 130:201–229.
- Corwin, D.L., and S.M. Lesch. 2003. Application of soil electrical conductivity to precision agriculture: Theory, principles, and guidelines. *Agron. J.* 95:455–471.
- Dionne, J.L., A.R. Peasant, G.M. Barnett, and W.N. Mason. 1989. Effect of temperature and moisture regimes and soil pH on alfalfa response to phosphorus applications. *Can. J. Plant Sci.* 69:1149–1163.
- Doolittle, J.A., K.A. Sudduth, N.R. Kitchen, and S.J. Indorante. 1994. Estimating depths to clay pans using electromagnetic induction methods. *J. Soil Water Conserv.* 49:572–575.
- Doss, B.D., and Z.F. Lund. 1975. Subsoil pH effects on growth and yield of cotton. *Agron. J.* 67:193–196.
- Duncan, R.R. 1991. The influence of soil pH on sorghum grain yields. *Commun. Soil Sci. Plant Anal.* 22:1605–1611.
- Fageria, N.K., and V.C. Baligar. 1999. Growth and nutrient concentrations of common bean, lowland rice, corn, soybean, and wheat at different soil pH on an Inceptisol. *J. Plant Nutr.* 22:1495–1507.
- Fox, R.H. 1979. Soil pH, aluminum saturation and corn grain yield. *Soil Sci.* 127:330–334.
- Havlin, J.L., and J.D. Beaton. 1998. *Soil fertility and fertilizers*. 6th ed. Prentice Hall, Upper Saddle River, NJ.
- Hensler, R.F., R.J. Olsen, and O.J. Attoe. 1970. Effect of soil pH and application rate of dairy cattle manure on yield and recovery of twelve plant nutrients by corn. *Agron. J.* 62:828–830.
- Kitchen, N.R., K.A. Sudduth, and S.T. Drummond. 1999. Soil electrical conductivity as a crop productivity measure for claypan soils. *J. Prod. Agric.* 12:607–617.

- Laslett, G.M., and A.B. McBratney. 1990. Further comparison of spatial methods for predicting soil pH. *Soil Sci. Soc. Am. J.* 54:1553–1558.
- Lauzon, J.D., I.P. O'Halloran, D.J. Fallow, A.P. Bertoldi, and D. Aspinall. 2005. Spatial variability of soil test phosphorus, potassium, and pH of Ontario. *Agron. J.* 97:524–532.
- Lund, E.D., V.I. Adamchuk, K.L. Collings, P.E. Drummond, and C.D. Christy. 2005. Development of soil pH and lime requirement maps using on-the-go soil sensors. *Proc. 5th Eur. Conf. on Precision Agric.*, Malmö, Sweden.
- McLean, E.O. 1982. Soil pH and lime requirement. p. 199–224. *In* A.L. Page et al. (ed.) *Methods of Soil Analysis: Part 2. Chemical and mechanical properties*. Agron. Monogr. 9. ASA and SSSA, Madison, WI.
- Mahler, R.L. 1983. Influence of pH on yield and N and P nutrition of alfalfa grown on an Andic Mission silt loam. *Agron. J.* 75:731–735.
- Ott, L. 1990. *Introduction to statistical methods and data analysis*. PWS Publ., New York.
- Patiram, R.N., and R.N. Prasad. 1990. Frequency of lime application to wheat–maize crop sequence on an acid soil of Sikkim. *J. Indian Soc. Soil Sci.* 38(4):723–726.
- Pearson, R.W., L.F. Ratliff, and H.M. Taylor. 1970. Effect of soil temperature, strength, and pH on cotton seedling root elongation. *Agron. J.* 62:243–246.
- Rechcigl, J.E., R.B. Reneau, Jr., D.C. Wolf, W. Kroontje, and S.W. VanScoyoc. 1986. Alfalfa seedling growth in nutrient solutions as influenced by aluminum, calcium, and pH. *Commun. Soil Sci. Plant Anal.* 17:27–44.
- Rhoades, J.D., N.A. Manteghi, P.J. Shouse, and W.J. Alves. 1989. Soil electrical conductivity and soil salinity: New formulations and calibrations. *Soil Sci. Soc. Am. J.* 53:433–439.
- Robbins, S.G., and R.D. Voss. 1989. Acidic zones from ammonia application in conservation tillage systems. *Soil Sci. Soc. Am. J.* 53:1256–1263.
- Sheets, K.R., and J.M.H. Hendrickx. 1995. Non-invasive soil water content measurement using electromagnetic induction. *Water Resour. Res.* 31:2401–2409.
- Staggenborg, S.A., R.K. Taylor, and J.P. Schmidt. 2001. Predicting spatial soils data from adjacent data-testing an accepted method. *Agron. Abstr.* Vol. 93. Publ. a08-staggenborg121058-0.
- Tsakelidou, K. 2000. Effect of calcium carbonate as determined by lime requirement buffer pH methods on soil characteristics and yield of sorghum plants. *Commun. Soil Sci. Plant Anal.* 31:1249–1260.
- Van Lierop, W., Y.A. Martel, and M.P. Cescas. 1980. Optimal soil pH and sufficiency concentrations of N, P and K for maximum alfalfa and onion yields on acid organic soils. *Can. J. Soil Sci.* 60:107–117.
- Viscarra Rossel, R.A., and A.B. McBratney. 1997. Preliminary experiments towards the evaluation of a suitable soil sensor for continuous 'on-the-go' field pH measurements. p. 493–502. *In* J.V. Stafford (ed.) *Precision agriculture '97*. Vol. 2. Technology, IT and management. Bios Scientific Publ., Oxford.
- Viscarra Rossel, R.A., and A.B. McBratney. 1999. Calibration of a lime requirement buffer for site-specific lime applications in southeastern Australia. p. 429–440. *In* J.V. Stafford (ed.) *Precision Agriculture '99*. Proc. of the 2nd Eur. Conf. on Precision Agriculture. Part I. Sheffield Academic Press, UK.
- Viscarra Rossel, R.A., and A.B. McBratney. 2000. A two-factor empirical deterministic response surface calibration model for site-specific predictions of lime requirement. *Prec. Agric.* 2:163–178.
- Walker, M.E., W.H. Marchant, and W.J. Ethredge. 1975. Effects of soil pH on forage yield and chemical composition of sorghum and millet. *Agron. J.* 67:191–193.
- Warmann, G.W. 1995. *Economics of liming cropland in Kansas*. No. MF-2137. Kansas State Univ. Agric. Exp. Stn. and Coop. Ext. Service, Manhattan.
- Watson, M.E., and J.R. Brown. 1998. pH and lime requirements. *In* Recommended chemical soil test procedures for the North Central Region. North Central Regional Publ. 221 (revised). Univ. of Missouri Agric. Exp. Stn., Columbia.
- Whitney, D.A., and R.E. Lamond. 1993. *Liming acid soils*. No. MF-1065. Kansas State Univ. Agric. Exp. Stn. and Coop. Ext. Service, Manhattan.
- Williams, B.G., and G.C. Baker. 1982. An electromagnetic induction technique for reconnaissance surveys of soil salinity hazards. *Aust. J. Soil Res.* 20:107–118.
- Williams, B.G., and D. Hoey. 1987. The use of electromagnetic induction to detect the spatial variability of the salt and clay contents of soils. *Aust. J. Soil Res.* 25:21–28.
- Yang, J., R.W. Blanchar, R.D. Hammer, and A.L. Thompson. 1996. Soybean growth and rhizosphere pH as influenced by a horizon thickness. *Soil Sci. Soc. Am. J.* 60:1901–1907.
- Zacharias, S., C.D. Heatwole, and J.B. Campbell. 1997. Spatial trends in the texture, moisture content, and pH of a Virginia Coastal Plain soil. *Trans. ASAE* 40:1277–1284.