Predicting Corn Emergence Rate with Topographic Features and On-the-go Sensing Technology

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Abstract.
Real-time sensor output during row-crop planting operations has the potential to improve control of multiple row-unit functions on-the-go. However, research is lacking on how best to maximize the utility of these new sensor systems across varying landscapes. Therefore, an investigation was conducted to determine if planter and other proximal soil sensor data, in combination with topographic features, could predict within-field variation in corn (Zea mays L.) emergence rate (ER) across multiple planting depth treatments. Research was conducted in Missouri, USA on a highly variable claypan soil field in 2020. Corn was planted with a four-row planter equipped with Precision Planting DeltaForce and SmartFirmer systems on each row unit. Four field-length strips of seed planting depth (3.8, 5.1, 6.4, and 7.6 cm) replicated three times were treatments to induce emergence variation. Machine learning approaches were applied to determine the predictive capability of planter sensors, soil apparent electrical conductivity (ECa), and topographic features (slope, flow direction, and topographic wetness index) in estimating corn ER. Field-scale results from the planting depth treatments showed that planting depth had a marginal influence on corn stands, with stand densities decreasing slightly at 6.4 and 7.6 cm. Additionally, a suite of predictors could effectively estimate ER across the study site, with similar accuracies observed among planting depths. Planter sensor variables representing estimates of inherent soil variability (i.e., OM and texture) were most useful in the ER prediction model, and were superior to estimates of furrow moisture and seed-to-soil contact. These results illustrate the ability to predict ER at a field scale, and can be used as a framework for further research and development of planter sensor systems targeting uniform corn emergence.

Keywords. *Soil Sensing, Precision Planting, Emergence Uniformity, Machine Learning*

Introduction

Research has found that corn seedling emergence is highly dependent upon seed-to-soil contact, soil moisture, aeration, and soil temperature (Alessi and Power, 1971; Gupta et al., 1988, Elmore et al., 2014). Studies have found optimum corn germination to occur at soil temperatures greater than 20 °C, at field capacity, and with good seed-to-soil contact (Schneider and Gupta, 1985). Generally, operators of row-crop seeding equipment target a planting depth, downforce, row-closing, and residue management strategy that optimizes these parameters. Across landscapes, however, spatial variability in seed zone soil properties often exists due to variations in soil texture, crop residues, and landscape attributes such as slope and aspect.

In an effort to improve seeding management across variable landscapes, precision agriculture research has explored varying seeding depths within a given field based upon changes in soil moisture (René-Laforest et al., 2015). Soil moisture estimated through a capacitance sensor was used as the guiding parameter because of the influence of soil moisture on germination, as well as the access to on-the-go soil moisture sensors. They found varying planting depth within a field improved corn root development and yield, a result attributed to planting shallower in relatively wet conditions and deeper in relatively dry conditions. Further research is needed to apply these results to more environments in the U.S. Midwest. In addition to sensor technologies, topographic features can give insight into soil water availability, movement, and accumulation across landscapes (Pachepsky et al., 2001). High-resolution elevation is now available through digital elevation models, as well as from machine data collected during field operations. An example often used is combining these landscape features into a calculated topographic wetness index that then can be related to crop performance (Kyveryga et al., 2011).

Many studies have applied machine learning to investigate agronomic questions (Gonzalez-Sanchez et al., 2014, Ransom et al., 2019; Qin et al., 2018). However, machine learning approaches have not been widely applied for estimating corn emergence parameters. Due to recent technology that allows for dense quantification of soil variability by planter sensor systems, as well as through data collected with unmanned aerial vehicle (UAV) imagery, high-resolution field-scale datasets can now be collected, which subsequently allow for the application of machine learning techniques to help answer agronomic questions related to crop emergence performance.

Commercially-available planting technology now exists that allows for varying seed depth on-the-go during row-crop planting. However, emergence performance information is needed to show how seed zone soil sensors can be best utilized to guide row-unit automation. Therefore, this study was conducted to determine if soil sensor data and topographic features could be used in a machine learning approach to predict corn emergence rate (ER).

Materials and Methods

Study Site and Treatment Layout

Research was conducted in 2020 in central Missouri (38°56’45.7” N 92°07’57.4” W) on a 14-ha production agriculture field. The western portion (2.6 ha) of the field was used for this study. The site was located within Major Land Resource Area 113, also known as the Central Claypan Area. The soil across the site was classified as a Mexico silt loam (fine, smectitic, mesic Vertic Epiaqualf). The field was chosen due to the inherent landscape variability that represented a typical claypan soil toposequence (summit, backslope, and footslope). Specifically, near the center of the field the slope was minimal, representing a more stable soil landscape (summit; Fig. 1). Moving N and S from the center of the field, the slope increased and was more representative of a backslope position. The N and S facing slopes also supplied aspect variability, which can be visualized through flow direction (Fig. 1c). Lastly, slope decreased and areas of upslope accumulation of soil and water existed at the northernmost and southernmost portions of the field (footslope; Fig. 1b).

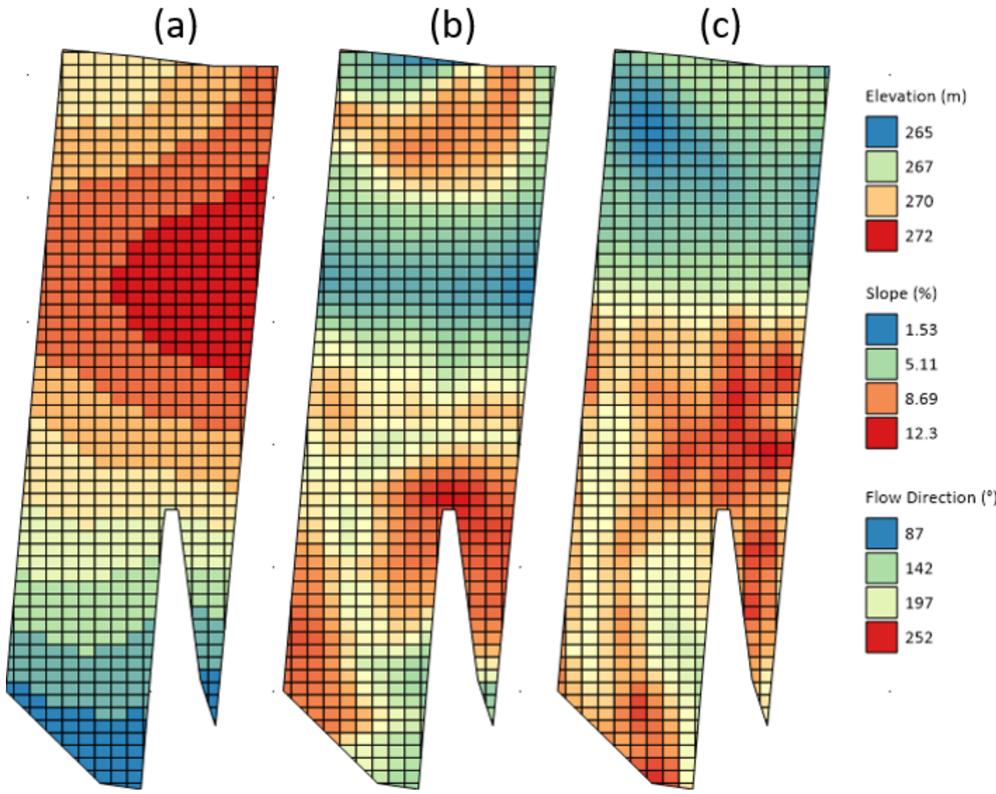

Fig. 1. Elevation (a), slope (b), flow direction (c) for the study site in central Missouri, USA.

Mechanical variability was induced at the study site through three replications of four planting depth treatments (3.8, 5.1, 6.4, and 7.6 cm). All depth treatments were 8 rows wide (two planter widths) and were imposed across the entire transect length. The target seeding rate for the study was 75,820 seeds ha^{-1}, and the corn hybrid used was Pioneer 0589 (Corteva Agriscience, Wilmington, DE, USA). Corn was no-till planted into soybean stubble on 20 April 2020 with a four-row planter (0.76 m rows).

The planter used in the study was equipped with MaxEmerge XP row units (Deere & Co., Moline, IL, USA). The row units did not include a residue management system (i.e., row cleaners, no-till coulters). The planter was attached to the three-point hitch of a John Deere 6110R tractor. The planter was ground-driven and equipped with Precision Planting finger-pickup seed meters, an active hydraulic downforce system (DeltaForce®), and SmartFirmers (Precision Planting, LLC., Tremont, IL, USA) on each row unit. No additional aftermarket components were present on the planter, and OEM rubber closing wheels were used.

The 6110R was equipped with automated machine guidance, where the steering was controlled through Deere's integrated automatic steering system (AutoTrac). This system utilized the StarFire 2 differential correction, which provided ±10 cm pass-to-pass accuracy. The average speed of the tractor during the seeding operation was 1.9 m s^{-1}. The "A-B" method of machine guidance was used, resulting in straight transects with a heading of 184 or 4°.

Planter Sensor Systems

Data from all Precision Planting sensor systems were logged to the Precision Planting 20|20 display (Generation 3) at 1 Hz. The GNSS position was derived from the StarFire 3000 receiver, allowing georeferencing of all data. The two systems providing data for analyses were DeltaForce and SmartFirmer. Data from the DeltaForce system consisted of ground contact (%), gauge wheel load (downforce; N), and downforce margin (N). Downforce margin is described as the minimum gauge wheel load (GWL) observed over a three second period. The hydraulic downforce system automatically adjusted row unit downforce or uplift to maintain a target gauge wheel load of 445 N. This technology improved the consistency of disk-opener operating depth at each of the targeted planting depth treatments.

The Precision Planting SmartFirmer used in the study is designed to mount to a planter row-unit behind the seed tube. This sensor replaces traditional seed firming devices. For this study, they were installed on each row of a 4-row planter. The lens of the SmartFirmer pressed against the sidewall, approximately 0.6 cm above the bottom of the slot created by the disk-openers. Data layers from the SmartFirmer consisted of by-row furrow moisture (%), temperature (°C), OM (%), CEC (cmol 100 kg^{-1}), clean furrow (%), and uniform furrow (%). These metrics, aside from temperature, were derived from the optical portion of the sensor that measures reflectance from five wavelengths in the visible and near infrared (VNIR) region (468, 592, 858, 1198, and 1468 nm).

UAV Data Collection

UAV image data were collected on 22 May 2020, which was 32 DAP and 20 d after the first emergence. Plants were between vegetative growth stages V2 and V4 at the time of data collection. The aerial images were collected from a Phantom 4 Advanced UAV imaging system (DJI, Shenzhen, Guangdong, China) with an onboard RGB camera. Images were taken sequentially for the entire study site at 0.5 frames per second, at a flight height of 10 m, and a speed of 2 m s^{-1}. More in-depth detail of the UAV data collection has been provided in Vong et al. (2022).

Stand Density and Day of Emergence

All emergence parameters were estimated based upon a deep learning model (ResNet18) trained with UAV imagery as detailed in Vong et al. (2022). Output from these models was used to create field-scale maps of stand density (plants m^{-1}) and days to imaging from emergence (d). Estimates of stand density and days to imaging from emergence estimates were considered successful with R^2 of >0.95.

The days to imaging from emergence parameter was converted to days from planting, then to growing degree days (GDD; °C) to account for temperature variations throughout the emergence period. This was performed by summing the GDD accumulated from planting to DOE, and was referred to as the cumulative growing degree days to emergence (GDDE).

Emergence Rate and Uniformity

Field-scale emergence rate relative to planting depth (ER) was derived using UAV-estimated GDDE. The ER was calculated by subtracting the observed GDDE from the mean GDDE at each planting depth. Therefore, positive values represent a delayed ER relative to the mean for a given planting depth. Likewise, negative values represent a quicker-than-average ER. These ER values were calculated for each 1 m length of each row across the entire site.

Soil Sensing and Terrain Features

Soil apparent electrical conductivity (ECa) from 0 to 0.3 and 0 to 0.9 m depths were measured across the entire site prior to corn planting using a Veris 3100 sensing system (Veris Technologies, Salina, KS, USA). In this study, only the 0 to 0.3 m data were used. The previously mentioned 6110R tractor and guidance system was used to pull the 3100, and data were collected at speeds of 2.2 m s^{-1} on a 9 m transect spacing.

Soil terrain features were calculated from the elevation data collected from the StarFire 3000 receiver and logged to the 20|20 display during planting. The elevation data were interpolated using inverse distance weighting (IDW) to a 6.1 m grid for analysis in Ag Leader's Spatial Management Software (SMS; Ag Leader Technology, Ames, IA, USA). Two metrics were subsequently calculated, and included slope and flow direction. These features were derived from the Spatial Analysis Toolbox in ArcGIS Pro (ESRI, Redlands, CA, USA).

Statistical Analysis

A machine learning approach was applied in all modeling strategies that utilized the field-scale data. The predictor variables for modeling the response variable of ER included all planter sensor metrics listed above (furrow moisture, OM, downforce margin, etc.), as well as soil ECa, slope, and flow direction.

Predictor and response variables were at varying spatial resolutions and needed to be joined for data analysis. Planter sensor data layers recorded to the 20|20 display were first merged with the gridded ECa and topographic features using the 'join and relates' feature in ArcGIS Pro. The join retained the row-level resolution of the data from the 20|20, which consisted of a grid cell that was one row wide (0.76 m) by 1 sec of travel (~2 m). Subsequently, the newly merged layer, consisting of all predictor variables, was joined to the to the UAV data layer containing ER. The ER data were in a vector format at a 1-m spacing down each row and were overlaid over the one-row wide grid of predictor variables. The spatially joined data typically resulted in two observations of ER data per one cell of joined predictor variables.

Multiple machine learning algorithms were evaluated (e.g., ridge regression, support vector machine regression, artificial neural network), but the random forest algorithm (RF) was chosen due to consistent performance and the ability for model interpretation. The RF models were fit and interpreted with the 'randomForest', 'randomForestExplainer', and 'ICEbox' packages in R Statistical Software (R Core Team, 2022). The RF algorithm is a supervised ensemble learning technique that can be used for classification or regression problems. It uses a bagging technique, where the data are split and regression trees are created in parallel (Leo et al., 2021). Within each tree, the RF randomly selects features to create a prediction model. In our scenarios, the number of variables evaluated at each split in the decision tree (mtry) was set to 3. The final (bagged) model, in our scenario, was an average of 500 separate regression trees. These trees were developed on 80% of the data and tested on the remaining 20%. The Pearson correlation coefficient (r), coefficient of determination (R^2) and root mean squared error (RMSE) were calculated to interpret performance of the model in the training and testing datasets.

Predictor significance was analyzed using the minimal tree depth distribution from the 'randomForestExplainer' package in R. These values represent the average depth within the ensemble of decision trees that each variable was used to partition the dataset. Therefore, smaller values correlated to more significant variables, as they were used more often at shallow tree depths. In addition to the minimal depth distribution, the individual conditional expectations (ICE) algorithm was applied to covariates of interest, and subsequent plots were created using the 'ICEbox' package in R (Goldstein et al., 2015). This feature allowed for the interpretation of how each variable was used in prediction by the RF model. Specifically, the ICE plots displayed the estimated conditional expectation curves, each of which reflected the predicted response as a function of the covariate of interest, conditional on the distribution of additional covariates. Because the curve intercepts varied, model predictions were "centered" in ICE plots for improved interpretation among the varying intercepts. In the centering process, each curve was "pinched" at the minimum observation of the given predictor variable of interest. In each plot, 10 percent of the entire training dataset was used for visualization.

Results and Discussion

Spatial Variability in SmartFirmer Metrics and Soil ECa

Data collected with the SmartFirmers showed strong spatial structure in several of the metrics, such as OM and furrow moisture (FIg. 2). In general, OM estimates were greatest where the slope was also the greatest (Fig. 1; FIg. 2). The correlation of higher OM to areas of greater slope and erosion aligns with findings from data collected from other similar soil types in the region (Conway et al., 2019). Spatial variability in furrow moisture was observed in the study field, with the highest estimates observed in the northern, central, and southern portions of the field. The largest area of high furrow moisture was observed in the middle of the field, coinciding with high elevation and low slope. In the north portion, high values coincided with areas with of high ECa (Fig 3). Some visible N-S striping aligning with the planting depth treatments was apparent in the furrow moisture maps, where deeper planting depths coincided with greater furrow moisture (FIg. 3). Similarly, clear differences in clean furrow and furrow uniformity values were observed between planting depths. In general, both clean furrow and furrow uniformity decreased with increasing planting depth. The response of these metrics was attributed to larger amounts of residue present in the furrow at the shallow planting depths.

Soil ECa showed similar spatial structure to furrow moisture. In most cases, high ECa coincided with areas of high furrow moisture (FIg. 2). This was not surprising, as ECa has been found to correlate to soil texture and water content (Corwin and Lesch, 2003; Sudduth et al., 2005). The two layers did deviate however, in the southwest corner, where a high furrow moisture was observed but a low soil ECa. The deviations could have been caused by differences in the sensing depth of the systems. In some portions of the field, the ECa estimates did not align with previous studies that have found ECa to increase in areas of high propensity of erosion (Kitchen et al., 2005). In our study, areas with the highest slope (south central) corresponded to lower ECa values. The cause of this phenomena was unknown, but could have been caused by the influence of soil water content and texture on ECa.

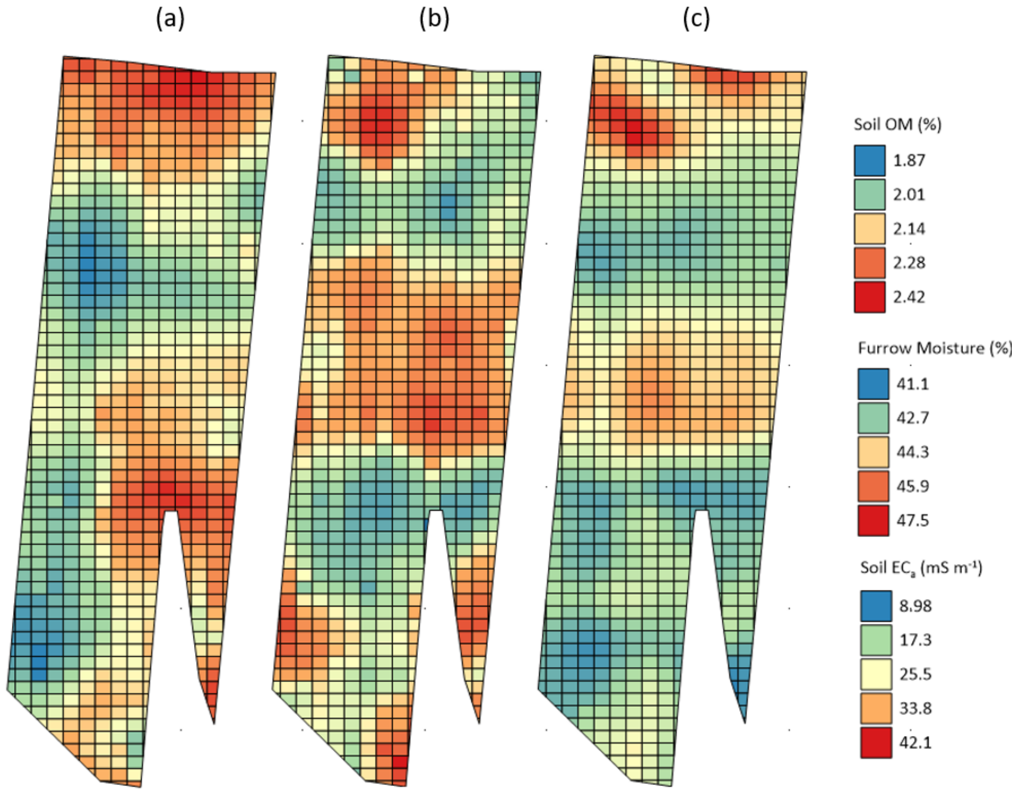

FIg. 2. Interpolated illustrations of Precision Planting SmartFirmer soil organic matter (OM; a), furrow moisture (b), and Veris soil apparent electrical conductivity (0-0.3 m; c) at the study site central Missouri, USA.

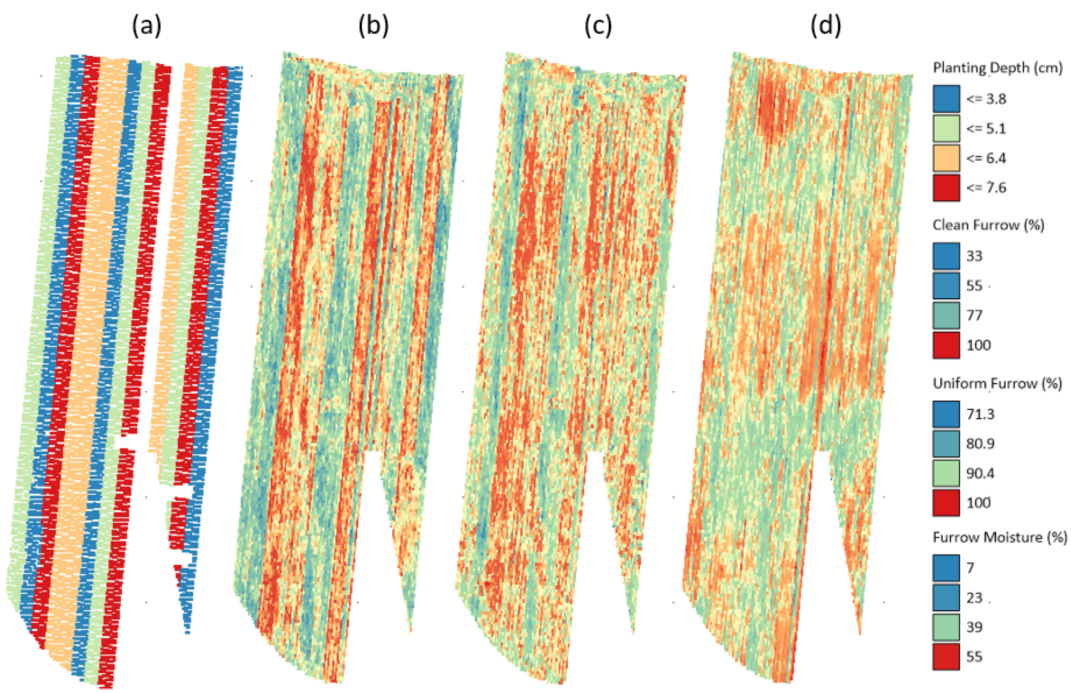

FIg. 3. Row-level illustrations of planting depth (a), Precision Planting SmartFirmer clean furrow (b), uniform furrow (c), and furrow moisture (d) across the study site in central, Missouri, USA.

Stand Density, GDDE, and ER

The clear effect of planting depth that was observed in GDDE was not as prevalent in ER (FIg. 4). This was expected, as the ER calculation was performed to mask the effect of planting depth for analysis across the site. Additionally, the ER maps also aid in visualizing spatial variability across the site. For example, the southern portion of the field had generally smaller ER than the central and northern portions, a feature that is not clear in the map of GDDE. Additionally, a cluster of high ER was observed in the north-central and north-western portions of the field, which coincided with areas of high furrow moisture, OM, and ECa. This zone was also north-facing and at a low-lying position in the landscape (Fig 1, FIg. 2). These results do not align with those presented by Stewart et al. (2021) on a similar soil type, who found more rapid emergence at footslope positions (higher soil moisture environment). The difference may have been caused by drier and warmer condition observations at planting in the years evaluated in their study. Collectively, these studies highlight the complex dynamic of soil, weather, and landscape effects on corn ER of a given soil type.

Additional mechanical variability was also observed through N-S “striping” of ER (FIg. 4). However, the striping did not align directly with row-level data collected by the planter sensor systems, suggesting that prior field operations were likely the cause. Throughout the field’s history, field operations have typically occurred N-S. Because of this, and because the field has been in no-tillage, these effects were likely caused by the influence of historical field traffic and residue distribution. These operations potentially caused variability in compaction and residue distribution across the field.

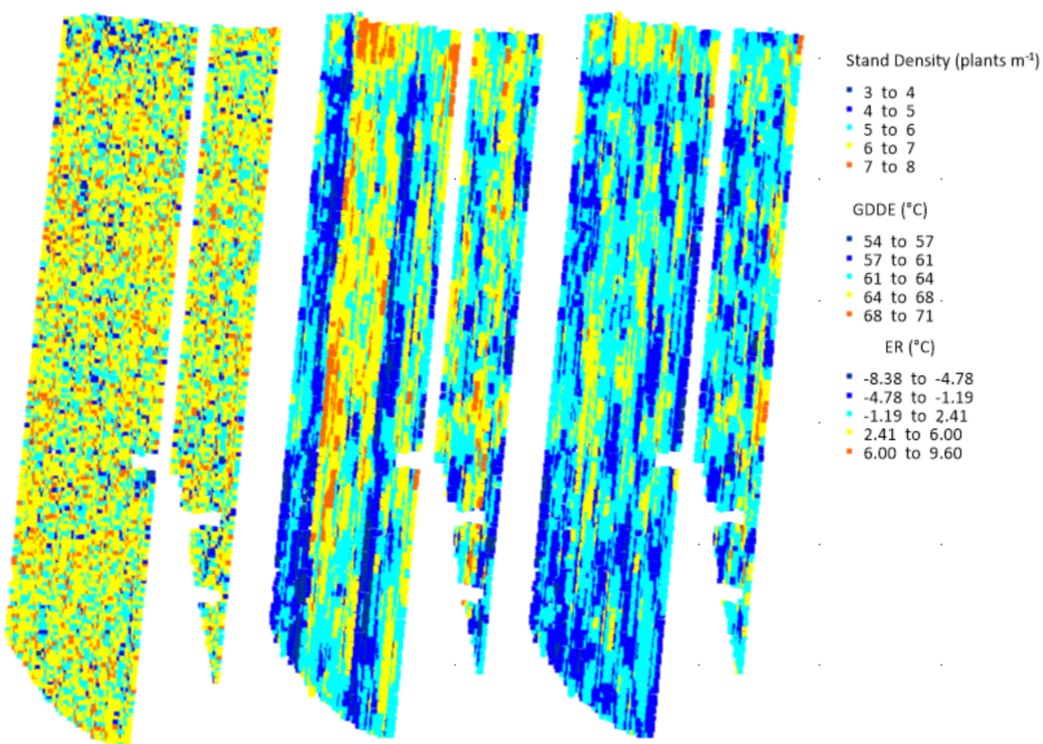

Fig 6. Corn stand density (a), growing degree days from planting to emergence (GDDE; b), and emergence rate (ER; c) estimated through unmanned aerial imagery at the study site in central Missouri, USA.

Modeling

The field-scale modeling of ER was performed to evaluate the impact of soil, machine, and landscape across the study site. The results from the ER model developed across planting depths showed positive relationships between predicted and UAV-estimated ER in the testing datasets (Table 1; Fig 7). At all depths, results from the testing datasets were similar (RMSE = 1.25 to 1.38°C). This suggests that despite differences in planter-based metrics, such as clean furrow, the random forest algorithm was able to decipher between areas of smaller (quicker) and larger (longer) ER at each planting depth.

Table 1. Prediction statistics of emergence rate by the soil sensor and terrain data layers at the four planting depths. The results represent model performance on the testing dataset used at each planting depth.

Model	r	R^2	RMSE (°C)
3.8 cm planting depth	0.86	0.75	1.25
5.1 cm planting depth	0.84	0.67	1.36
6.4 cm planting depth	0.85	0.71	1.27
7.6 cm planting depth	0.84	0.74	1.38

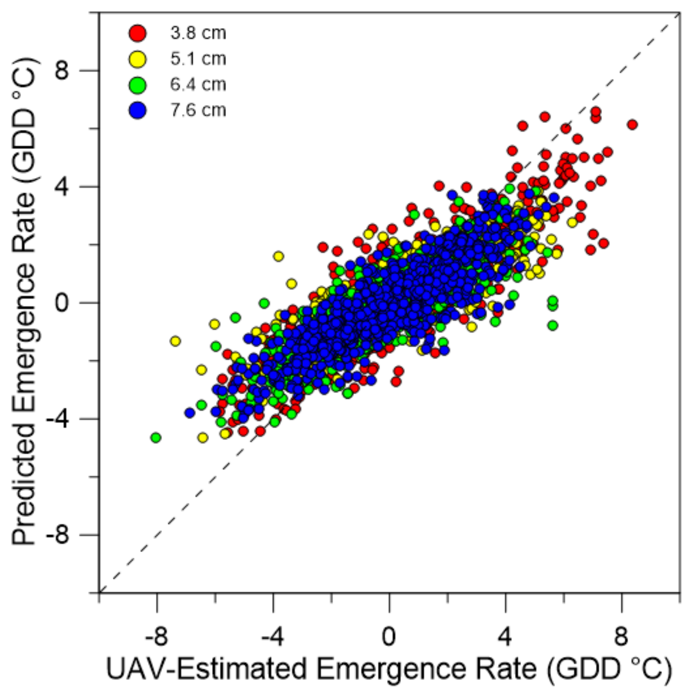

FIg. 5. The UAV-estimated emergence rate in relation to predicted emergence rate for the testing data sets at each planting depth in central Missouri, USA. Model predictions were calculated independently for each planting depth.

Variable Significance

Not surprisingly, the most important variables for prediction varied among planting depth (FIg. 6). This was attributed to differences in seed zone properties at each depth, which influenced sensor metrics (e.g., clean furrow; Fig 8). Despite the variation, several variables were consistently useful in the models. At each planting depth, flow direction was one of the top four predictors. This was likely due to the N-S aspect of the field. The response of ER to aspect as discussed above is noted, where clusters of smaller ER were observed on the southern portion and higher ER observed on the northern portion of the field. In addition to flow direction, slope, OM and, soil ECa were also consistently top variables for prediction. This was likely due to these metrics capturing inherent soil spatial variation at the site, and can be observed in Figure 2.

Interestingly, metrics such as clean furrow (indication of seed-to-soil contact) or furrow moisture were useful at some depths but were not typically the most important variables for prediction. This indicates that furrow moisture was likely adequate to initiate germination at all planting depths. Additionally, although more residue was present in the furrow at the shallow planting depths, it did not have a large impact on ER when compared to terrain features and other soil sensor data (e.g., SmartFimer OM and ECa). Collectively, the results suggest that inherent soil variability associated with landscape variation was the driving factor for ER. These results are promising, because many of these inherent variables could be estimated prior to planting, allowing for a depth, residue management, or GWL prescription prior to the actual planting operation. Subsequently, these prescriptions could then be "fine-tuned" by real-time sensing of seed zone soil properties.

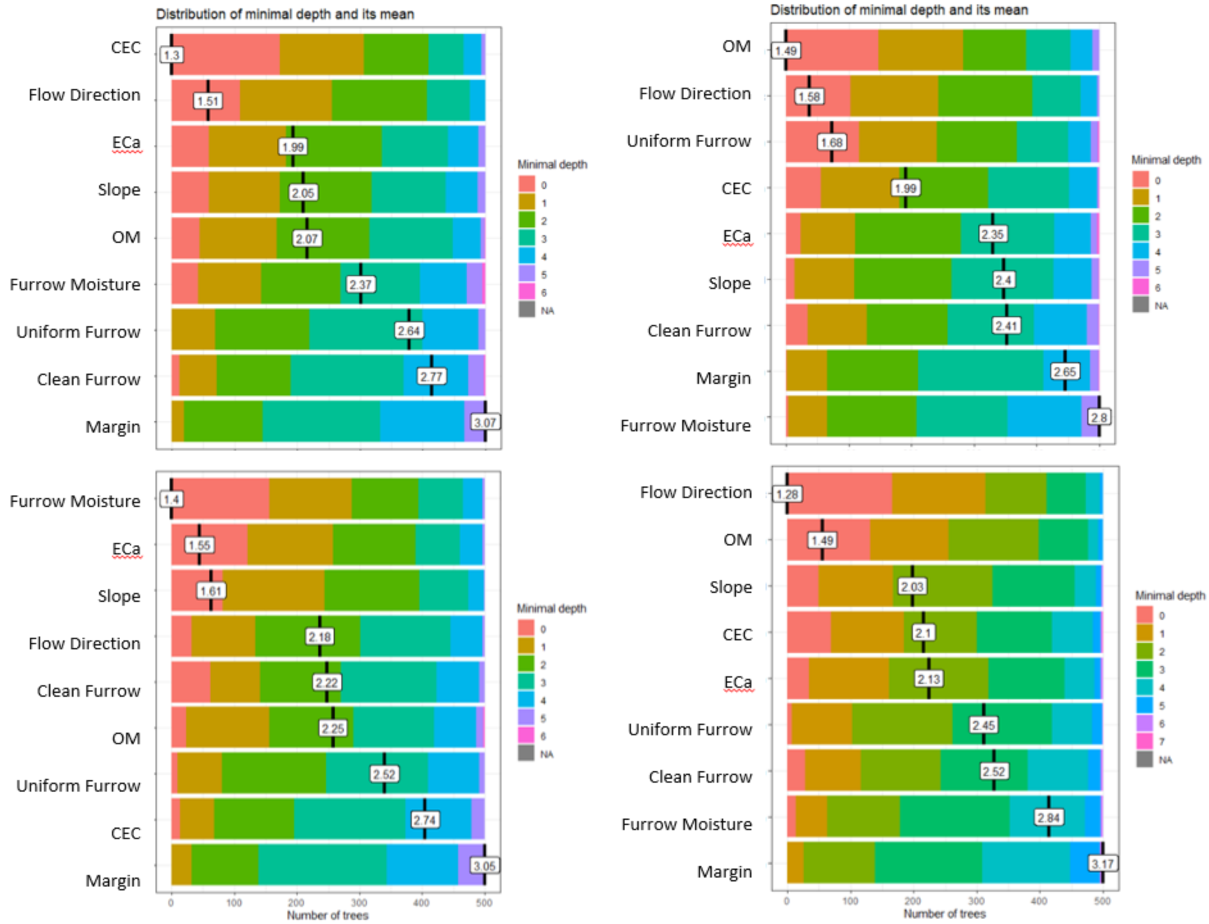

FIg. 6. Distribution of minimal depth for each predictor variable at the 3.8 cm (top left), 5.1 cm (top right), 6.4 cm (bottom left) and 7.6 cm (bottom right) depths in the random forest modeling approaches.

Variable Use in Random Forest Models

Temporally Variable Predictors

The ICE plots allowed for an interpretation of how specific variables were used by the model. Three planter sensor-based metrics were assessed (furrow moisture, clean furrow, downforce margin; FIg. 7). Furrow moisture was evaluated due to the known impact of soil moisture on germination, and because commercially available equipment controls planting depth based upon furrow moisture (e.g., Precision Planting SmartDepth). Clean furrow was evaluated because it was a proxy for seed-to-soil contact, another important factor for seed germination. Additionally, potential exists to guide residue management in real-time with this or a similar estimate of furrow residue. Lastly, downforce margin was assessed because in our study, downforce margin was the most useful metric from the DeltaForce system for estimation of ER. Further, a significant percentage of planters are equipped with active or static downforce systems that can sense GWL, allowing for high resolution quantification of variability in soil resistance.

Results found that, at all depths except 7.6 cm, estimates of emergence rate increased with furrow moisture. An example of the 3.8 and 7.6 cm depth can be found in FIg. 7. The lack of clear response observed at 7.6 cm was attributed to smaller amounts of variability in furrow moisture present at the 7.6 cm depth. These results suggest that targeting a lower furrow moisture generally decreased ER at our study site. These results would likely invert under drier conditions (e.g., late planting date). Therefore, a soil moisture-driven variable depth system likely should have a dynamic target that incorporates a low and high soil moisture threshold.

The ICE for clean furrow at varying ER predictions showed a negative response at shallow and deep planting depths, illustrating that ER predictions decreased as clean furrow increased irrespective of depth. These results would align with recommendations from Precision Planting, which suggest targeting a clean furrow value of greater than 95%, which would result in an estimate of less than 5% residue in the furrow. Therefore, these results suggest that clean furrow estimates could be used to guide residue management systems to optimize seed-to-soil contact at shallow planting depths in no-tillage conditions.

In our study, downforce margin (minimum GWL) was the most useful metric from the DeltaForce system in estimating ER. However, the significance in the model was low compared to the other predictor variables. At the shallowest depth, a negative correlation was observed between downforce margin and model predictions (FIg. 7). This may indicate that seeds planted in areas with low margin may not have been at the target planting depth, were dropped during row-unit bounce, and/or were placed in soil with high amounts of resistance (Badua et al., 2021; Brune et al., 2018). Collectively, these factors could result in seeds planted at a depth less than the target of 3.8 cm, in little contact with the soil, and/or into compacted soils. A similar, negative relationship was observed at the deeper planting depth although the magnitude of the response decreased. This could have been due to seeds planted in areas of low margin emerging quicker in some cases because they were closer to the soil surface. At shallow depths, lower margin values may have correlated to areas where the row-unit was bouncing out of the soil, and subsequently misplacing seed. On the contrary, at deeper planting depths, low margin values may have simply been caused by planter row-units not reaching the target depth (i.e., no GWL).

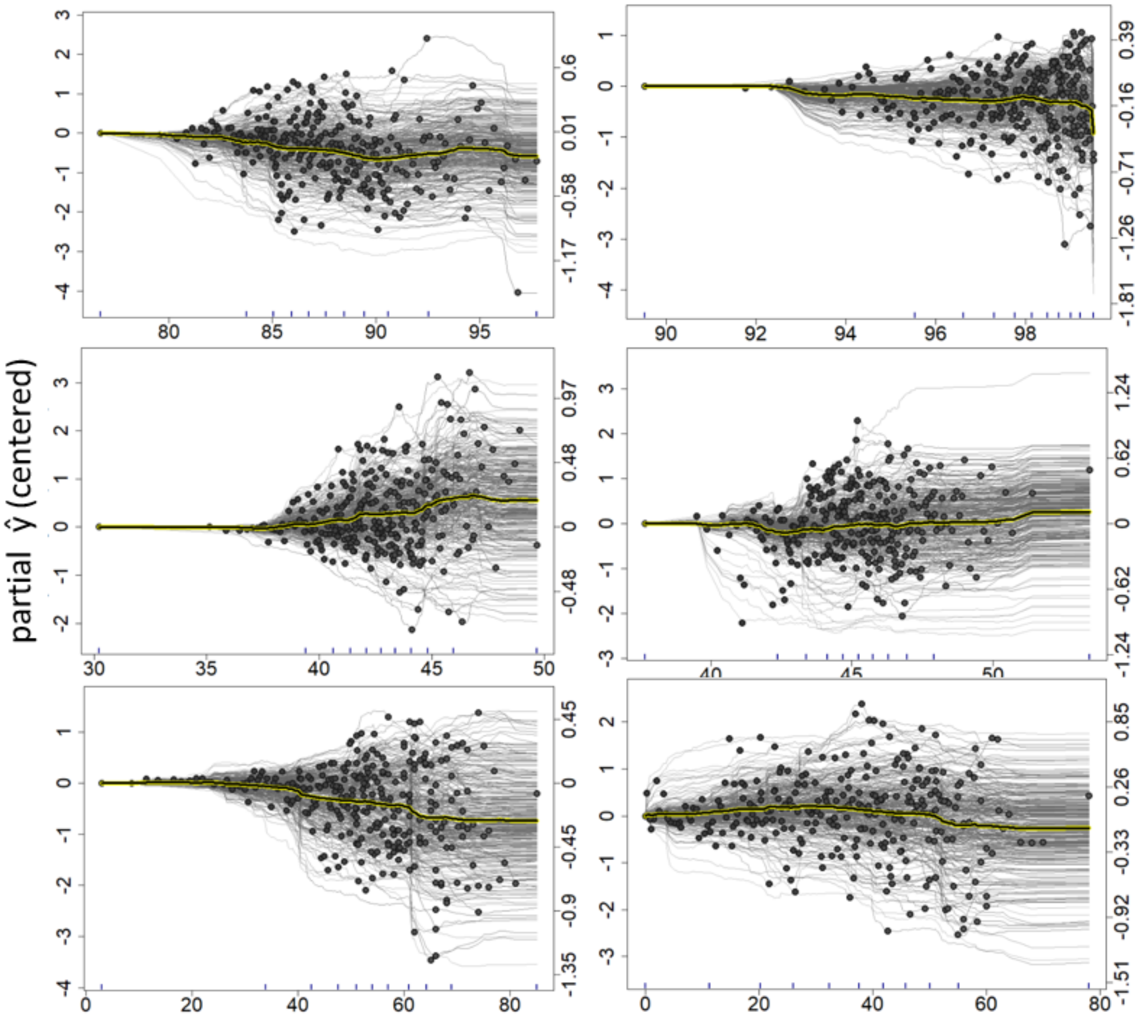

FIg. 7. The individual conditional expectation plot for SmartFirmer clean furrow (%; top), furrow moisture (%; middle), and downforce margin (lb_f; bottom) in the random forest model predicting emergence rate at the 3.8 cm planting depth (left column) and 7.6 cm depth (right column).

Temporally Stable Predictors

In addition to planter-sensor metrics, ICE plots of three inherent soil properties were also evaluated (flow direction, ECa, and SmartFirmer OM). Each of these variables were highly significant in all ER planting depth models, with the exception of OM at the 6.4 cm planting depth. In general, the relative relationship of ER to these three inherent soil properties were similar among depths. Thus, for simplicity, ICE plots were created from predictor variables at the 7.6 cm depth. This depth was chosen because the temporally variable metrics (e.g., furrow moisture and clean furrow) were low in significance, which was attributed to the lack of variability in these metrics at the deeper depth. Therefore, the responses to the temporally stable variables were more clearly defined.

The lowest ER was estimated in areas with high flow direction values (FIg. 8), which generally corresponded to south-facing slopes at the site (FIg. 2). Thus, the southern aspect of the field may have stayed warmer throughout the emergence period, resulting in a quicker emergence. The use of ECa in modeling showed smaller ER estimates in areas of low ECa (FIg. 8). On the contrary, higher OM was associated with a decrease in estimated ER. Collectively, these responses show that corn emerged quickest on soils that were south-facing, high in OM, and exhibited low ECa. However, significant variability still existed in these responses, suggesting there were complex interactions and potential areas to improve row-unit management to minimize corn ER.

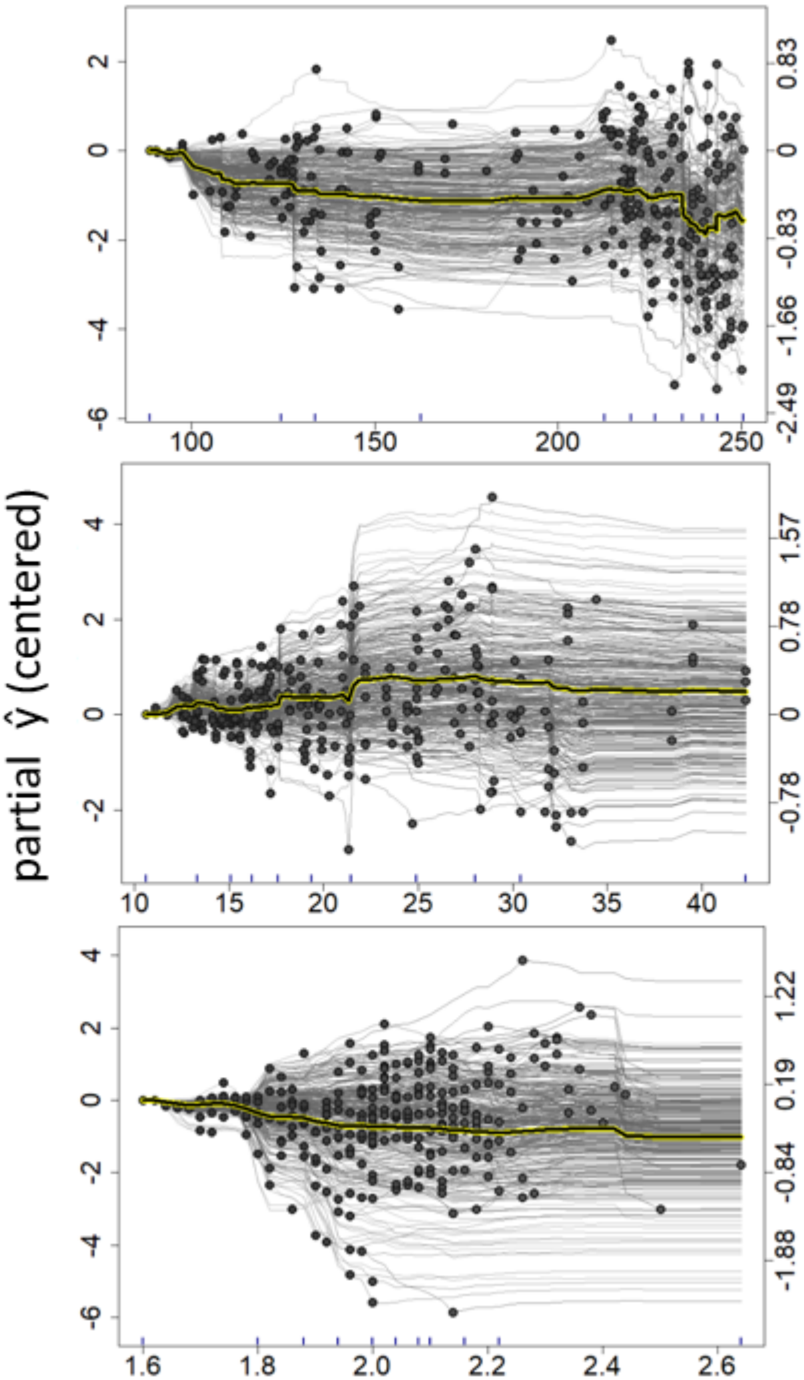

FIg. 8. The individual conditional expectation plot for surface water flow direction (°; top), soil apparent electrical conductivity (mS m^{-1}, middle), and SmartFirmer OM (%; bottom) in the random forest model predicting emergence rate at the 7.6 cm planting depth.

Conclusions

Outcomes from the ER analysis show the potential for combining multiple spatial data layers, both sensor and terrain-based, to predict corn ER. Factors important for predicting ER varied with depth, but these findings showed that a variety of layers were often useful in prediction, including SmartFirmer and DeltaForce metrics, as well as topographic features like surface water flow direction. Therefore, further work is needed to determine whether automated row-unit control could utilize these parameters to adjust in real-time and improve ER, and likely increase emergence uniformity.

Although this research was only conducted on one soil type in one year, it provides a framework for future research evaluating precision seeding technologies at the field scale. Additionally, the results give insight into potential significant and dynamic planter and soil landscape variables that influence emergence performance. As these are better understood and predicted, they can more reliably be used in planting operations to optimize corn emergence uniformity.

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References

Alessi, J. and Power, J.F., 1971. Corn emergence in relation to soil temperature and seeding depth 1. Agronomy Journal. 63:717-719.

Badua, S. A., Sharda, A., Strasser, R., & Ciampitti, I. 2021. Ground speed and planter downforce influence on corn seed spacing and depth. Precision Agriculture. 22:1154-1170.

Conway, L.S., N.R. Kitchen, K.A. Sudduth, D.B. Myers, A.J. Lindsey, and P.R. Carter. Comparing organic matter estimations using two farm implement mounted proximal sensing technologies. In: Proceedings of the 5th Global Workshop on Proximal Soil Sensing, May 28-31, 2019, Columbia, Missouri. p 47-52.

Coronel, E. G., Alesso, C. A., Bollero, G. A., Armstrong, K. L., & Martin, N. F. 2020. Field-specific yield response to variable seeding depth of corn in the Midwest. Agrosystems, Geosciences & Environment, 3, e20034. https://doi.org/10.1002/agg2.20034

Corwin, D.L. and Lesch, S.M., 2003. Application of soil electrical conductivity to precision agriculture: theory, principles, and guidelines. Agronomy Journal. 95:455-471.

Cox, W. J., & Cherney, J. H. 2015. Field-scale studies show site-specific corn population and yield responses to seeding depths. Agronomy Journal. 107:2475–2481. https://doi.org/10.2134/agronj15.0308

Elmore, R., M. Al-Kaisi, and M. Hanna. 2014. Corn seeding depth: Back to the basics. Integrated

Crop Management News. Ames: Iowa State University Extension. Retrieved from https://extension.umd.edu/sites/default/files/_docs/Agronomy%20News%20May%201%202014.pdf

Elmore, R. W. and L. J. Abendroth. 2007. Allelopathy: a cause for yield penalties in corn following corn? Integrated crop management newsletter. Iowa State University. 25 Oct 2010.

Goldstein, A., A. Kapelner, J. Bleich, and E. Pitkin. 2015. Peeking inside the black box: Visualizing statistical learning with plots of individual conditional expectation. Journal of Computational and Graphical Statistics. 24: 44-65.

Gonzalez-Sanchez, A., J. Frausto-Solis, and W. Ojeda-Bustamante. 2014. Predictive ability of machine learning methods for massive crop yield prediction. Spanish. Journa lof Agriculture Research. 12:313–328. doi:10.5424/ sjar/2014122-4439.

Gupta, S.C., E.C. Schneider, and W.B. Swan. 1988. Planting depth and tillage interactions on corn emergence. Soil Science Society of America Journal. 52:1120–1127.

Hummel, J.W., K.A. Sudduth, and S.E. Hollinger. 2001. Soil moisture and organic matter prediction of surface and subsurface soils using an NIR soil sensor. Computers and Electronics in Agriculture. 32: 149-165.

Jamison, V.C., D.D. Smith, and J.F. Thornton. 1968. Soil and water research on a claypan soil. Tech. Bull. 1397. USDA-ARS, Washington, DC.

Kitchen, N.R., K.A. Sudduth, and S.T. Drummond. 1999. Soil electrical conductivity as a crop productivity measure for claypan soils. Journal of Production Agriculture. 12:607–617.

Kyveryga, P. M., T. M. Blackmer, and P. C. Caragea. 2011. Categorical analysis of spatial variability in economic yield response of corn to nitrogen fertilization. Agronomy Journal. 3: 796-804.

Leo, S.; M.D.A. Migliorati, and P.R. Grace. Predicting within-field cotton yields using publicly available dataset and machine learning. Agronomy Journal. 113: 1150–1163

Nelson, D. W., and L.E. Sommers. 1996. Total carbon, organic carbon, and organic matter. Methods of soil analysis: Part 3 Chemical methods. 5:961-1010.

Nemergut, K.T., P. R. Thomison, P.R. Carter, and A.J. Lindsey. 2021. Planting depth affects corn emergence, growth and development, and yield. Agronomy Journal. 113: 3351-3360.

Pachepsky, Y. A., Timlin, D. J., & Rawls, W. J. (2001). Soil water retention as related to topographic variables. Soil Science Society of America Journal, 65(6), 1787–1795. https://doi.org/10.2136/sssaj2001. 1787

Pioneer. (2013). Corn planting and stand establishment (Field Facts). Pioneer.

Precision Planting. 2018. SmartFirmer: Setup & Operation for Gen 2 20/20 Display. Retrieved from https://s3.amazonaws.com/pp3-products/file-1585250294/SmartFirmer%20Operators%20Guide%20-%20Gen3%20(955714).pdf

Qin, Z., Myers, D. B., Ransom, C. J., Kitchen, N. R., Liang, S.-Z., Camberato, J. J., et al. 2018.

Application of Machine Learning Methodologies for Predicting Corn Economic Optimal Nitrogen Rate. Agronomy Journal. 110, 2596– 2607. doi: 10.2134/agronj2018.03.0222

R Core Team. 2022. The R project for statistical computing. Retrieved from https://www.r-project.org

René-Laforest, F. F. 2015. Real-time variable control technologies for precision agriculture. (Master's thesis, McGill University, Montreal, QC, Canada). Retrieved from https://escholarship.mcgill.ca/concern/ theses/fx719q20j

Ransom, C. J., Kitchen, N. R., Camberato, J. J., Carter, P. R., Ferguson, R. B., Fernández, F. G., et al. 2019. Statistical and machine learning methods evaluated for incorporating soil and weather into corn nitrogen recommendations. Computers and Electronics in Agriculture. 164:104872. doi: 10.1016/j.compag.2019.104872

Sadler, E.J., K.A. Sudduth, S.T. Drummond, E.D. Vories, and P.E. Guinan. 2015b. Long-term agro-ecosystem research in the Central Mississippi River Basin: Goodwater Creek Experimental Watershed weather data. Journal of Environmental Quality. 44:13–17. doi:10.2134/jeq2013.12.0515

Schneider, E. C., and S.C. Gupta. 1985. Corn emergence as influenced by soil temperature, matric potential, and aggregate size distribution. Soil Science Society of America Journal, 49: 415–422.

Stewart, S., N.R. Kitchen, M.A. Yost, L.S. Conway, and P. Carter. 2021. Planting depth and within-field soil variability impacts on corn stand establishment and yield. Agrosystems, Geosciences & Environment 4:e20186.

Sudduth, K. A., N. R. Kitchen, W. J. Wiebold, W. D. Batchelor, G. A. Bollero, D. G. Bullock, D. E. Clay et al. 2005. Relating apparent electrical conductivity to soil properties across the north-central USA. Computers and Electronics in Agriculture 46: 263-283.

Thomason, W. E., Philips, S. B., Alley, M. M., Davis, P. H., Lewis, M. A., & Johnson, S. M. 2008. In-row subsoil tillage and planting depth influence corn plant population and yield on sandy-textured MidAtlantic Coastal Plain soils. Crop Management, 7, 1–12. https://doi. org/10.1094/CM-2008-0519-01-RS

Vong, C.N., L.S. Conway, A. Feng, J. Zhou, N.R. Kitchen, and K.A. Sudduth. 2022. Corn emergence uniformity estimation and mapping using UAV imagery and deep learning. Computers and Electronics in Agriculture 198: 107008.

USDA. 2020. Agricultural Statistics Service. U.S. Gov. Print. Office, Washington, DC