
# Seeing What Sampling Misses: Finding Hidden Yield Barriers with Multi-Sensor Soil Sensing

**Tyler J. Lund[1], Eric D. Lund[1], Chase R. Maxton[1]**

**[1]Veris Technologies, Salina, Kansas, USA**

**A paper from the Proceedings of the**

**17th International Conference on Precision Agriculture and 11th Brazilian Congress on Precision and Digital Agriculture**

**13-15 July 2026**

**Porto Alegre, Brazil**

*Abstract.*

*Yield maps show where a crop struggled; they rarely explain why. Grid soil samples add trusted laboratory measurements, but their interpretation is limited by sampling density and depth. This case study evaluated whether adding proximal soil sensor data to conventional grid sampling improved interpretation of yield variability and management decisions in a central Kansas rain-fed maize field. Two information scenarios were compared: yield data plus one-hectare grid soil samples, and the same information supplemented with proximal soil sensing.*

*The lab-only interpretation ruled out shallow organic matter, cation exchange capacity (CEC), phosphorus, and potassium as primary yield drivers and identified acidity and base status as plausible management concerns. Sensor-informed analysis showed that the acidity signal was part of a broader soil-landscape and profile pattern. When scanned, on-the-go bulk apparent electrical conductivity ($EC_a$) data were used to estimate yield potential across seven soil zones, attainable yield declined from approximately 15.3 to 9.0 t/ha and followed a strong linear pattern ($R^2$ = 0.94).*

*Additionally, CoreScan profile measurements and deep-core samples showed that low-yield locations differed from the high-yield location below the standard grid-sampling depth in pH, clay, CEC, organic matter, and sodium saturation. The sensor-informed scenario did not eliminate the lime recommendation; it improved the quality of the advice. It allowed lime response to be treated as a zone-specific, testable hypothesis rather than a uniform expectation across all low-pH or low-yield areas.*

*Higher-density pH sensing also provided up to 251 pH observations compared with 27 grid samples, a 9.3x increase in observation density for refining variable-rate prescription accuracy while laboratory pH and buffer pH remained the recommendation anchor. The results suggest that modern soil sensing does not replace lab analysis or eliminate uncertainty, but it can narrow hypotheses, improve variable-rate prescription accuracy, and support targeted trials for input response, compaction investigation, profile amendments, and yield-goal-based input management.*

*Keywords. precision agriculture, soil sensing, yield variability, soil pH, electrical conductivity, topsoil depth, $EC_a$-derived yield-potential analysis, site-specific management*

# Introduction

Precision agriculture often starts with two trusted layers: yield maps and laboratory soil samples. Together they show where crop performance and soil chemistry vary, but they do not always answer the questions that drive management: what is causing yield to vary, what can be done about it, and how should inputs or management changes be targeted? This case study uses one central Kansas rain-fed maize field to evaluate how yield diagnosis and management response change when proximal soil sensing is added to yield and laboratory soil data.

Laboratory soil analysis remains the foundation for evaluating fertility and lime need because it provides controlled chemical measurements that can be compared with established sufficiency and recommendation guidelines. However, conventional grid sampling is often sparse relative to the spatial complexity of a field. A soil sample may accurately describe the point where it was collected while still leaving uncertainty about conditions between sample points, below the sampled depth, and physical properties that are best measured in situ.

That uncertainty matters because interpretation eventually becomes a management decision. When the cause of yield variation is unclear, a farmer or advisor can choose the wrong response, apply a reasonable input in the wrong place, or set yield expectations without knowing whether a zone is inherently limited or limited by a correctable condition. A lime recommendation, fertility change, compaction investigation, or yield-goal adjustment may all be defensible from partial information, but each carries cost if the diagnosis or boundary is wrong. Additional information is valuable when it narrows the likely causes of yield variation, sharpens prescription boundaries, and focuses follow-up sampling or trials where profitable response is most likely.

Proximal soil sensing can add spatial, physical, and vertical context to laboratory and yield data. Bulk apparent electrical conductivity ($EC_a$) can describe soil-zone patterns related to texture, water storage, topsoil depth, and salinity. Field pH sensing can improve the spatial resolution of acidity and alkalinity management. Profile measurements, including depth-specific $EC_a$, Vis-NIR optical reflectance, moisture, and insertion force, can indicate whether soil conditions below the surface help explain yield differences, with insertion force providing an in situ screen for compaction or root restriction. Vis-NIR optical measurements can also support carbon investigation and baseline stock estimates for emerging regulatory and ecosystem-market applications when locally calibrated.

This case study compares two practical information scenarios. The first is the interpretation available from 2024 maize yield and conventional 1 ha grid samples alone. The second adds proximal soil sensing, profile measurements, and terrain. The goal was to evaluate how each added layer changed diagnosis, management confidence, and the spatial basis for variable-rate decisions.

# Materials and Methods

## Field and Yield Data

The case study was conducted in a central Kansas rain-fed production field with substantial within-field yield variation. The field has been managed under long-term no-till production, and intensified crop rotations have increased the need to identify yield-limiting factors more precisely. The field represented a common precision-agriculture problem: yield maps showed clear spatial differences in crop performance, but the cause of those differences was not obvious from yield data alone.

The analysis used 2024 maize yield, reported as metric tons per hectare (t/ha), as the primary crop-performance layer. Yield data were assembled with lab soil samples, proximal soil sensor measurements, and topographic variables in a common spatial dataset so that lab-only and sensor-informed interpretations could be compared at matched locations. The spatial distribution of yield, laboratory, and sensor observations used in the case study is shown in Fig 1.

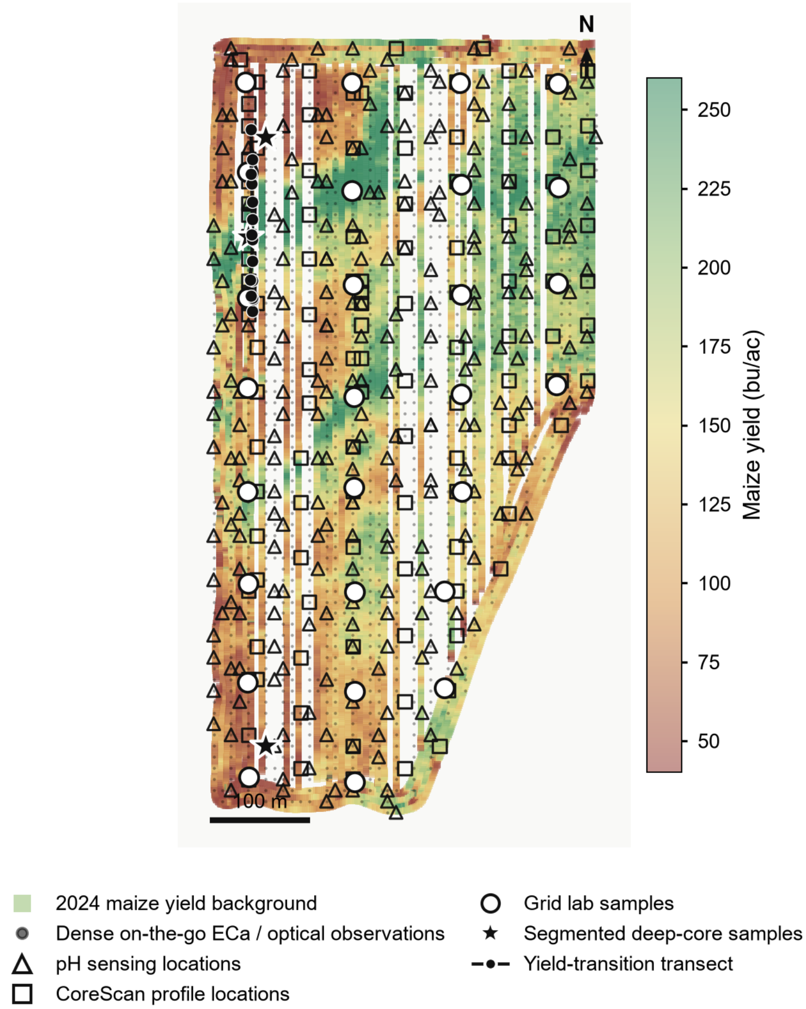


**Fig 1.** Field data locations used in the case study. The colored background shows 2024 maize yield monitor data. Symbols identify conventional grid soil samples, pH sensing locations, CoreScan profile locations, segmented deep-core samples, and the targeted yield-transition transect. Dense on-the-go $EC_a$ and optical observations are shown as small black scan-path points for spatial context

## Laboratory Soil Sampling

Conventional soil sampling was conducted on a 1 ha grid. The dataset included 27 grid soil samples collected from the 0-15 cm depth, with sample locations representing the center of each grid cell. Samples were analyzed for pH, buffer pH, phosphorus, potassium, organic matter, cation exchange capacity (CEC), base saturation, and related fertility properties.

These data represented the lab-only reference layer available for interpreting yield patterns and considering lime and fertility management actions. Laboratory values were retained as point observations for the correlation analysis.

## Proximal Soil Sensor Measurements

Soil sensor measurements were organized by the soil property or condition they helped characterize rather than by the platform used to collect them. This was important because several soil scanning platforms can carry similar sensor technologies. The agronomic question was not which platform performed best, but how each measured soil property changed yield interpretation and management decisions.

The soil scanning platforms used in this case study are commercial tools rather than manual research-only sampling methods: the ProScan, CoreScan, and U3 systems (Veris Technologies, Salina, Kansas, USA) are automated systems allowing readings to be collected approximately 8 to 12 seconds per location. This makes sampling densities such as the 0.4 ha sampling resolution, or about 2.5 measurement locations per hectare, used in this study practical at commercial field scale; under suitable conditions, probe-based collection can approach 28 ha per hour. The sensor measurements and commercial platforms are summarized in Table 1 and shown in Fig 2.

**Table 1. Soil sensor measurements used to support case-study interpretation.**

| Sensor technology | Sensing mechanism / method | Soil property or agronomic condition characterized | Platforms used or applicable |
|---|---|---|---|
| Bulk apparent electrical conductivity ($EC_a$) | Electrode-based contact sensing. A known electrical current or voltage is introduced into the soil, and the response is measured between electrode contacts to estimate $EC_a$. | Spatial soil variability associated with texture, water-holding capacity, CEC, and salinity where present. | U3: on-the-go $EC_a$ at 1 Hz on 15 m transects.<br>ProScan: rapid $EC_a$ point measurements, typically more than 2 per ha.<br>CoreScan: depth-specific profile $EC_a$ at 1 cm increments to 60 cm. |
| Soil pH electrode | Ion-selective pH electrodes metalloid tips measure soil acidity | Soil acidity and alkalinity | U3 and ProScan: Automated Point-based pH sensing at approximately 3-8 cm, typically more than 2 per ha.<br>MSP3: on-the-go pH provides ~20 pH readings per ha |
| Penetration resistance / insertion force | Penetrometer-style force sensing during probe insertion. | Root restriction or compaction context; used to evaluate whether physical resistance patterns helped explain yield variation or profile interpretation. | ProScan: insertion force from 0-40 cm.<br><br>CoreScan: profile force from 0-60 cm. |
| Vis-NIR Optical reflectance | Dual-wavelength visible and near-infrared reflectance through a soil-contact optical window 660 nm red and 950 nm wavelengths. | Organic matter/carbon context, soil color or profile differences, and other optical soil-response patterns. | U3: runner-mounted optical/OM sensing at approximately 3-8 cm..<br><br>CoreScan: profile optical readings by depth at 1 cm increments to 60 cm |
| Capacitance moisture | Capacitance-based dielectric sensing. | Profile moisture status; used primarily to interpret probe-based layers where moisture differences could influence readings, and secondarily as possible water-related yield context. | CoreScan: depth-specific profile moisture at 1 cm increments to 60 cm |

**Fig 2.** Veris MSP3, U3, ProScan, and CoreScan systems (Veris Technologies, Salina, Kansas, USA)

### Topographic Measurements

Topographic variables were included to provide landscape context for interpreting yield and sensor patterns. Elevation data were based on the USGS 1 m bare-earth digital elevation model tile, produced through the 3D Elevation Program, with elevations referenced to NAVD88 in UTM coordinates (U.S. Geological Survey 2023). Slope, curvature, and relative elevation were derived from that elevation surface.

### Data Pairing and Analysis

All data layers were assembled into a common spatial master dataset. Laboratory samples were retained as point observations and matched to nearby yield and sensor observations. Sensor observations were matched to nearby yield, lab, or analysis locations according to project matching rules, and match-distance fields were retained for quality control.

Pearson correlations, yield-class summaries, $EC_a$-context grouping, and $EC_a$-derived yield-potential screening were used as descriptive tools to evaluate relationships among yield, laboratory variables, sensor measurements, and topographic variables. These analyses were used to guide agronomic interpretation and identify likely management questions for follow-up, rather than as standalone proof of causation.

### Interpretation Scenarios

The analysis was structured around two practical information scenarios. The lab-only scenario represented the conclusions a farmer or advisor could draw from 2024 maize yield data and conventional 1 ha grid soil samples. The sensor-informed scenario used the same yield and laboratory data, then added proximal sensor and terrain measurements to evaluate how interpretation and management decisions changed.

Results were interpreted through the same practical questions a farmer or advisor would face after reviewing the field data: what was impacting yield, what management action might be justified, and where that action should be targeted.

## Results and Discussion

### Lab-Only Scenario: Yield and Grid Soil-Test Interpretation

The lab-only scenario began with the 2024 maize yield map and 27 conventional grid soil samples. From this information alone, a farmer or advisor could make a sensible first-pass lime and fertility plan, but the evidence answered the three management questions with different levels of confidence.

For the first question, what was impacting yield, the clearest lab-only answer was partly a process of elimination. In a central Kansas dryland field, shallow CEC and organic matter would often be expected to explain yield differences because they are associated with texture, water-holding capacity, aggregation, nutrient mineralization, past productivity, and future yield potential. In this field, however, neither shallow CEC nor organic matter was meaningfully related to yield (CEC r = 0.04; organic matter r = -0.14), so the lab-only evidence did not support a simple surface soil-type or inherent-productivity explanation.

The fertility path was also narrowed. P1 phosphorus was unrelated to yield, and potassium values were above common sufficiency levels according to Kansas State University soil-test interpretation guidelines, despite a moderate yield correlation (Ruiz Diaz 2024). Therefore, a direct P or K deficiency explanation was not supported. With the CEC/organic matter and phosphorus/potassium explanations weakened, the most actionable lab-only lead became acidity and lime need: yield was positively associated with pH, buffer pH, and especially calcium saturation. The lab-only evidence is summarized in Table 2, selected yield relationships shown in Fig 3 and with the spatial view shown in Fig 4.

**Table 2. Grid soil-test property summary and Pearson correlation with 2024 maize yield.**

| Soil property | Min | Median | Max | SD | CV (%) | r with yield |
|---|---|---|---|---|---|---|
| pH | 5.2 | 5.8 | 6.4 | 0.37 | 6.3 | 0.43 |
| Buffer pH | 6.2 | 6.6 | 6.8 | 0.13 | 2.0 | 0.46 |
| Organic matter (%) | 2.2 | 3.0 | 3.6 | 0.37 | 12.4 | -0.14 |
| CEC | 12.6 | 15.2 | 21.6 | 1.86 | 12.1 | 0.04 |
| P1 phosphorus | 15 | 35 | 58 | 12.2 | 34.2 | 0.09 |
| Potassium | 160 | 245 | 358 | 54.1 | 21.3 | 0.41 |
| Calcium saturation (%) | 42.4 | 56.4 | 64.1 | 6.16 | 11.3 | 0.68 |
| Magnesium saturation (%) | 15.3 | 22.0 | 39.8 | 5.11 | 22.8 | -0.19 |
| Hydrogen saturation (%) | 8.9 | 18.8 | 34.5 | 7.39 | 39.1 | -0.46 |
| Sodium saturation (%) | 0.0 | 0.0 | 1.8 | 0.41 | 295.5 | -0.37 |

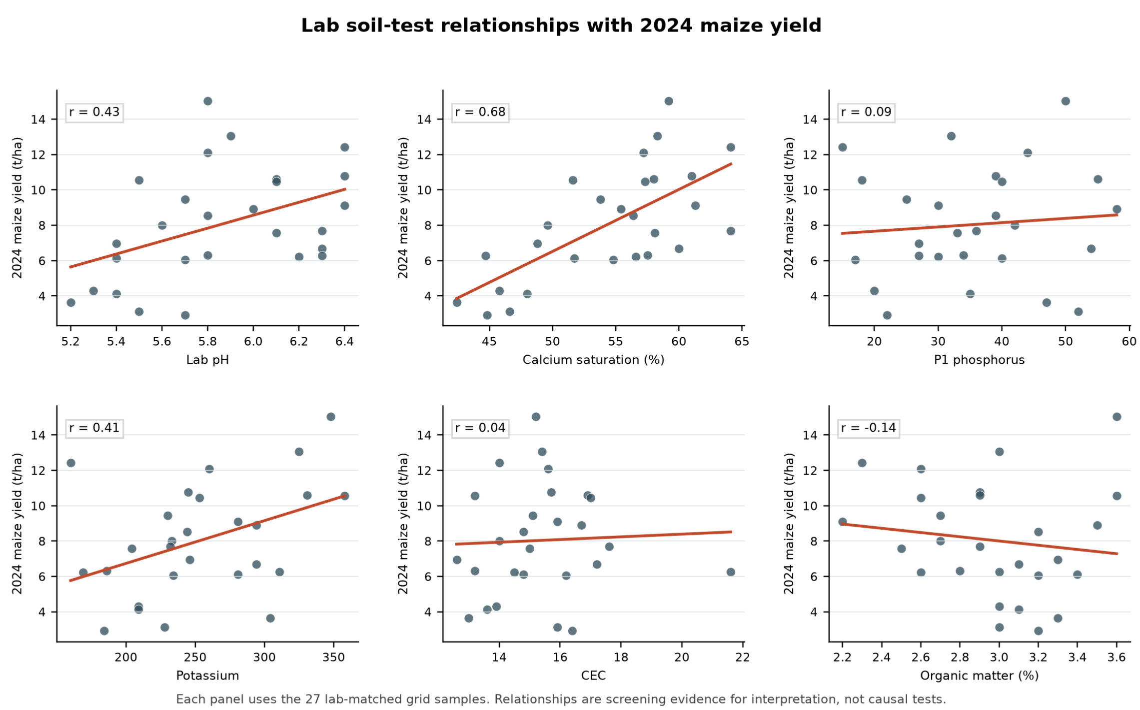


**Fig 3.** Relationships between selected laboratory soil-test values and 2024 maize yield at the 27 lab-matched grid locations. Relationships are screening evidence for interpretation, not causal tests

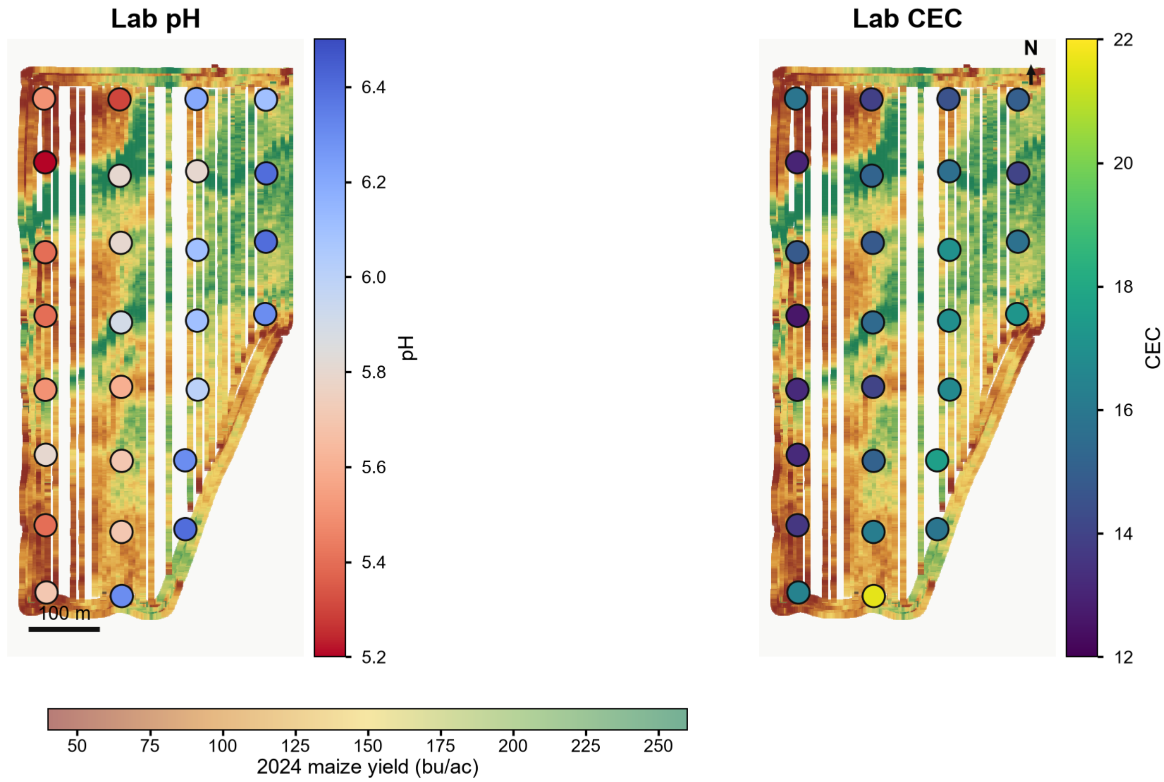


**Fig 4.** The colored background shows 2024 maize yield, while point symbols show conventional grid-sample pH and shallow CEC. Low pH provided an actionable lime lead, but shallow CEC did not explain the yield pattern, leaving uncertainty about whether yield differences were caused by a correctable acidity issue or by deeper soil-profile conditions

In practical terms, the lab-only interpretation answered the second question, what could be done, more confidently than it answered the first. A straightforward recommendation would be to lime the low-pH areas and maintain fertility. However, that answer should not be over-sold: some mid-pH locations were already high yielding, and among the 27 lab-matched locations, samples with pH between 5.7 and 6.2 ranged from approximately 2.9 to 15.1 t/ha. That range across about 0.5 pH unit suggests pH may be part of the story, or spatially associated with another factor, rather than the whole explanation.

The third question, where action should be targeted, was answered only at grid resolution. A farmer could build a conventional lime prescription from the 1 ha samples, but the map would rely heavily on interpolation between widely spaced points, increasing the risk of applying lime where it was not needed or missing acidic areas between samples. An additional limitation applied to yield-goal management. Because the lab-only data did not identify a clear physical, biological, or inherent soil driver of yield, they provided a weak basis for deciding whether low-yield areas were inherently limited or limited by a correctable condition. The sensor-informed scenario therefore tested whether the lime-centered interpretation held, sharpened, or needed to be revised once denser spatial and profile measurements were added.

## Sensor-Informed Scenario: Adding Spatial and Profile Context

Adding proximal sensor and terrain measurements changed the lab-only interpretation from a lime-centered answer to a more layered diagnosis. $EC_a$ was treated as a spatial soil-context measurement that integrates soil properties affecting current flow, including texture, water content, salinity where present, and related profile differences. $EC_a$ was not interpreted as a direct measurement of any single soil property.

Previous work has shown that $EC_a$ and terrain attributes can help delineate soil and productivity zones, so these layers were evaluated here as field-scale context for yield interpretation (Fraisse et al. 2001; Kitchen et al. 2003; Kitchen et al. 2005). The strongest field-scale sensor-informed relationships with yield were not pH alone. Dense on-the-go $EC_a$ and elevation were both strongly associated with 2024 maize yield, while slope and pH sensing added additional context (Fig 5). This did not dismiss the lime hypothesis; rather, it suggested that acidity was nested inside a broader soil-landscape pattern that could not be fully resolved from grid samples alone.

A cross-correlation screen was also prepared to show how the main laboratory, sensor, terrain, and yield layers related to one another at the grid-sample locations (Fig 5). The first row shows sensor and terrain correlations with yield, while the remaining rows show how those layers corresponded with grid-sample soil-test properties.

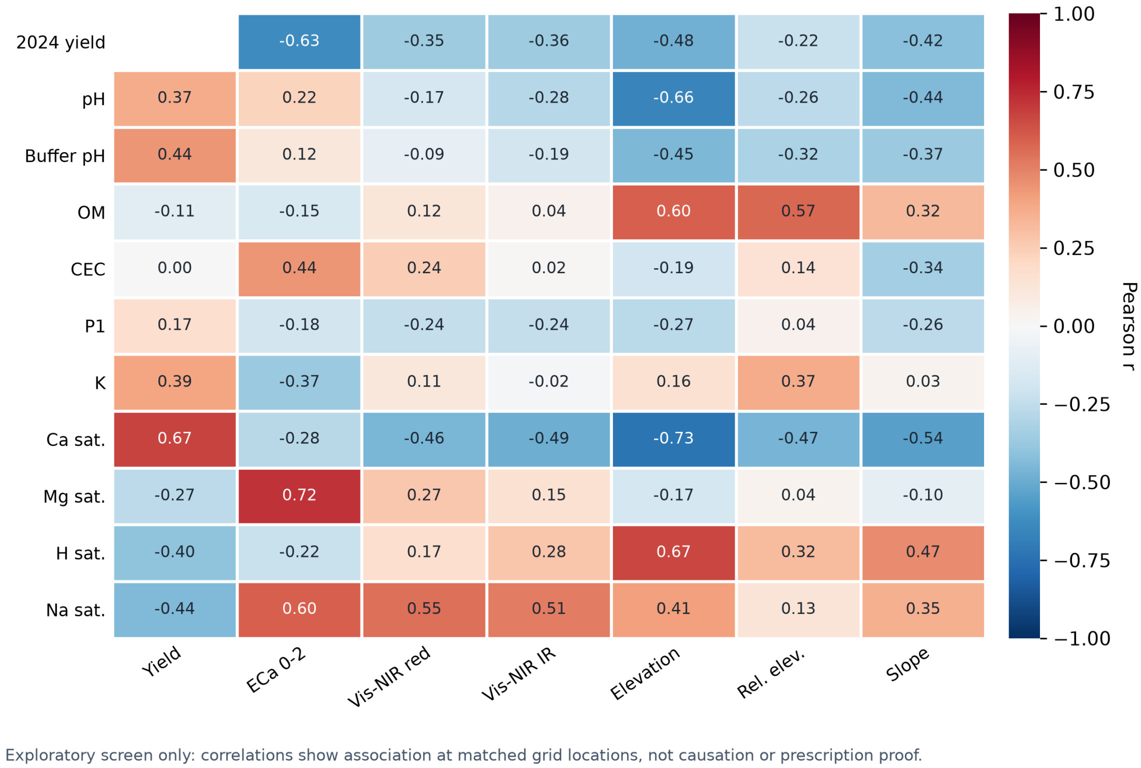


**Fig 5.** Cross-correlation screening among 2024 maize yield, grid soil-test properties, dense sensor layers, and terrain variables at grid-sample locations. Values are Pearson r; the first row shows sensor and terrain relationships with yield, and remaining rows show associations between laboratory properties and sensor/terrain layers.

Because prior work has used soil/landscape attributes and boundary-line approaches to evaluate field-scale yield response, the $EC_a$ relationship was evaluated as a yield-potential layer rather than only as another correlation (Kitchen et al. 2003; Shatar and McBratney 2004). Dense $EC_a$ scan data were divided into seven $EC_a$ zones, and an $EC_a$-derived potential yield was estimated from the upper-performing observations within each zone. This analysis showed that attainable yield declined systematically as $EC_a$ increased: the $EC_a$-derived potential yield declined from approximately 15.3 t/ha in the lowest $EC_a$ zone to 9.0 t/ha in the highest $EC_a$ zone, and the $EC_a$-zone potential curve was strongly related to median $EC_a$ (linear $R^2 = 0.94$). This was the clearest sensor-informed evidence that yield potential was being organized by a measured soil physical/profile property, not by pH alone. The $EC_a$-derived yield-potential screening is shown in Fig 6.

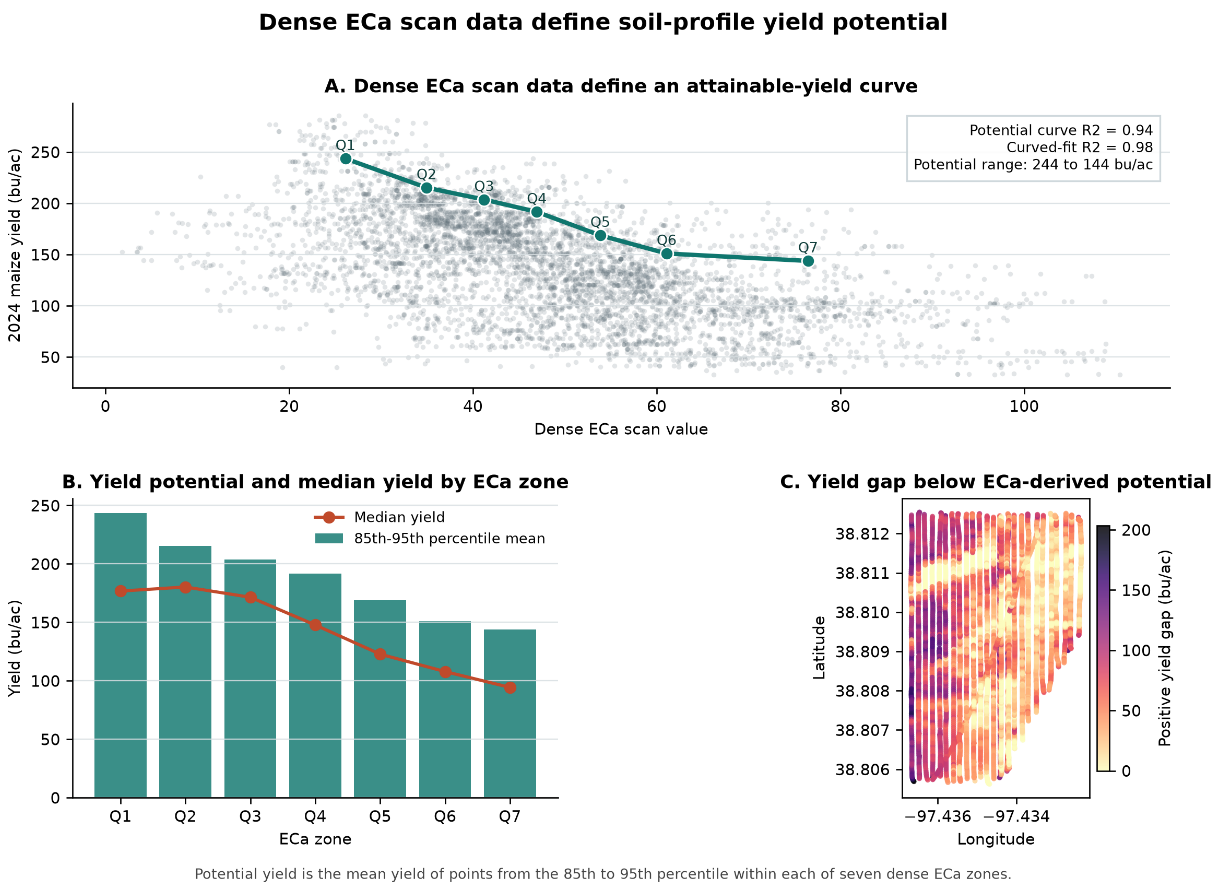


**Fig 6.** $EC_a$-derived yield-potential screening. Dense $EC_a$ scan data were divided into seven zones, and potential yield was estimated as the mean yield of observations from the 85th to 95th percentile within each zone. The attainable-yield curve declined from approximately 15.3 to 9.0 t/ha across $EC_a$ zones, while the map shows locations with positive yield gaps below their $EC_a$-derived potential

The underperformance layer shown in Fig 6C was calculated as the positive gap between observed 2024 maize yield and the $EC_a$-derived potential for that $EC_a$ zone. Instead of asking whether a low-yield area was simply below the field average, this layer asked whether that area was below what the field had already achieved under similar $EC_a$ conditions. Those positive yield-gap areas are where pH, compaction, fertility, drainage, or other correctable limitations become the next questions. In contrast, areas with low yield but little gap from their $EC_a$-derived potential are better candidates for yield-goal, seeding-rate, nitrogen-rate, rotation, conservation, or lower-input management rather than assuming a uniform lime or fertilizer response.

The sensor-informed management decision was therefore more specific than the lab-only decision. Lime remained justified where laboratory pH and buffer pH supported it, and higher-density pH sensing improved the spatial accuracy of the prescription. However, the $EC_a$-derived potential and underperformance layer suggested that not every low-pH or low-yield area should be interpreted the same way. Acidic areas that were also underperforming their $EC_a$-defined potential became stronger candidates for lime-response testing, while low-yield areas already near their $EC_a$-defined potential were better candidates for adjusted yield expectations, follow-up sampling, or investigation of profile, terrain, or physical constraints.

## Advanced Profile Assessment: Yield-Transition Transect

The first sensor-informed interpretation narrowed the explanation and improved the management hypothesis, but it also raised an advanced question: was the $EC_a$-defined condition something that is correctable, or was it an inherent soil-profile limitation that should be managed with adjusted yield goals, rotation, conservation, or lower input intensity? To investigate that question, a targeted CoreScan profile assessment was conducted.

The field was then probed with CoreScan at approximately 0.4 ha resolution so that any profile insight from the follow-up work could be related back to the full-field pattern and used to guide spatial management. Within that field-scale profile dataset, a north-to-south yield-transition transect was selected where 2024 maize yield increased from a low-yield area to a high-yield central area and then declined again. This transect was used as a targeted diagnostic deployment rather than as a replacement for the earlier field-scale sensor interpretation. Its purpose was to test whether the pH and base-status question raised by grid sampling was actually part of a deeper soil-profile and landscape pattern, and whether similar profile conditions were present in separate poor-yielding areas. The field-scale CoreScan locations, targeted yield-transition transect, and segmented deep-core sample locations are shown in Fig 1.

Across the transect, CoreScan profile $EC_a$ provided visual and quantitative evidence that the yield pattern was not simply a surface chemistry pattern. The high-yield central portion maintained lower-$EC_a$ deeper into the soil profile, while both low-yield areas transitioned more abruptly into higher-$EC_a$ subsoil at shallower depths. For the screening check, yield and CoreScan measurements were summarized in 15 m transect bins, and a simple two-variable regression used mean 40-60 cm $EC_a$ and elevation as predictors. That model explained about 90% of the descriptive yield variation along the transect, but it was used only as diagnostic support because the transect was targeted and small. The resulting side-view profile is shown in Fig 7.

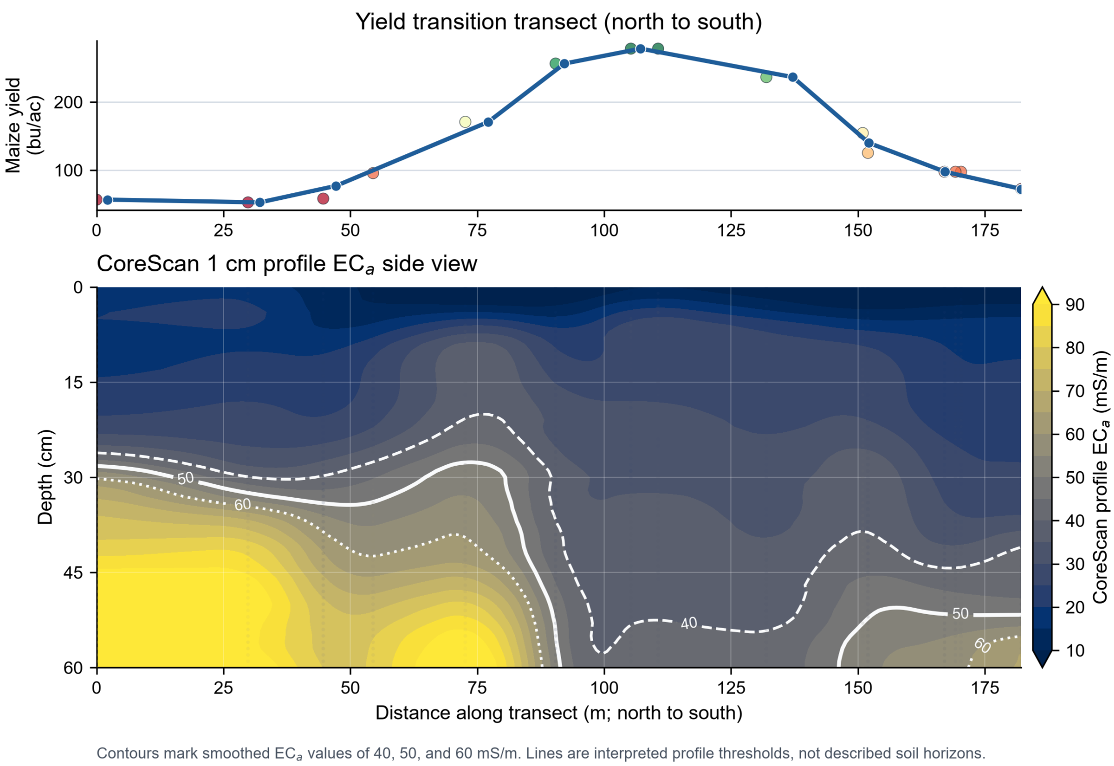


**Fig 7.** CoreScan 1 cm profile $EC_a$ side view across the north-to-south yield-transition transect. Contours labeled 40, 50, and 60 represent $EC_a$ values in mS/m, not depth. Contours are smoothed for visualization and are interpreted as profile thresholds rather than described soil horizons

One practical value of the profile-sensing approach is that the information can also be viewed as a field-scale diagnostic surface rather than only as a statistical output. Similar to medical imaging, 3D CoreScan visualization can help a farmer or advisor see where yield patterns align with changes deeper in the soil profile. A field-scale 3D view is shown in Fig 8.

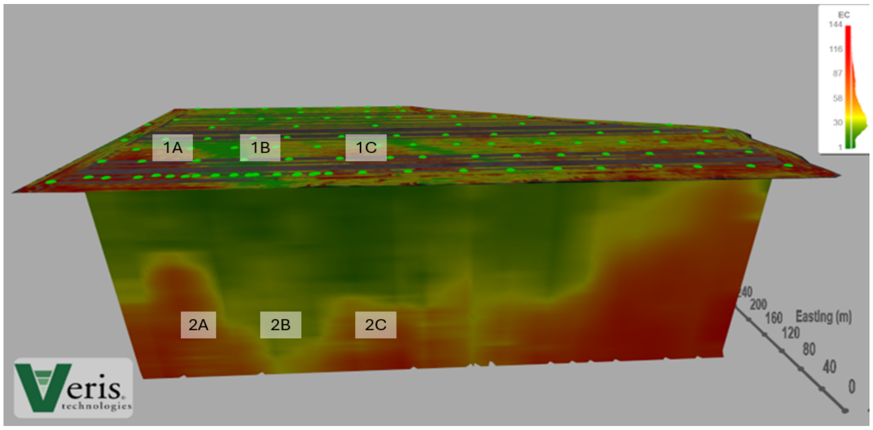


**Fig 8.** Practitioner-facing 3D CoreScan visualization with 2024 maize yield displayed on the field surface and profile $EC_a$ visible below the surface near the yield-transition transect. Paired labels connect surface yield zones with the corresponding profile condition below: low-yield areas 1A and 1C align with shallow, abrupt profile changes at 2A and 2C, while the higher-yield central area 1B aligns with deeper lower-$EC_a$ profile material at 2B.

Insertion force was evaluated as a compaction or root-restriction screen because compaction is a common explanation for poor yields and can lead to costly mechanical interventions if assumed incorrectly. Shallow insertion force from 0 to 20 cm had a moderate negative relationship with yield along the transect, but deeper force metrics did not show a consistent pattern. The force layer therefore remained useful as a constraint check, especially for identifying areas that may warrant compaction or traffic-pattern investigation. In this case, however, it helped rule out compaction as the primary explanation for the yield transition and narrowed the diagnosis toward soil-profile and topographic interpretation rather than a broad mechanical response.

### Segmented Deep-Core Follow-Up

Because the CoreScan measurements identified a specific profile-based uncertainty, they provided a defensible basis for the additional expense of segmented deep-core sampling. Follow-up samples were collected from the low-yield north and high-yield central locations along the transect, with an additional non-contiguous low-yield location used to evaluate whether similar profile conditions occurred outside the transect. The segmented deep-core laboratory results are shown in Fig 9.

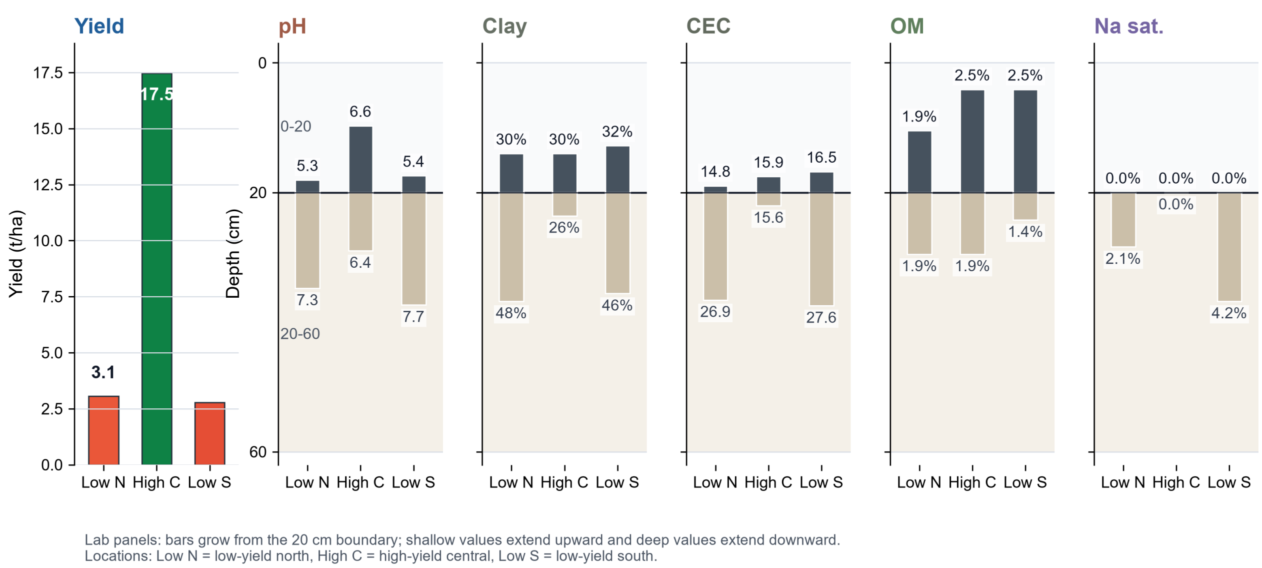


**Fig 9.** Segmented deep-core laboratory results at targeted low- and high-yield profile locations. Bars above the centerline represent 0-20 cm results; bars below the centerline represent 20-60 cm results

The segmented laboratory results supported the sensor interpretation. At the standard shallow depth, the low-yield and high-yield locations were not separated strongly enough by CEC or organic matter to explain the observed yield difference. At deeper depths, however, the low-yield locations had higher clay and CEC than the high-yield location, and the low-yield south location had a stronger sodium-saturation signal. The pH pattern also differed by depth: the low-yield locations had acidic shallow soil over substantially more alkaline subsoil (pH 5.3-5.4 at 0-20 cm and 7.3-7.7 at 20-60 cm), whereas the high-yield central location remained near neutral in both layers (pH 6.6 and 6.4). The alkaline subsoil pH itself should not be interpreted as proof of toxicity to maize; rather, the abrupt pH contrast, together with higher clay, CEC, and sodium saturation at depth, indicated a different profile environment than the high-yield location. The corresponding CoreScan profile line plots are shown in Fig 10.

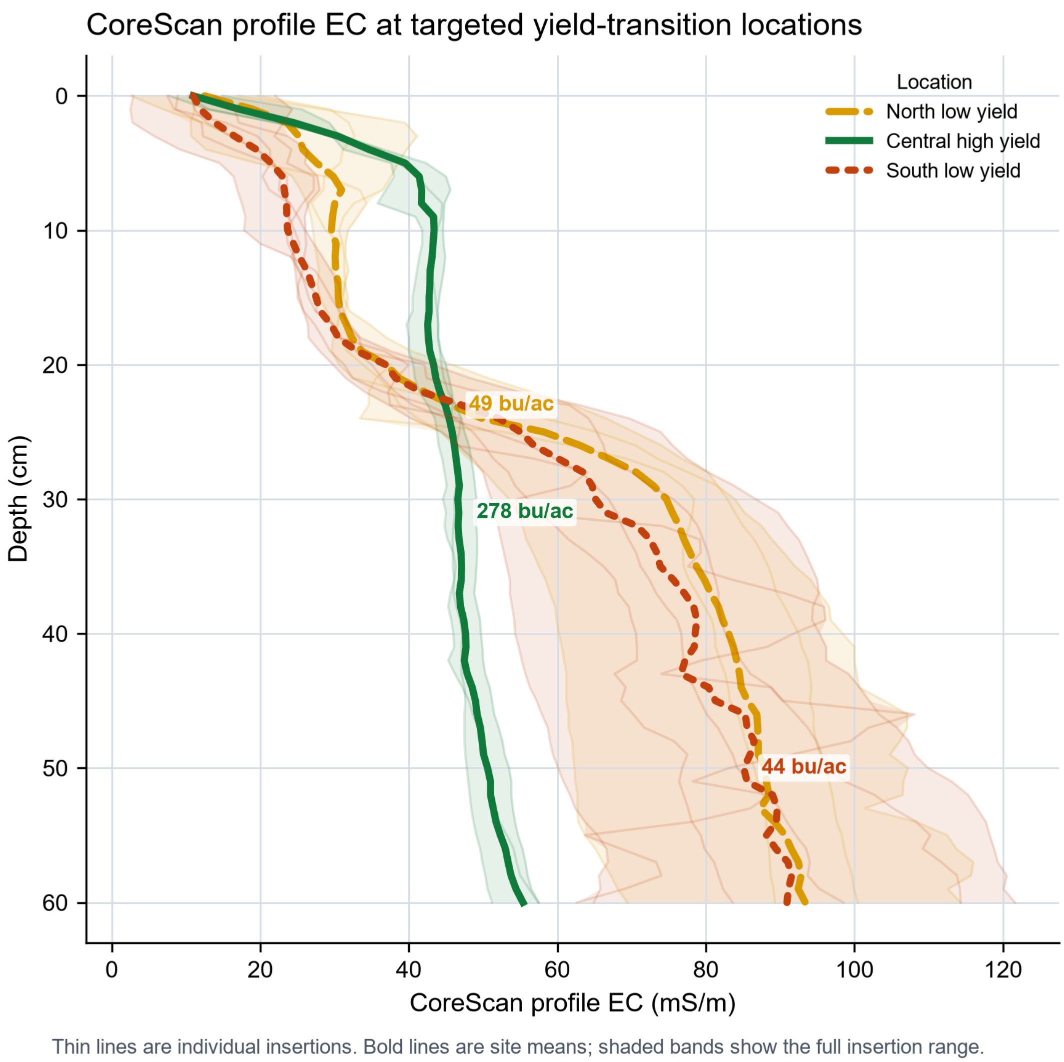


**Fig 10.** Targeted CoreScan profile EC at low-yield north and high-yield central transect locations and one additional non-contiguous low-yield location. The high-yield central location maintained a more consistent profile, while the low-yield locations showed a sharper transition to higher EC around 20-30 cm. The 0-20 cm and 20-60 cm sampling depths were selected because of this transition near 20 cm.

These results do not prove that any single property caused the yield loss. Instead, they show why the shallow lab-only interpretation was incomplete: shallow grid samples identified a possible lime response, while sensor-guided profile assessment showed that response potential likely depended on deeper soil conditions and landscape-related profile differences.

### Management Implications and Targeted Trial Concepts

The management hypothesis should not be that lime will make every low-yield zone equal to the highest-yielding zone in the field. A more defensible hypothesis is that lime may help acidic locations move closer to the yield potential of their $EC_a$/topographic soil-profile class, while profile and landscape constraints may continue to limit the absolute yield ceiling among zones.

The resulting sensor-informed management and trial concepts are summarized in Table 3.

**Table 3. Sensor-informed management and trial concepts.**

| Question | Suggested trial or management response | Reasoning |
|---|---|---|
| Where is lime most likely to pay? | Run lime-response strips within low-pH areas stratified by $EC_a$/topographic class. | Tests whether acidic areas in stronger profile environments respond more than acidic areas in constrained profile environments. |
| Are low-yield profile zones amendable? | Use deep-core evidence to evaluate gypsum/calcium-based amendment trials only where sodium or base-cation imbalance is confirmed. | The low-yield south location showed a deeper sodium-saturation signal, but amendment decisions need targeted confirmation. |
| Is compaction part of the limitation? | Use insertion force, traffic/headland history, and field inspection to target compaction checks or tillage/traffic trials. | Force was a useful screen but was not a stand-alone yield explanation along the transect. |
| How should inputs be placed while causes are tested? | Use yield-goal-based seed, fertilizer, and nitrogen rates by sensor/topographic yield-potential zones. | Avoids over-investing in constrained zones while maintaining input support where response potential is higher. |
| Where should future sampling go? | Target transition zones and large yield-gap areas rather than adding only more uniform grid samples. | Sensors identified where the interpretation was uncertain and where additional samples were most likely to change the decision. |

## Conclusions

This case study showed that the conclusions available from yield and conventional grid soil samples were useful but incomplete. The lab-only scenario reasonably identified acidity and base status as actionable management concerns. However, the lab-only scenario could not determine whether low pH was the primary limitation, a symptom of a broader soil-profile condition, or one factor interacting with other constraints.

Adding proximal sensor and terrain data changed the interpretation. The high-resolution $EC_a$ layer showed that yield variation was organized by soil-landscape zones that were not captured by shallow grid samples. CoreScan profile measurements and targeted segmented deep cores then showed that the yield-transition pattern corresponded with deeper profile differences, including subsoil $EC_a$, clay, CEC, organic matter, pH, and sodium saturation. Insertion force provided an additional screen for physical restriction and helped rule out compaction as the primary explanation for the yield transition, reducing the risk of pursuing an unnecessary or poorly targeted mechanical intervention.

The practical value of the sensors was not that they answered every question, but that they made the next management question more specific. Rather than recommending lime uniformly across all low-pH or low-yield areas, the sensor-informed interpretation supports a more targeted, testable, and economically disciplined strategy. Each $EC_a$ soil-profile class can be treated as having its own yield ceiling, with pH and base status influencing how close acidic locations are likely to move toward that ceiling.

Practically, this creates the basis for zone-specific lime-response trials and prescriptions. Acidic locations that are underperforming their sensor-defined potential become stronger candidates for response testing, while areas with profile or landscape constraints may require amendment, compaction investigation, rotation changes, conservation practices, or more conservative yield goals. Until correctable limitations are proven, seed, fertilizer, and nitrogen rates can be managed according to realistic yield potential.

If lime-response trials confirm a profitable response, ProScan, MSP3, and U3 are all platform options for higher-density pH mapping; in this field, pH sensing provided up to 251 locations compared with 27 grid samples, a 9.3x increase in observation density for refining lime prescription precision while laboratory pH and buffer pH remain the recommendation anchor. Dense scanned $EC_a$ data also provide a spatial foundation for yield-goal, seeding-rate, nitrogen-rate, and other zone-based management decisions. Overall, the sensor-informed approach improved the odds that inputs would be placed where they could do the most good while avoiding overconfidence in any single data layer.

## References


Fraisse, C. W., Sudduth, K. A., and Kitchen, N. R. (2001). Delineation of site-specific management zones by unsupervised classification of topographic attributes and soil electrical conductivity. *Transactions of the ASAE*, 44(1), 155-166.

Kitchen, N. R., Drummond, S. T., Lund, E. D., Sudduth, K. A., and Buchleiter, G. W. (2003). Soil electrical conductivity and other soil and landscape properties related to yield for three contrasting soil-crop systems. *Agronomy Journal*, 95, 483-495.

Kitchen, N. R., Sudduth, K. A., Myers, D. B., Drummond, S. T., and Hong, S. Y. (2005). Delineating productivity zones on claypan soil fields using apparent soil electrical conductivity. *Computers and Electronics in Agriculture*, 46, 285-308.

Ruiz Diaz, D. (2024). Soil test interpretations and fertilizer recommendations in Kansas. Kansas State University Agricultural Experiment Station and Cooperative Extension Service. MF2586.

Shatar, T. M., and McBratney, A. B. (2004). Boundary-line analysis of field-scale yield response to soil properties. *The Journal of Agricultural Science*, 142(5), 553-560.

U.S. Geological Survey. (2023). USGS 1 Meter 14 x63y429 KS_Statewide_2018_A18. U.S. Geological Survey.