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REGULAR ARTICLE

Maize root distributions strongly associated with water tables in Iowa, USA

Virginia A. Nichols · Raziel A. Ordóñez · Emily E. Wright · Michael J. Castellano · Matt Liebman · Jerry L. Hatfield · Matt Helmers · Sotirios V. Archontoulis

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Abstract
Aims Root distributions determine crop nutrient access and soil carbon input patterns. To date, root distribution data are rare but needed to improve knowledge and prediction of cropping system sustainability. In this study, we sought to (i) quantify variation in maize (*Zea mays*) and soybean (*Glycine max*) roots by depth and environment across Iowa, USA and (ii) identify environmental factors explaining the most variation.
Methodology Over three years we collected soil cores from 0 to 210 cm in 16 maize and 12 soybean field experiments at grain filling. Root mass, length, carbon (C) and nitrogen (N) were determined at 30 cm increments, coupled with crop, soil, management, and weather-related measurements.
Results Percentage of root mass located in the top 30 cm varied from 52 to 94% in maize and 54–84% in soybean. Variation in maize root distributions was strongly associated with depth to water tables, variation in soybean with soil physical attributes. Root C:N ratios were highly variable with no depth-pattern, averaging 20 and 30 for soybean and maize, respectively. In both crops, specific root lengths increased with depth to 60 cm, and thereafter remained constant.
Conclusions Field studies of roots should consider depth to water tables and soil moisture measurements, as they influence vertical root distributions.

Keywords Root mass · Root length · Root distribution · Specific root length · Root nitrogen · C:N ratio · Water table

Abbreviations

C	Carbon
N	nitrogen
SRL	specific root length
US	United States

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V. A. Nichols (✉) · R. A. Ordóñez (✉) · E. E. Wright · M. J. Castellano · M. Liebman · S. V. Archontoulis
Department of Agronomy, Iowa State University, Agronomy Hall, Ames, IA, USA
e-mail: vnichols@iastate.edu
e-mail: ordonez@iastate.edu

J. L. Hatfield
National Laboratory for Agriculture and the Environment, USDA-ARS, Ames, IA, USA

M. Helmers
Department of Agricultural and Biosystems Engineering, Iowa State University, Ames, IA, USA

Introduction

Crop roots are an important component of agroecosystems. Roots influence soil carbon inputs (McGranahan et al. 2014; Rasse et al. 2005), the biological activity of soil (Gregory 2006; Sokol and Bradford 2019), and resistance of soil to erosion

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(Gyssels et al. 2005), all of which impact long-term productivity of a system. While the absolute amount of crop roots is significant, the vertical distribution of root systems has substantial implications. The distribution of roots controls when and where crops have access to water and nutrients, and thus determines overall productivity and susceptibility of nutrients to leaching (Dunbabin et al. 2003; Hammer et al. 2009; Tron et al. 2015). Total root mass is an important indicator of soil carbon inputs (Farrar et al. 2012; Kätterer et al. 2011; Russell et al. 2009), but recent studies have suggested the location and quality of the inputs have significant consequences for long term carbon storage and present opportunities for large-scale carbon sequestration (Dietzel et al. 2017; Kell 2012).

Understanding both genetic and environmental controls of root distributions is critical when looking to optimize crops for carbon sequestration or nutrient retention (Kell 2011; Lynch 2013). Despite this importance, there is limited data and thus a poor understanding of how crop roots behave in the field. While several studies have compared crop roots under varying tillage (e.g. Ball-Coelho et al. 1998; Dwyer et al. 1996; Fiorini et al. 2018), fertilization (e.g. Kaspar et al. 1991; Qin et al. 2005) and water (e.g. Follett et al. 1974; Kuchenbuch and Barber 1988; Wang et al. 2003) regimes, they are limited to few environments and measured variables. Additionally, they utilize varying methodologies (date, position, and depth of sampling) making it difficult to compare and synthesize studies to move beyond descriptive results. Moreover, most field root studies in the Midwest were done over 25 years ago (see Table 1 in Ordóñez et al. 2018a). Both cultivars and management practices have drastically changed since that time, and while the effects on aboveground traits have been well-documented,there is less information on belowground aspects (Chen et al. 2014; Keep et al. 2016; Reyes et al. 2015; York et al. 2015).

Iowa is located in the center of the United States' (US) Corn Belt region (Omernik 1987), an area dominated by grain row crop production (USDA 2017). Iowa leads the US in maize (*Zea mays*) and soybean (*Glycine max*) production, with these two crops occuping ~75% of the agricultural land in the state (USDA 2017). Recent studies in Iowa have examined maize and soybean root dynamics (Dietzel et al. 2017; Ordóñez et al. 2018b), but none has explored root distributions across a wide range of environmental and management conditions. Quantitative understanding of the extent and causes of variation in root attributes is required to accurately predict crop responses to changes in climate or management. To our knowledge, no study has reported crop root distributions across a wide range of environments sampled using consistent methodology. We approached this study with the following objectives:

1. Quantify variation in root attributes by depth and environment using consistent sampling methodology applied over many environments.
2. Identify factors contributing to variation in root attributes considering soil, management, and weather variables.

To achieve our objectives, over a period of three years we collected in- and between-row replicated soil cores to 210 cm depth from 16 maize and 12 soybean field trials. We divided the cores into 30 cm increments and determined root mass, length, and carbon (C) and nitrogen (N) contents. This data was augmented with various crop, soil, management, and weather-related measurements. Based on previous literature, our hypotheses were: (i) the C:N ratio of roots will increase with depth (Dietzel et al. 2017; Fiorini et al. 2018), (ii) the maximum rooting depth will be strongly associated with the depth to the water table (Ebrahimi-Mollabashi et al. 2019; Follett et al. 1974; Ordóñez et al. 2018b), (iii) the specific root length (SRL) will increase with depth for both crops (Allmaras et al. 1975), and (iv) decreasing tillage intensity will cause roots to concentrate in the top soil layer (Anderson 1988; Ball-Coelho et al. 1998).

Materials and methods

Experiments

Data were collected at Iowa State University Research and Demonstration farms (Iowa State University 2018) and long-term research sites (see Jarchow et al. 2015) located across Iowa. Maize data were collected from nine sites, and soybean from eight (Fig. 1).

Varieties were chosen each year to reflect modern genetics available in the marketplace; a summary of variety use can be found in Online Resource 1. All maize plots received N fertilizer based on the site's maximum-return-to-N rate (Sawyer et al. 2006) ranging from 160 to 210 kg N ha^{-1} and soybean received no N

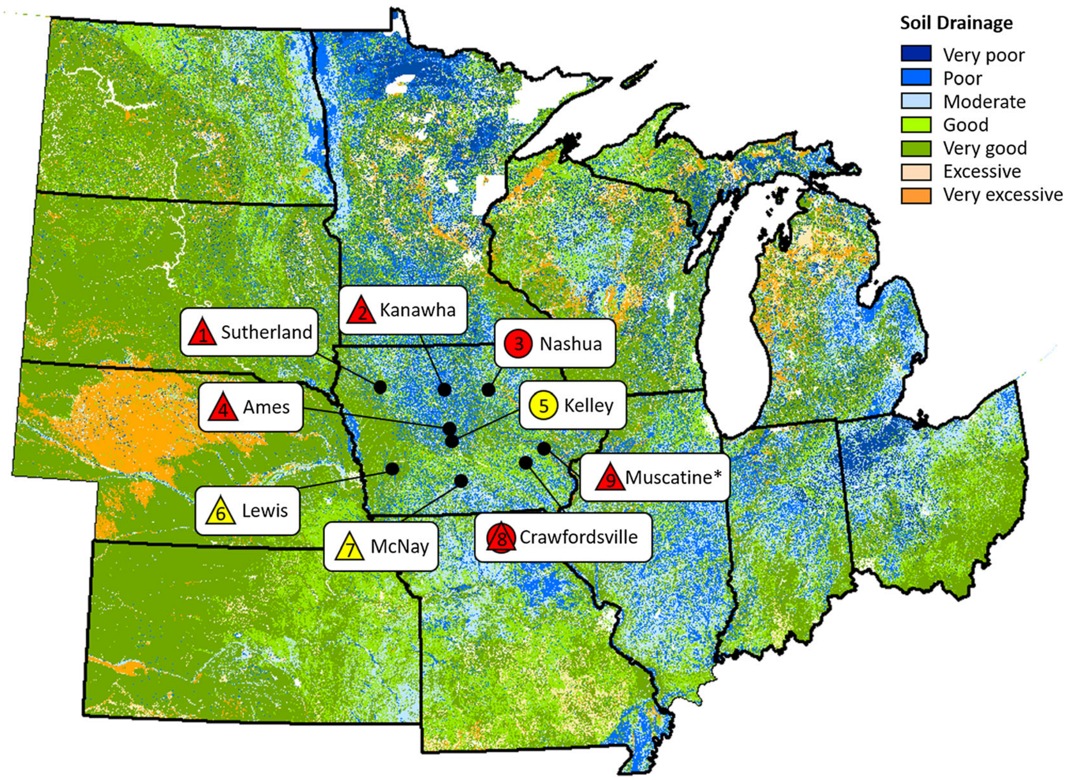

Fig. 1 Geographic distribution of the nine experimental locations included a range of water managements (triangles: nonartificial drainage; circles: subsurface drainage at 1.2 m depth) and tillages (red:tilled; yellow:no-till) located on soils classified as having poor to very good soil drainage (SSURGO 2018); more details about site managements are available in the supplementary materials **Irrigated site with only maize*

fertilizer. Other nutrients, weeds, and diseases were managed adequately, while sub-surface drainage and tillage managements were representative of the production area (Fig. 1). For reference, maize grain yields varied from 6.9 to 17.4 dry Mg ha^{-1}, and soybean varied from 2.8 to 4.8. More details concerning yields can be found in Online Resource 1.

Measurements

Roots were sampled using a hydraulic-driven soil probe (Giddings Machine Company, Colorado USA) with a 6.2 cm inner diameter core to a depth of 210 cm. Root sampling was timed to coincide with peak root mass for maize (R2; Amos and Walters 2006) and soybean (R5; Stanley et al. 1980). Across the field trials and years this occurred from 65 to 105 days after planting. Soil cores were taken to a depth of 210 cm to ensure the maximum rooting depth was captured. All plots were part of larger experiments, and one core was taken in each of three plots arranged in randomized complete block designs, except for Site 8 (Crawfordsville**;** Fig. 1) which had only two replicates. Individual plot sizes ranged from 360 to 3600 m^2. Within a plot, cores were taken from a representative row with standard plant densities. A site-year combination is hereafter referred to as an environment. All environments (16 maize, 12 soybean) had cores sampled from a planted row, while a subset (11 maize, 10 soybean) had an additional core taken halfway between planted rows (online resource 1). Between-row cores were not taken in all environments due to weather and/or time constraints. All environments and crops had 76 cm row spacing, except for Site 3 (Nashua; Fig. 1) in which soybeans had 25.4 cm row spacing. In summary, each environment was represented by three in-row soil cores (except for Site 8), with a subset of environments having an additional three between-row soil cores. All experiments were instrumented with soil moisture and temperature sensors (METER Group, Pullman Washington USA) at 15 and 45 cm depths (see Togliatti et al. 2017) and water table sensors (METER Group) at 3 m depths. All field trials were part of a yield forecasting network (Forecast and Assessment of Cropping Systems 2018) that utilizes environment-specific calibrated Agricultural Production SIMulator (APSIM) models (Keating et al. 2003).

Soil samples were soaked in a solution of sodium hexametaphosphate ($(NaPO_3)_6$; 10 g L^{-1}) to break up soil aggregates. Following 10 min of soaking, samples were placed in tube and sprayed with a mixutre of pressurized water and air. Floating roots were recovered using a 530 um sieve. Remaining organic particles were separated from live roots using tweezers, and root tissues were stored at 4 °C in a 70/30 alcohol-water solution until scanning using an Epson Perfection V800 photo Pro Scanner (Seiko Epson Corporation, Japan) with a transparent poly-methyl-methacrylate tray. Images were aquired at 720 DPI and analyzed using WinRHIZO Pro software (Regent Instruments Inc., Quebec Canada). Samples were then dried at 60 degrees Celcius for 72 h, weighed, and ground. The percent C and N by mass of ground root samples was determined on combined in- and between-row samples from each plot using a Vario Micro Cube CHNS Elemental Analyzer (Elementar Americas). Soil texture data was measured on in-row cores from each plot using laser diffractometry (Miller and Schaetzl 2012) with a Malvern Mastersizer 3000 and a HydroEV attachment (Malvern Panalytical Ltd., UK) on 30 cm soil depth increments. Soil C was measured in 30 cm soil depth increments at each site in 2014/2015. Pedotransfer functions utilizing soil texture and soil C measurements were used to calculate bulk density and plant-available-water for each soil layer using the appropriate equations. (Saxton and Rawls 2006).

Statistics

Data processing

All data manipulation and graphics were done in R version 3.5.2 (R Core Team 2013) with the tidyverse (Wickham 2017), readxl (Wickham and Bryan 2018), viridis (Garnier 2018) and lubridate (Grolemund and Wickham 2011) packages. Variables potentially related to crop root variation were measured and/or calculated (Table 1). Missing data were interpolated using predictions from the calibrated APSIM models (see Measurements Section).

We described the vertical distribution of root mass in the soil profile using three methods. Firstly, we fit a variety of non-linear models to the cumulative root mass by depth for each environment (Archontoulis and Miguez 2015) using the nlstools package (Baty et al. 2015). Based on Akaike's information criterion (AIC; Bozdogan 1987) we chose a modified-logistical function (Fan et al. 2016), from which we extracted the maximum depth of rooting and the depth at which 90% of the total root mass had accumulated (Schenk and Jackson 2002). Secondly, we fit a normalized exponential decay function using depth increment as a continuous variable for each replicate. Lastly, we calculated the percentage of total root mass found in the top 30 cm in each replicate. In this study, we were interested in investigating how relative root distributions are affected by the environment, rather than the absolute amount of roots. However, in our dataset the absolute and relative amount of root mass in the top 30 cm were linearly related for both crops (Online Resource 1).

Data analyses

Tillage was evaluated as both a continuous and categorical variable. For categorical analyses, sites were classified as binary (tilled, no-till; Fig. 1); this variable is subsequently referred to as tillage class. For analysis as a continuous variable, the tillage intensity was assigned a value based on the amount of residue remaining on the soil surface at planting (unpublished data), with 1 representing 100% of the residue remaining on the surface (no-till), 5 representing complete burial of residue (moldboard plowing). Intermediate values corresponded to practices falling between these two extremes (e.g. discing, field cultivation, chisel plowing, strip tillage). Drainage was assigned a categorical value based on whether the site had artificial drainage tile installed (yes, no; Fig. 1). Differences in maize N fertilizer management were described using two categories: method of application (broadcast versus injected) and timing (all applied at planting versus split-application), and were treated as fixed effects. All sites received maximum-return-to-N rates (Sawyer et al. 2006), so the exact amount of N applied was not included in the analyses.

The effect of fixed continuous (tillage intensity, depth increment) and categorical (crop, drainage, tillage class, N application method, N application timing) variables on responses was assessed using a mixed model with environment as a random effect and a combination of fixed effects and their interactions as appropriate

Table 1 Summary of crop, management, weather, and soil variables used to explain variation in root distributions

	Units	Range in Values Across Environments	
		Maize	Soybean
Crop			
Crop biomass at root sampling (R2 maize, R5 soybean)	Mg ha^{-1}	17.1–29.4	5.8–11.0
Total root mass 0–210 cm	kg ha^{-1}	195–880	115–625
Management			
Tillage intensity; 1 = no-tillage, 5 = mold-board plowing	Categorical	1–4	1–4
Crop seeding rate	Seeds m^{-2}	8.0–8.8	25–47
Weather			
Days† saturated (30 cm increments; Fig. 3) [a]	days*	0–95	0–90
Days† with optimum [b] soil moisture 0–30 cm[a]	%*	31–92	51–98
Days† with deficit [b] soil moisture 0–30 cm[a]	%*	0–68	0–44
Days† with excessive [b] soil moisture 0–30 cm[a]	%*	0–18	0–19
Soil temperature 0–30 cm[a,d]†	^{0}C*	18–27	18–24
Average growing season air temperature [d]†	°C	19.9–24.1	20.1–23.9
Yearly average air temperature [d]	°C	8.5–12.9	8.5–12.0
Growing-degree-days[d]†, T_{base} = 10 °C, T_{max} = 30 °C	°C-days	812–1157	793–1102
Precipitation[d]†	Mm	137–572	76–557
Radiation[d]†	MJ m^{-2}	1529–2134	1333–2215
Soil			
Avg. water table depth 1–3 weeks before sampling[a]	cm*	115–240	113–218
Organic matter 0–30 cm	%*	2.9–5.1	3.5–5.0
Organic matter 0–180 cm	mean %*	1.0–2.7	1.1–2.7
Total plant available water 0–180 cm[c]	mm*	79–370	266–370
Bulk density 0–30 cm[c]	g cm^{-3}*	1.14–1.44	1.14–1.32
Bulk density 0–180 cm[c]	mean g cm^{-3}*	1.31–1.52	1.31–1.52

[a] Measured data supplemented with modelled data when necessary

[b] Optimal soil moisture was defined as 80 to 120% of field capacity[c]

[c] Calculated using texture-based pedotransfer functions (Saxton and Rawls 2006)

[d] From weather station located on each site (https://mesonet.agron.iastate.edu/)

†From 10 days after planting to day of root sampling

*Plot data were averaged within an environment/site

(online resource 1) using the lme4 (Bates et al. 2015) and lmerTest (Kuznetsova et al. 2017) packages. Variance components were assessed by manually calculating the ratio of environmental to total variance.

We fit predictive models to both the depth to 90% root mass accumulation and the percentage of root mass in the top 30 cm of soil, using the predictors in Table 1. We chose to use the percentage of root mass in the top 30 cm of soil because root mass in this layer demonstrated the largest raw and relative variation compared to root mass in other layers (Fig. 4). In-row cores were available for more environments compared to between-row cores, so we used only the in-row data. Additionally root length and root mass were highly correlated (Pearson's r = 0.92), so we restricted predictive model fitting to root mass data. For this analysis we eliminated the single irrigated site with only maize data (Site 7 Muscatine, Fig. 1). To investigate the most important predictors (Table 1) of the two responses (depth to 90% root accumulation, percentage in top 30 cm), we fit three predictive models. We performed a partial-least-squares (PLS) regression in R using the pls package (Mevik et al. 2018) selecting the number of components that resulted in the lowest average leave-one-out root-meansquared-error (RMSE), with feature importance estimated using the caret package (Kuhn 2018). Ridge-regressions both without (Hoerl and Kennard 1970) and with a least absolute shrinkage and selection operator (LASSO; Tibshirani 2011) were done using the glmnet package (Friedman et al. 2010). All predictors were centered and scaled before model fitting to eliminate effects of measurement units. Many of the potential model predictors (Table 1) were highly correlated. Features included in the prediction models were analyzed for collinearity using the corrplot package (Wei and Simko 2017), eliminating one predictor from pairs with absolute correlations larger than 0.60. A complete description of feature selection for each response variable is included in supplementary material (online resource 1). We also calculated Pearson's correlation coefficient of the response with each predictor using the cor function of base R.

We chose to only report model fits on the percent mass in the soil surface because (i) it is easily interpreted, (ii) it is often reported, (iii) the predictive models for both responses were similar.

Results

The 2016 growing season followed average trends in both precipitation and temperature, 2017 was dry with a warm spring and early planting, and 2018 was wet with a cool spring leading to late planting, followed by a warmer-than-average growing season (Fig. 2 top panels). The varying precipitation patterns across locations and years coupled with varying drainage managements resulted in a range of soil water conditions (Fig. 2 bottom panel). The percentage of the growing season with optimum, deficit, and excess water in the top 30 cm for maize and soybean is found in Table 1 (visualizations in online resource 1)**.**

Root carbon-to-nitrogen ratios

Depth did not have a significant effect on maize root C:N ratios, with a mean profile value of 30 ($n = 288$, $sd = 8$; Fig. 3). For soybean, depth was significant when considering the entire profile ($n = 146$, $p < .001$), but this was driven by small sample sizes below 150 cm ($n = 4$; a minimum of 2.5 mg of roots were required for analysis). When these values were excluded, depth was no longer significant, with a mean C:N ratio of 20 ($sd = 2$). The environment (site-year) contributed a third of the total variance in both maize and soybean C:N ratios, and models including the random effects of environment fit significantly better than ones without ($p < .001$). Tillage, tillage intensity, N fertilizer placement and timing, and drainage did not affect C:N ratios (maize or soybean), and predictive models produced poor fits.

Root mass and length

In-row values of root mass were highest in the top 30 cm (2.6 and 1.4 Mg ha^{-1} for maize and soybean, respectively; Fig. 4). Between rows, maize and soybean root mass was lower (0.7 and 0.6 Mg ha^{-1}, respectively) compared to in-row values, and the mass was more evenly distributed across the profile. When root mass in each sampling position was normalized to the value in the top layer and compared across environments, maize and soybean did not exhibit statistically different exponential decay parameters (online resource 1). The sampling position significantly affected the decay parameter ($p < .001$), with in-row root mass decreasing 1.5 times faster than between-row. The change in decay parameter between sampling positions was slightly more dramatic in maize compared to soybean ($p = 0.04$). The maximum rooting depth, as predicted by the fitted modified logistic equation, did not vary by crop, position, or their interaction, with a mean value of 153 cm (online resource 1).

Root length followed the same general patterns as root mass. Overall, the specific root length (SRL; ratio of root length to root mass) for both crops was higher for between-row samples compared to in-row samples, with the difference being largest in the top layer. For both sampling positions, SRL was lowest in the surface layer, intermediate from 30 to 60 cm, but from 60 to 180 cm the ratio did not significantly change with depth for either crop (Table 2). Including the random effect of environment significantly improved model fits in the top layer ($p = 0.03$ and $p < .001$ for maize and soybean, respectively), but not below 60 cm where it accounted for <5% of the total variation. In the top 30 cm, soybean root ratios were not significantly affected by tillage class, tillage intensity, N fertilizer placement or timing, or drainage. In both sampling positions, maize SRL increased as tillage intensity increased (SRL increased

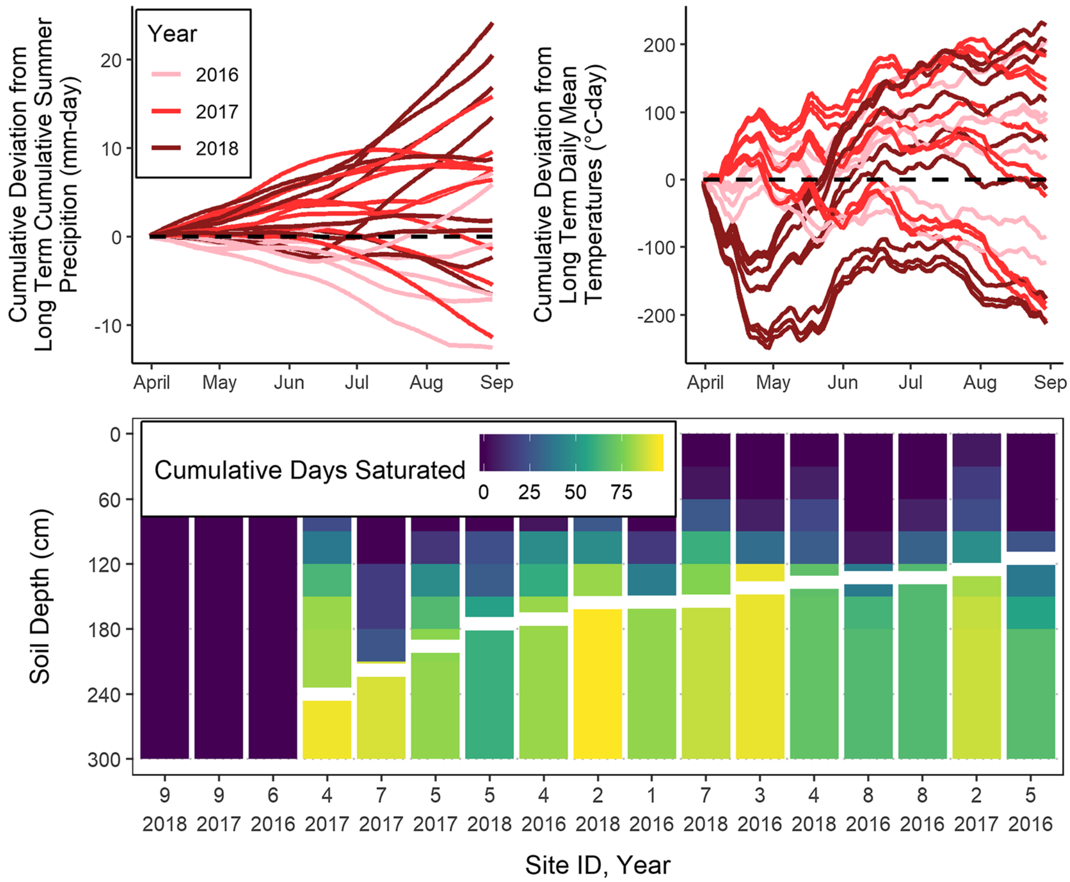

Fig. 2 Variation in precipitation (*top left panel*), temperature (*top right panel*) and (*bottom panel*) number of days a soil layer was saturated from crop emergence through root sampling; white lines indicate water table depths averaged two weeks prior to root sampling in maize plots (for soybean see Online Resource 1); Site ID numbers are provided in Fig. 1

by an estimated 5 m g^{-1} from no-till to discing; $p = 0.04$) but were unaffected by drainage.

Predictors of root distributions

Within a crop, all three predictive models produced similar RMSE values. All models identified the water table as the strongest predictor for maize, while it had minimal importance in soybean. The LASSO regression results are presented as they allow predictor effects to shrink to 0, and correlations of predictors with the root distribution are included for reference (Fig. 5). In maize, water-related factors including average water table depth and surface soil water status were consistently important predictors. For soybeans, the water-holding capacity of the soil profile (as calculated by pedotransfer functions; Saxton and Rawls 2006) was identified as the most important predictor by all models, although water-related factors (water table, drought days) were also important.

Discussion

This study provides new data on maize and soybean vertical root distributions across different environments and management systems. This data can greatly assist parameterization of crop models applied in the US Corn Belt, help agronomists estimate soil carbon and nitrogen balances (Brye et al. 2002; Poffenbarger et al. 2017), and aid in predicting crop responses to changing climates and management (Hatfield et al. 2013). Our consistent measurement protocol allowed us to find associations between vertical root distributions and environmental variables. Below we discuss key findings by root attribute.

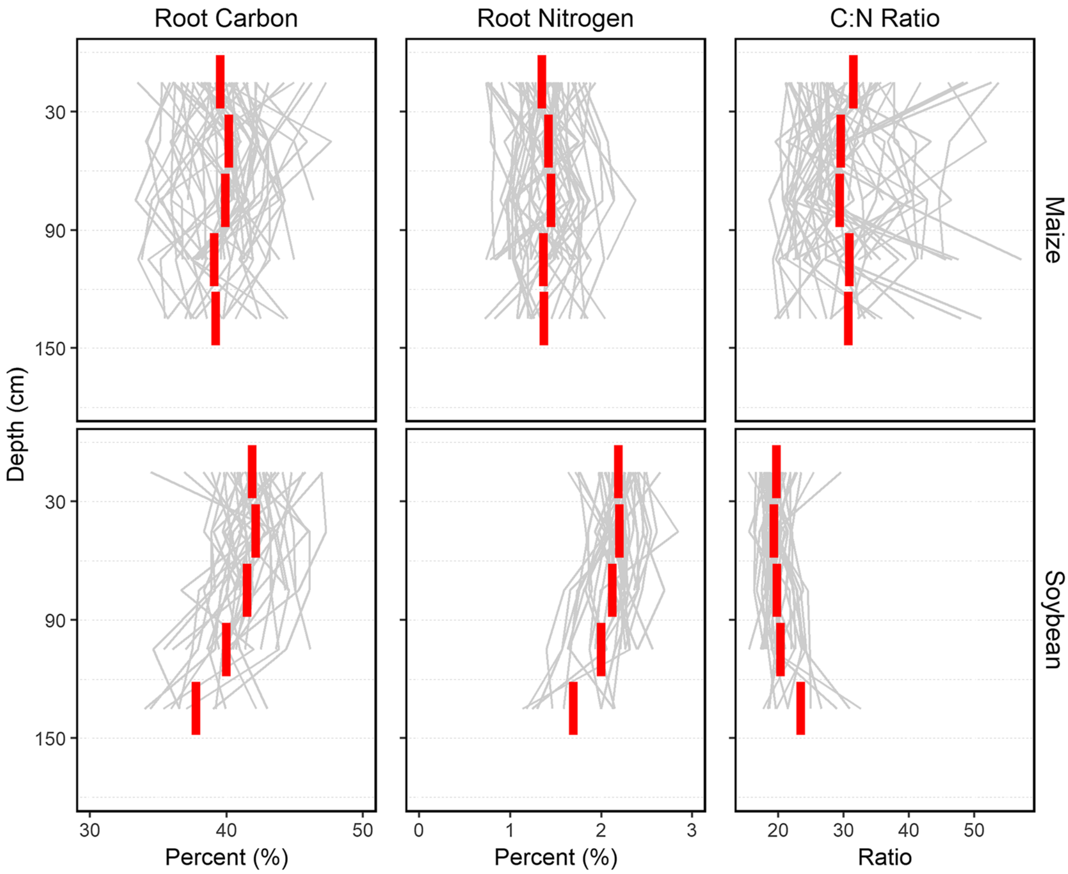

Fig. 3 Root carbon and nitrogen contents and their ratio by depth and crop, lines represent replicates, bold bars represent means for each layer

Root mass

Interestingly, the normalized root distribution profile within a sampling position was the same for soybean and maize, indicating qualitative categorization of root types (taproot versus fibrous) do not translate to distinct quantitative categories (Fig. 4). This certainly merits further exploration, and more direct comparisons of other crop rooting patterns across many different environments are needed. The average maximum rooting depth found in our study (153 cm) is only slightly deeper than those reported by others (Fan et al. 2017; Ordóñez et al. 2018b), and is similar to the rooting depth reported in the Soil Survey Geographic Database (SSURGO 2018). While the average root mass distributions did not vary by crop, the factors driving differences in distributions were distinct for maize compared to soybean (Fig. 5). This is unsurprising, considering these two crops have fundamentally different growth patterns. Structurally, maize root systems consist of many first order roots (tap, seminal, nodal) while soybeans have only one (tap; Lynch 2013; Rich and Watt 2013). Additionally, soybean varieties grown in Iowa are indeterminate (Archontoulis et al. 2014a, b) and their roots continue growing for approximately one month after maize roots have stopped (Ordóñez et al. 2018b). These different growth habits affect when roots are sensitive to certain environmental conditions. In-season comparative measurements of root mass distributions would allow more detailed parsing of these effects.

We found that the strongest predictor of relative maize root investment in the top 30 cm of the soil is the average depth to the water table two weeks before maximum crop mass is achieved; deeper water tables are associated with roots more evenly distributed vertically throughout the soil profile. This expands recent finding from Ordóñez et al. (2018b) regarding the strong relationship between maximum root depth and water table depth. The response is also consistent with the results reported by a Minnesota field study

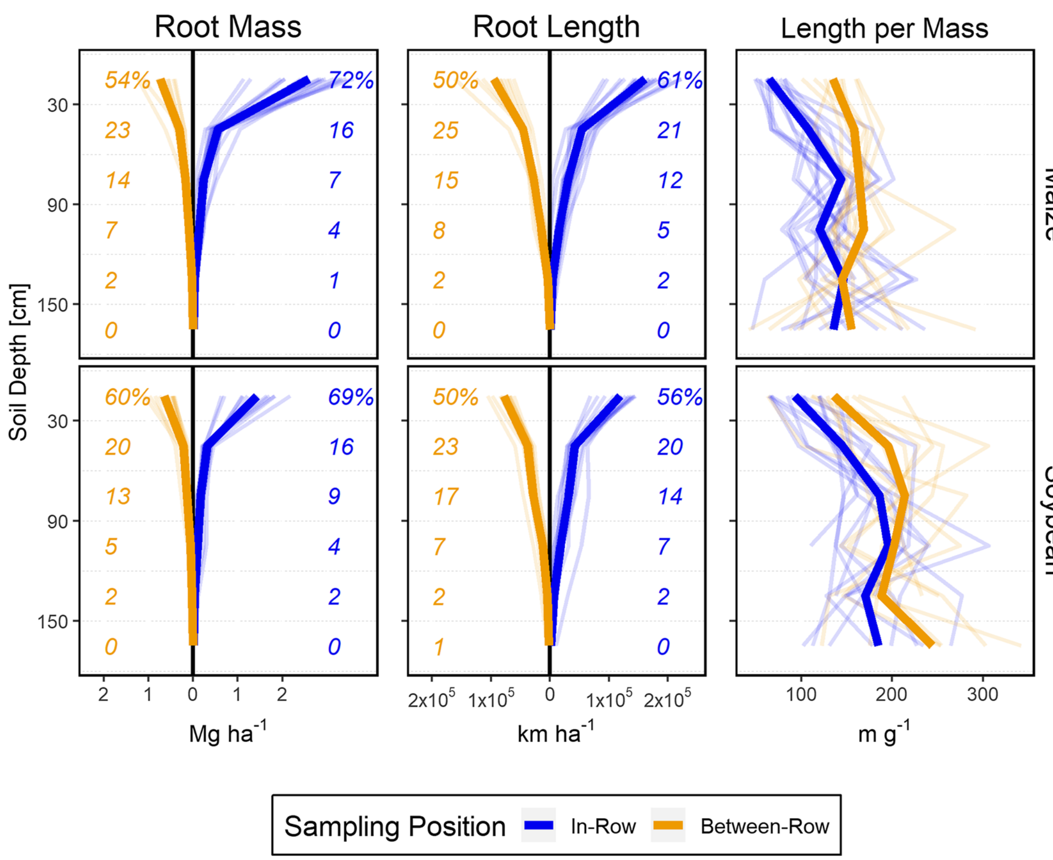

Fig. 4 Between- (light) and in-row (dark) measurements of root mass, length, and their ratio averaged within (thin lines) and across (bold lines) environments; root mass and length panels include the mean percent roots found in a given profile increment

(Follett et al. 1974), providing further support that water tables are a major predictor of maize root distributions in the Midwest. This has important implications for field studies, especially plant breeding programs seeking to select for root traits; water tables must be accounted for when selecting genotypes in fields, especially in the US Corn Belt that has shallow water tables (Fan et al. 2013). Our results also demonstrate measuring or modeling the soil water status in the top 30 cm is important when assessing root responses to treatments. While weather, management, and general soil variables are often available and easy to report, the addition of water table and surface soil moisture measurements should be included in field studies of roots. Additionally, crop models should incorporate the effects of water tables on root distributions to accurately capture root responses to changes in weather patterns or management (Hartmann et al. 2017; Ebrahimi-Mollabashi et al. 2019; Kimball et al. 2019).

Table 2 Specific root lengths (m g^{-1}) observed compared to Midwestern literature values (Allmaras et al. 1975; Follett et al. 1974; Bonifas and Lindquist 2009; see Online Resource 2)

	Maize		Soybean	
Sampling Position	In-Row	Between-Row	In-Row	Between-Row
Literature Values*	5-164		17-33	
Surface, 0–30 cm	65	136	94	133
Sub-surface, 60–180 cm	136	157	184	208

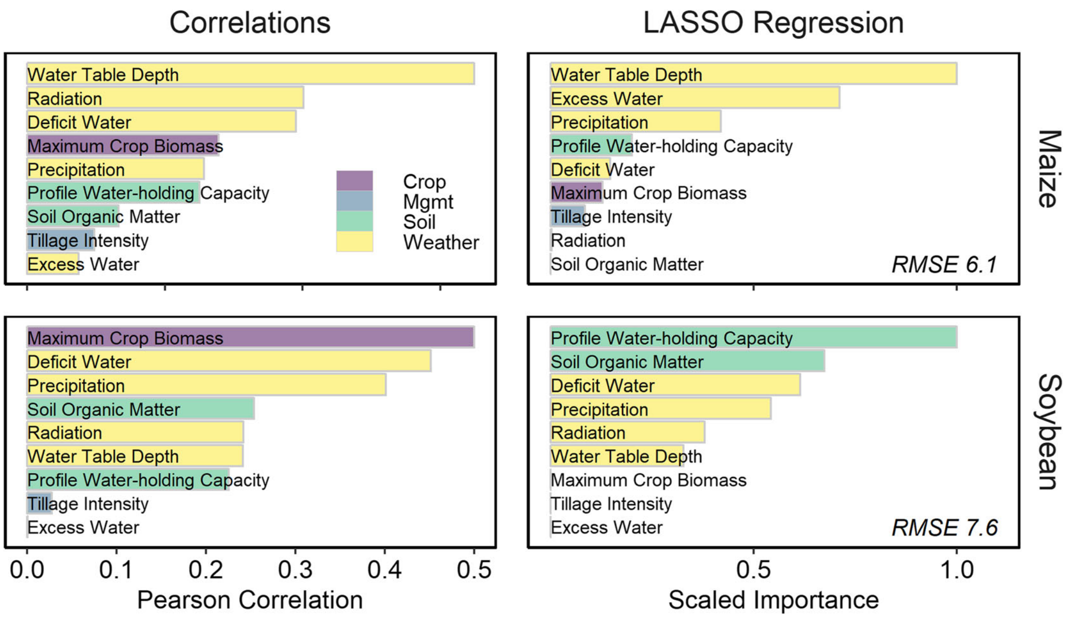

Fig. 5 Correlations and scaled importance of predictors based on LASSO regression models for the relative amount of root mass allocated to the top 30 cm of the soil

Contrary to our hypothesis, while the importance of tillage was not trivial, it was a minor factor in describing relative root investments in the top 30 cm of the soil for both maize and soybean. Tillage and soil moisture are often confounded, with zero-tillage soils exhibiting high soil moistures compared to tilled soils. Previous studies have been unable to tease apart whether roots concentrate in the top layers in no-till systems due to high bulk densities restricting root penetration, or higher soil moisture fostering root growth (Anderson 1988; Ball-Coelho et al. 1998). Our observations suggest in Iowa, moisture status of the top 30 cm is more important than tillage history in determining maize root investments (Fig. 5). This could be because in Iowa soils, the change in bulk density when converting to no-till systems is less drastic than changes associated with controlled wheel traffic (Kaspar et al. 1991; Logsdon and Karlen 2004). We did find reduced tillage was associated with increased maize SRL in the top 30 cm, consistent with other studies (Anderson 1988; Fiorini et al. 2018). The SRL has consequences for the root system's surface area and water uptake calculations (Huth et al. 2012), so this result is important to consider in modeling.

In soybean, the direct relationship between the soil profile's water-holding capacity and surface root investment was weak. However it does suggest that as the soil profile can hold more water, soybeans invest less roots in the surface. Again, our statistical models indicated many factors must be considered when predicting root responses.

Root C:N ratios

The high plot-to-plot variability in C:N ratios, poor predictive model fits, and lack of relationship with depth in our study imply field-scale measurements are not meaningful for predicting C:N root ratios. Our data suggest C:N ratios respond strongly to the micro-environments induced by soil heterogeneity (Stueffer et al. 2006). Until further research on this subject is available, assuming a constant crop-based value for all depths and environments may be sufficient. Our mean values for soybean (20) and maize (30) match general patterns of higher C:N ratios in grasses compared to legumes, with our maize value closely matching previous studies (Dietzel et al. 2017; Fiorini et al. 2018).

In contrast to other studies, we did not find a significant depth effect, which could be due to several factors including timing of sampling, cleaning methodology, and/or differences in soil increments studied. In other studies (Dietzel et al. 2017; Fiorini et al. 2018) the increase in C:N ratio with depth was driven by differences within the top 30 cm, where they utilized smaller depth increments than we did (5 and 10 cm increments). By sampling in 30 cm increments to a deeper depth (210 cm versus 55 and 100 cm), we may not have been able to detect the small differences that occur within the top 30 cm. However, the increases in C:N ratio with depth Dietzel et al. (2017) and Fiorini et al. (2018) found were small compared to the variation we observed in our more extensive environment sampling. Fiorini et al. (2018) found contradicting effects of tillage on C:N ratios with respect to maize and soybean, and in our study we did not see a significant tillage effect (Fig. 3).

Specific root lengths

For all sampling positions and depths, the average SRL for maize in our study was in accordance with Midwestern literature, but our measured values were much higher forsoybean compared to literature (Table 2) (Allmaras et al. 1975; Follett et al. 1974;Bonifas and Lindquist 2009). This could be due to breeders in-directly selecting for higher SRLs, higher planting densities used in modern production systems driving root architectural changes (Cardwell 2010; Duvick 2005), differing methodologies for quantifying root lengths (Himmelbauer et al. 2004), or simply due to the cultivars used in our field studies. Our results again demonstrate the necessity for comparing root measurements collected using identical methodologies. In both crops, the SRLs increased with depth, but this was driven by differences in the top 60 cm of the soil. Below 60 cm, the ratio did not change. Measurements taken below 60 cm can therefore be extrapolated to deeper depths when necessary.

Sampling position

Unsurprisingly, sampling position had a drastic effect on observed root distributions and characteristics (Fig. 4). The shape of the root profile significantly changed depending on where the sample was taken relative to the planted row. While the total profile's root mass can be adjusted to account for the sampling position (Ordóñez et al. 2018a), it is not valid to assume the same correction for mass by layer (online resource 1). In-row samples exhibited larger variation in root mass and length compared to between-row samples; depending on the researcher's goal this information can help inform where to sample relative to the planted row (York 2018). The sampling position also influenced the observed SRL but did not affect the vertical SRL pattern. Sampling away from rows may lead to a lower estimate of SRL compared to in-row, however the difference is smaller than the difference between changes with depth. It is therefore more important to capture the changes in SRLs by depth than by sampling position.

Conclusions

This dataset relates the relative vertical distribution of crop root systems with their growing environment. We observed large variation in how roots are distributed throughout the soil profile, and found the drivers of this variation were unique for maize compared to soybean. For maize, water-related measurements, including water table depths and surface soil moisture, are important predictors this variation. For soybean, soil physical attributes - water-holding capacity, organic matter content - were more important. However, the range of factors contributing to the overall variability in root distributions suggest integrated tools that incorporate multiple factors and their interactions should be used for predicting crop root vertical distributions. We found our field-collected data did not support common qualitative root distinctions, reiterating the need for large-scale and standardized root data collection. Our dataset offers a unique resource for model testing, and due to the range in weather, soil, and managements represented it is applicable for production environments across the US Corn Belt. Large-scale assessments of genotype-environment-management root interactions are needed, and this study can help guide those efforts. For example, ensuring a consistent water table and measuring surface soil moisture can better isolate and identify genetically-controlled differences in roots in a field environment.

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