# Chapter 4

# Molecular analysis shows taxonomic partitioning of root placement by depth in a prairie plant community

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## Abstract

The question of how diversity affects ecosystem resilience is urgent in the face of climate change, yet poorly addressed for belowground contexts. In particular, it is not clear to what extent different species change their behavior when grown in mixed root communities to achieve better partitioning of the available functional and spatial niches. In mixed root samples taken from varying depths in a tallgrass prairie restoration managed for biomass production, we identified taxa by using microfluidic PCR and high-throughput sequencing to obtain DNA barcodes for the *ITS2* region, and asked whether taxa from different functional groups had recognizable spatial roles or co-occurrence patterns. We found that grasses increased in prevalence with depth and forbs from the Asteraceae decreased with depth, and consequently that grasses and forbs showed negative co-occurrence (spatial segregation) overall. Most other taxa were found equally at all depths and showed random or positive co-occurrence, suggesting that there is little overall spatial partitioning at this site. Aboveground cover and belowground read abundance were positively correlated, but with a lower slope for grasses than for dicots. We suggest that in this managed, high-evenness system on uniform, fertile soils, the relatively small fraction of belowground biomass found in the form of grass roots in deep soil layers may be disproportionately important for functions such as water uptake, N leaching prevention, and C storage that affect the resilience of the whole ecosystem.

## Introduction

In a rapidly changing world, one of the most pressing questions in ecology is which ecosystem properties promote stability and which lead to rapid state changes. It is now well recognized that diversity generally promotes resilience in ecosystem productivity (Tilman et al. 2001), partly through facilitation but primarily through functional complementarity that allows more effective partitioning and therefore more complete exploitation of niche space, producing a more stable overall allocation of resources across the community (Fornara and Tilman 2008, 2009, De Deyn et al. 2008). This implies that the resilience benefits of niche partitioning will only be realized if different species in the community possess functions that are actually complementary to each other. For example, N and water availability are often strongly anticorrelated in grassland soils, leading *Festuca ovina* and *Achillea millefolium* to extract N from different depths when competing in mixed-species stands than when they are grown alone, while *Phleum pratense* and *Trifolium pratense* showed no such vertical partitioning (Jumpponen et al. 2002).

In addition to functional complementarity, the resilience of grassland systems may rely on diversity in *spatial* partitioning as well. Prairie plant communities are noted for maintaining a large proportion of their biomass below ground (Jackson et al. 1996), and the importance of belowground interactions between species with differing root traits for determining community productivity has long been recognized (Weaver 1919, Bardgett et al. 2014). Grassland plant communities may be more strongly structured belowground than aboveground (Kesanakurti et al. 2011, Hiiesalu et al. 2012, Wilson 2014) and the physiological capacity to exploit soil resources may be a strong predictor of competitive success (Tucker et al. 2011, de Kroon et al. 2012, Hendriks et al. 2015). Therefore, to understand the potential responses of multispecies communities to destabilized conditions such as a changing climate, it is necessary to understand the physical placement of the different species in the community as well as the between-species differences in resource allocation and niche partitioning strategies.

Progress in understanding these belowground dynamics is slowed by the challenges of studying belowground environments, especially for mixed-species samples. Because harvesting root systems requires digging and root systems show extreme spatial variability that increases the sample size needed to characterize a system, all methods are laborious and most require destructive harvests, often in the form of massive excavations to identify roots by physically tracing them to the plant crown (Weaver and Voigt 1950). Visual identification of roots based on anatomical or morphological characteristics is sometimes possible (Wardle and Peltzer 2003) but is an inherently low-throughput method that requires a trained specialist and becomes much more challenging for very fine roots or highly diverse communities. Minirhizotron methods can provide some information on root placement, but have limited success at distinguishing between species (Rewald et al. 2012).

With the increasing availability of high-throughput DNA sequencing, molecular methods now provide a partial solution to this dilemma. DNA-based methods can use smaller samples and therefore less-destructive sampling techniques, allow distinctions between visually identical roots, and permit quantitative comparisons. Additionally, because DNA persists to some extent in dead tissue, sequencing potentially can integrate longer timescales by detecting species that are present in the community but were dormant or senesced at the time of sampling. The internal transcribed spacer between the 5.8S and 26S regions of the nuclear ribosomal DNA (ITS2) is a popular choice for barcoding of mixed root species recovered from soil: It is easily extracted from all plant groups, widely used in root sequencing (Jackson et al. 1999) and therefore well represented in databases, and short enough (~200 bases) to sequence on an Illumina platform. Although higher taxonomic resolution can be obtained from multiple barcodes (e.g. *rcbL* and *matK*; Staats et al. 2016), assigning identities to multiple barcodes in mixed samples is challenging (Rewald et al. 2012) and ITS2 alone provides comparable resolution to other single barcodes (Chen et al. 2010, Fahner et al. 2016).

The objective of this study was to identify the root species present at varying soil depths (0-100 cm) in a restored prairie in central Illinois, and to use these identities to infer differences in species roles for water usage, N uptake, and carbon storage. We used a DNA metabarcoding approach: we collected fine root samples by coring and extracted whole-community DNA for ITS2 amplicon library construction (Fliudigm Access Array) followed by sequencing (Illumina MiSeq 2x300), then identified the detected sequences to genus level by database search and compared the resulting abundance estimates against those from aboveground surveys.

## Methods

### Experimental site

Our experimental site is the University of Illinois Energy Farm (Urbana, Illinois, USA: 40.06N, 88.19W, elevation 220 m), where five plots of restored prairie were planted in 2008 (four 0.7 Ha plots plus one 3.8 Ha plot). The site has a continental climate with a mean annual temperature of 11°C and approximately 1 m of precipitation annually. It is established on deep, highly fertile Mollisol soils (Argiudolls, mapped as Dana, Flanagan and Blackberry silt loam) with organic C contents more than 1% throughout the top 50 cm (Figure 4.1). The site was used for agriculture for at least 100 years before establishment of the current experiment. For further details on the establishment and management of the site, see previous work by (Zeri et al. 2011, Smith et al. 2013, Masters et al. 2016).

The prairie plots were established by seeding with a mix of 28 species native to Illinois (Table 4.1). Species were chosen to balance four stated goals: Maximum biomass production, ecosystem resilience, trophic diversity, and locally adapted species. Seeds were obtained from Pizzo and Associates (Leland IL), treated at planting time with a mycorrhizal inoculum (“AM 120”; Reforestation Technologies International; Gilroy CA) that is primarily *Glomus intraradices* (Neal Anderson, RTI Inc.; personal communication), and overseeded with a spring oat (*Avena sativa*) cover crop. The plots were mowed after senescence each year and the above-ground biomass was baled and removed. 25 of these 28 species remained detectable in 2011 (Feng and Dietze 2013) and in 2012 a total of 32 species were censused in the plots, with the five most common species *Andropogon gerardii*, *Sorghastrum nutans*, *Ratibida pinnata*, *Helianthus grosseserratus*, and *Coreopsis tripteris* collectively providing about 75% of total cover (Table 4.1).

### Sample collection

To characterize the spatial distribution of species with depth, we collected mixed root samples on July 15-18 of 2013, after most late-season grasses were well emerged but before most early-season plants began to senesce. At 24 locations (one in each quadrant of each 0.7 Ha plot, two in each quadrant of the 3.8 Ha plot), we used an 8 cm bucket auger to collect roots and soil from five depth increments (0-10, 10-30, 30-50, 50-75, and 75-100 cm) of 3 cores within a 2 m radius. We pooled all three cores from each location, collected a ~0.5-1 kg subsample of mixed roots and soil from each depth, and returned the remaining material to the holes. The resulting 120 samples were stored on ice in 1-gallon Ziplok bags for transport to the laboratory, then frozen at -80 °C the same day and stored until further analysis.

To characterize the genetic diversity of our target species and generate a mock community for use as a sequencing control, we collected voucher specimens on August 31 and September 1, 2013. For each of the 33 plant species present in aboveground surveys (X. Feng, unpublished data), we located 3-5 individuals, identified them to species by leaf and flower morphology, and used a trowel to extract roots still attached to their well-identified crown. We pooled all roots from each species, placed them in Ziplok bags, placed them on ice for transport to the laboratory, and froze them at -80 °C the same day for storage until further analysis.

### Root recovery

To separate roots from soil, we thawed mixed samples overnight at 4 °C, then screened them through a 2 mm sieve followed by manually picking all visible roots using forceps. The picking process took about 30-90 minutes per sample and all sieves, forceps, and gloves were wiped with ethanol immediately before use to minimize contamination by non-sample DNA. After root picking, a subsample of the root-free bulk soil was collected and lyophilized, then ground and combusted to determine total carbon and nitrogen content (4010 CHNSO Elemental Analyzer; Costech, Valencia CA).

We then rinsed all roots in three changes of sterile water, with the final rinse including 10 minutes of sonication to dislodge any residual soil from the root surface, then lyophilized all samples and stored them at room temperature. Single-species root voucher samples were treated identically to the mixed root samples, with the exception that bulk soil had been removed at collection time and therefore no sieving or hand-picking steps were necessary.

### DNA extraction and amplification

To maximize extraction of DNA from tough root tissue, we ground all samples once in a dry mortar and pestle at room temperature, then again in liquid nitrogen to a very fine powder. We then weighed ~100 mg of tissue from each sample and extracted whole DNA using a Powersoil-htp isolation kit (Mo Bio Laboratories, Carlsbad CA) according to the manufacturer’s directions, including an optional initial bead-beating step (GenoGrinder; 4 x 30 sec at 1750 RPM, 2 min between rounds) followed by a 60 min incubation at 65 °C with 1% proteinase K. We then performed a post-extraction cleanup using materials from the same kit (E. Adams, Mo Bio; personal communication): We diluted the DNA to a volume of 100 µL with DNAse-free water, added 50 µL of bead beating solution and inverted to mix, then added 25 µL each of solutions C2 and C3, inverted to mix, and centrifuged at 10000 xg for 2 minutes. We then collected the supernatant, added 2 volumes of solution C4, vortexed, and loaded the sample onto a spin filter. Finally, we washed with 500 µL of solution C5 and eluted with 50 µL of C6.

After extraction, we submitted whole DNA to the W.M. Keck Center (Urbana, IL, USA) for amplification and sequencing. In addition to DNA extracted from mixed samples, we included water extractions as a negative control on the DNA extraction + PCR + sequencing process taken as a whole (Figure C.1), a mock community of DNA from 29 species combined in equimolar quantity plus one species (*Heliopsis helianthoides*) at twice the concentration of the others (Figure C.2), and nominally pure extracts of root DNA from four species with high aboveground abundance (*Andropogon gerardii*, *Sorghastrum nutans*, *Silphium perfoliatum*, and *Elymus nutans*; Feng 2014; Figure C.3). The second internal transcribed spacer of the nuclear ribosome gene (ITS2) was amplified from each sample by microfluidic PCR using the Fluidigm Access Array chip and sequenced by synthesis for 2x301 paired-end cycles (MiSeq, V3 chemistry, Illumina Inc, San Diego CA). The 5’ linker construct for each sequence consisted of Illumina flowcell-binding primer i5, Fluidigm linker pad CS1, and plant-specific ITS2 primer S2F (Chen et al. 2010) for a final forward linker sequence of 5'-AATGATACGGCGACCACCGAGATCT-ACACTGACGACATGGTTCTACA-ATGCGATACTTGGTGTGAAT. The 3’ linker construct for each sequence consisted of the Illumina flowcell-binding primer i7, a 10-base oligonucleotide barcode that was unique for each sample, Fluidigm linker pad CS2, and plant-specific ITS2 primer S3R (Chen et al. 2010) for a final reverse linker sequence of 5'-CAAGCAGAAGACGGCATACGAGAT-XXXXXXXXXX-TACGGTAGCAGAGACTTGGTCT-GACGCTTCTCCAGACTACAAT, where XXXXXXXXXX indicates the variable barcode sequence.

### Data processing

The raw Illumina read files were preprocessed by sequencing center staff before delivery by using CASAVA 1.8 to remove sequencing primers, PhiX reference reads, and reads from unrelated samples sequenced in the same flowcell lane. We then used cutadapt 1.8.1 (Martin 2011) to trim primers, discard all reads that did not begin with the expected primer, and trim 3’ bases with a Phred quality score below 20. We then joined the overlapping ends of each read using the RDP maximum likelihood algorithm (Cole et al. 2013) as implemented in Pandaseq 2.10 (Masella et al. 2012) using a minimum alignment quality of 0.8, a minimum assembled length of 25 bases, and a minimum overlap of at least 20 “bits saved” (corresponds to ~10 bases; see Cole et al. 2013). We then used the split\_libraries\_fastq.py script in QIIME 1.9.1 (Caporaso et al. 2010) to assign sequences to samples by barcode matching.

To assign sequences to taxonomic units, we used a de novo clustering approach. We dereplicated sequences and removed singletons and suspected PCR chimeras using VSEARCH 2.0.4 (Rognes et al. 2016), extracted full-length ITS2 variable regions using ITSx 1.0.11 (Bengtsson-Palme et al. 2013), clustered the results using VSEARCH with a similarity threshold of 99%, and assigned taxonomy to each cluster using BLAST+ (Camacho et al. 2009) against the GenBank nt database. We then mapped taxonomy for the full dataset by using VSEARCH to search the full sequence file (including singletons and chimeras) against these cluster centroids, also with a similarity threshold of 99%. After taxonomy assignment, we collapsed all clusters assigned as the same phylotype (species, genus, or family depending on the analysis of interest) into single taxon groups using the phyloseq 1.16.2 package (McMurdie and Holmes 2013) in R 3.3.1 (R Core Team 2016), then corrected for between-sample differences in sequencing depth by transforming raw read counts for each taxon group into sample proportions. Taxa with a mean abundance less than 1% per sample were removed from plots, but included in multivariate analyses.

To visualize the effects of depth and C/N content on root community composition, we performed nonmetric multidimensional scaling followed by permutational MANOVA using the adonis function of vegan 2.4-1 (Oksanen et al. 2016) in R 3.31 (R Core Team 2016), using Jaccard distance as the response variable; depth, C, and N as environmental variables; ‘plot:location’ as a blocking effect. To assess species co-occurrence patterns, we used the package cooccur 1.3 (Griffith et al. 2016) in R 3.31.

Full analysis scripts and raw sequence data are available online (https://github.com/infotroph/Prairie\_seq).

## Results

The MiSeq run and sequence cleanup produced ample, high-quality sequences for the planned analysis: The raw file contained 1286163 plant ITS2 reads, of which 730235 were successfully end-paired, quality filtered, and assigned back from barcodes to samples. These clean reads contained 494505 unique sequences, of which 459986 were observed only once in the dataset (singletons). Of the 34519 sequences observed at least twice, 2219 were identified as probable or borderline PCR chimeras by vsearch. These chimeric sequences accounted for a total of 8526 reads, or ~1.2% of the raw dataset. A further 75 sequences were identified as incomplete or undetectable ITS2 regions by ITSx, leaving a total of 32225 ITS2 sequences to be clustered at 99% similarity into 1347 OTUs, which we then used as reference sequences at 99% similarity to map the 730235 reads (singletons included) of the cleaned sequence file, for a final sequence-by-sample table of 576650 reads. Sample coverage was excellent, with 110 of the 120 mixed root samples having more than 1000 reads (1355-8998), sufficient for confident analysis. There was no apparent change in total read count between samples from differing depths.

After obtaining best-match barcode identities for each of the 1347 OTUs clustered at 99%, we collapsed OTUs to phylotypes by combining groups of OTUs that all yielded the same taxon as their top BLAST hit. When we collapsed at the species level, we obtained 158 phylotypes that were identified as coming from 70 genera across 16 families, which is notably higher than the 32 species, 22 genera, and 6 families known from site vegetation surveys (Table 4.1). Many samples contained high read counts from several different “species” of genera that have only one known species at the site (Figure C.2). From this we infer that, at least with current databases, ITS2 barcode identities may be more reliable at the genus level than the species level.

Of the genera detected both belowground and aboveground, per-plot mean belowground read proportion was positively correlated with percent aboveground cover, but the slope of the relationship was much lower for grasses than for any dicot group (Figure 4.2), possibly indicating a lower sensitivity to detect grasses by this ITS method. Similarly, the number of reads obtained from grasses in our mock community was consistently lower than calculated from input DNA concentrations, and neither of two species from the Lamiaceae was ever detected either in the mock community or the mixed samples (Figure C.2).

To test for spatial partitioning between species, we examined how often pairs of species were found together in a given sample. Most species co-occurred with each other at rates broadly compatible with random occurrence. Of the pairs that appeared nonrandom, more were positively correlated (overdispersion) than were negatively correlated (spatial partitioning), and there were no evident differences in co-occurrence rate between samples from different depths (Figure C.5). However, these effects differed between functional types: Species from the Asteraceae showed neutral to positive co-occurrence with species from all families, while Poaceae species had positive co-occurrence with other Poaceae but negative co-occurrence with most species from other families (Figure 4.3).

The overall taxonomic makeup of roots shifted with depth: The proportion of reads identified as grasses increased from roughly 10% of near-surface reads to approximately one-third of reads in the 75-100 cm layer. Forbs from the Asteraceae declined somewhat with depth, while legumes were relatively consistent across depths (Figure 4.4). These partitionings were consistent across groups within each functional type: When grouped by genus, all grasses were more abundant in deep layers than near the surface (Figure C.4). Within the Asteraceae, only *Silphium* was more abundant in middle layers rather than shallow, possibly attributable to being the only genus at the site with a mix of tap-rooted (*S. lacinatum*, *S. terebinthinaceum*) and fibrous-rooted (*S. integrifolium*, *S. perfoliatum*) species.

Our observation of increasing grass dominance in deeper layers was supported by multivariate analyses: Nonmetric multidimensional scaling produced a first axis highly correlated with depth (Figure 4.5), with grasses associated with deeper layers, Asteraceae with shallow layers, and legumes orthogonal to the depth axis. The largest single explanatory variable was sampling location, which we treated as a conditioning variable and which explained ~40% of total inertia; after accounting for location, depth added a small (~8%) but significant (PERMANOVA pseudo-F=8.7; p=0.001) further increase in inertia explained. Organic C, N, and C:N were all strongly anticorrelated with depth and neither they nor their interactions with depth added any further explanatory power (PERMANOVA; all R2 < 0.01; all p > 0.4).

## Discussion

Root placement in our prairie plots appears to be weakly partitioned by taxonomy, with grasses increasing in abundance relative to forbs at greater depths (Figure 4.4) but little evidence of spatial patterning among other functional groups (Figure 4.3). The aboveground and belowground abundances of most species appeared to scale together (Figure 4.2), but with very different slopes for grasses than for dicots. Given the high overall proportion of reads identified as Asteraceae and especially given their dominance in the shallow soil layers that contain over 80% of the total root mass in this system (Figure 4.1), it is likely that much of the root mass in these plots originates from forbs rather than grasses. However, even if grass root mass in the deep soil layers is small relative to the surface and relative to other taxa, it may still be ecologically important for access to water, nutrient economy, and carbon storage.

One goal of this study was to infer the species composition of root mixtures, to allow richer insights from other studies where bulk biomass samples are collected without identifying their component mixtures. We found that most genera were at least occasionally present at all depths, that the majority of the sequences obtained were from forbs in the Asteraceae, that these were especially dominant in the shallow soil layers, and that despite grasses dominating aboveground measurements of cover and biomass we detected few reads from grass roots near the surface and only some in the deeper layers. Considering biomass and taxon identity together, it is thus likely that relatively shallow forb roots account for a substantial fraction of the root C input to this prairie. However, this does not necessarily mean that grasses are a minor component of total root mass: To attempt a quantitative conversion from reads to tissue mass requires knowing the potentially species-specific relationships between root biomass and DNA yield (Rewald et al. 2012, Zeng et al. 2015), which we did not attempt to characterize here. The lower slope of grasses in the aboveground-belowground relationship (Figure 4.2) and the apparent lower detection of grasses in our mock community (Figure C.2) are suggestive of a possible extraction or sequencing bias against grasses, but even if present we expect this to be constant across samples and thus should not affect comparisons of relative functional group dominance between depths.

An additional caution for our method is that the precision and accuracy of our barcode identifications are limited by the taxonomic resolution of the ITS2 region, the potential for intraspecific variation (Álvarez and Wendel 2003), and the completeness of available sequence databases. Following previous workers (e.g. Fahner et al. 2016), we regard all species identities from this dataset to be tentative, and in a few cases even genus assignment was uncertain. This was particularly evident in the C4 grasses, for many of which we obtained BLAST ties with multiple best results widely spread across the PACMAD clade. However, because our site has only a few congeneric species (Table 4.1) and our hypotheses were focused at the level of phylogenetically-distinct functional groups, further refinements of sequence identity are unlikely to change the conclusions. Using multiple primer sets may help to increase taxonomic resolution and would be straightforward to add to future work using the Fluidigm PCR platform (Brown et al. 2016), but in our mixed-sample setting the bioinformatic challenge of resolving multiple markers would likely be prohibitive (Fahner et al. 2016).

Previous work on the spatial structure of grassland root communities has found mixed results. An old-field site in Ontario (Kesanakurti et al. 2011) was similar to ours in finding positive correlations between aboveground and belowground abundance and in finding less roots from grasses than expected from aboveground data, but differed in finding very strong spatial partitioning. This difference may be attributable to differences in spatial scale (they extracted individual roots from 5x5x5-cm soil blocks, we pooled roots from multiple cores in each ~2 m sampling area) or to differing environmental controls in a heterogeneous old-field environment than in a planted site under active crop management. By contrast, two grasslands with differing soil water regimes in Wyoming showed co-occurrence patterns much like those we observed, with most species present in all samples and only weak changes in detection with depth (Frank et al. 2015). In addition, mapping of individual roots at the mm scale in these same Wyoming grasslands were consistent with our finding of more positive than negative species co-occurrences (Frank et al. 2015). Taken together, these findings support the conclusion of Price and co-workers (2012) that belowground community structure is largely determined by *abiotic* filtering; perhaps we should not be surprised to find little spatial structure in our highly fertile, previously tilled, evenly planted, annually mowed site.

Although root mass in the deep soil was low relative to the surface layers, these roots are likely to be ecologically important. By allocating proportionally more roots to the deep soil than other groups, the grasses in this prairie may gain access to more reliable water supplies and reduced competition for nutrients that help maintain their aboveground dominance. Even small increases in the amount of deep root can contribute to drought survival of grasses (Nippert et al. 2012), reduce N leaching losses (Smith et al. 2013), and increase soil C storage (De Deyn et al. 2008, Anderson-Teixeira et al. 2013), implying that the taxonomic partitioning we observed is likely to increase the management value of prairie restorations as well as their ecological resilience.

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## Table and Figures

Table 4.1: Plant species planted or found present (\*) during aboveground vegetation surveys of permanent quadrats in prairie restoration plots at the University of Illinois Energy Farm. Mean and standard deviation of stem abundance and percent cover across growing season 2012 were recalculated from X. Feng (unpublished data).

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Functional type | Family | Species | % cover | sd |
| C3 grass | Cyperaceae | *Carex bicknellii* | 1.4 | 2.3 |
| C3 grass | Poaceae | *Elymus canadensis* | 2.2 | 3.4 |
| C4 grass | Poaceae | *Andropogon gerardii* | 34.3 | 13.7 |
| C4 grass | Poaceae | *Schizachyrium scoparium* | 3.0 | 3.4 |
| C4 grass | Poaceae | *Sorghastrum nutans* | 21.2 | 10.5 |
| Forb | Asteraceae | *Coreopsis palmata* | 0.1 | 0.5 |
| Forb | Asteraceae | *Coreopsis tripteris* | 4.9 | 6.1 |
| Forb | Asteraceae | *Echinacea pallida* | 0.1 | 0.4 |
| Forb | Asteraceae | *Felicia hirta*\* | 0.3 | 0.8 |
| Forb | Asteraceae | *Helianthus grosseserratus* | 7.2 | 8.2 |
| Forb | Asteraceae | *Heliopsis helianthoides* | 0.1 | 0.3 |
| Forb | Asteraceae | *Parthenium integrifolium* | 0.4 | 1.2 |
| Forb | Asteraceae | *Ratibida pinnata* | 8.3 | 5.4 |
| Forb | Asteraceae | *Rudbeckia hirta*\* | 0.0 | 0.2 |
| Forb | Asteraceae | *Rudbeckia subtomentosa* | 2.9 | 4.2 |
| Forb | Asteraceae | *Silphium integrifolium* | 1.6 | 2.8 |
| Forb | Asteraceae | *Silphium laciniatum* | 0.2 | 0.8 |
| Forb | Asteraceae | *Silphium perfoliatum* | 0.5 | 2.0 |
| Forb | Asteraceae | *Silphium terebinthinaceum* | 0.1 | 0.7 |
| Forb | Asteraceae | *Solidago canadensis*\* | 3.2 | 6.4 |
| Forb | Asteraceae | *Solidago rigida* | 1.3 | 2.7 |
| Forb | Asteraceae | *Symphyotrichum novae-angliae* | 4.0 | 3.8 |
| Forb | Asteraceae | *Taraxacum officinale*\* | 0.1 | 0.5 |
| Forb | Lamiaceae | *Monarda fistulosa* | 1.0 | 2.0 |
| Forb | Lamiaceae | *Pycnanthemum virginianum* | 0.6 | 0.8 |
| Forb | Plantaginaceae | *Penstemon digitalis* | 0.5 | 2.2 |
| Forb | Plantaginaceae | *Veronicastrum virginicum* | 0.2 | 0.8 |
| N fixer | Fabaceae | *Astragalus canadensis* | 0.0 | 0.2 |
| N fixer | Fabaceae | unidentified *Baptisia* sp.\* | 0.1 | 0.4 |
| N fixer | Fabaceae | *Baptisia alba* | 0.7 | 1.5 |
| N fixer | Fabaceae | *Dalea purpurea* | 0.2 | 0.6 |
| N fixer | Fabaceae | *Desmodium canadense* | 4.8 | 5.7 |
| N fixer | Fabaceae | *Lespedeza capitata* | 0.2 | 0.5 |

\*Indicates a species not present in the seed mix planted during plot establishment in 2008.

Figure 4.1: (a) total root mass of prairie plots measured in mid-August of 2011 Replotted from(Replotted from Anderson-Teixeira et al. 2013) and 2014 (Replotted from Black et al., in prep). Error bars show mean ± 1 standard deviation of 24 cores. Remaining panels show means of soil properties measured when the plots were established in 2008 replotted from(replotted from Smith et al. 2013): (b) soil texture; (c) soil organic C and N content; (d) soil bulk density.

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Figure 4.2: Correlation between percent aboveground cover (horizonal axis) and read proportion per root sample (vertical axis). Points are genus means for one experimental plot (N=5 plots); bars are 1 standard errors in each direction. Root proportions are averaged across all depths.

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Figure 4.3: Standardized effect sizes for observed co-occurrence rates. Each point is one pair of species; violin shapes show density distribution for each group. Vertical axes show family identity of the first species in the pair, panel labels show the family identity of the second species. Co-occurance was defined as mixed root samples with more than 1% of ITS2 reads from both species. Larger positive effect sizes indicate species pairs that are found together in more samples than expected for independently-oocurring species; negative values indicate pairs that are found together less than expected.

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Figure 4.4: Relative abundance (fraction of reads from each sample) as a function of sample depth for each observed plant family. Sequences were clustered at 99% similarity and identified to species according to the closest BLAST match against the Genbank nt database. Taxa were then collapsed by family and groups with a mean abundance less than 1% per sample were removed for plotting.

Figure 4.4: Relative abundance (fraction of reads from each sample) as a function of sample depth for each observed plant family. Sequences were clustered at 99% similarity and identified to species according to the closest BLAST match against the Genbank nt database. Taxa were then collapsed by family and groups with a mean abundance less than 1% per sample were removed for plotting.

Figure 4.5: Nonmetric multidimensional scaling plot showing centroids for all detected species. Red: Poaceae. Green: Asteraceae. Blue: Fabaceae. Black: Other families. Grey crosses: Low-abundance species, unlabeled for figure clarity. Pink arrows show best fits for environmental vectors of depth in soil, organic C and N content, and C:N ratio.

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# Appendix C

# Supplemental figures for taxonomic partitioning of root placement

Figure 4.S1: Read counts obtained from water controls, binned by assigned genus. Each panel shows reads from a separate aliquot of DNA-free water processed simultaneously through the same DNA extraction, PCR, and sequencing pipeline as the root samples. Notice that the y-axis shows raw read counts (not sample proportions as in other figures) and that the scale differs between panels.

Figure C.1: Read counts obtained from water controls, binned by assigned genus. Each panel shows reads from a separate aliquot of DNA-free water processed simultaneously through the same DNA extraction, PCR, and sequencing pipeline as the root samples. Notice that the y-axis shows raw read counts (not sample proportions as in other figures) and that the scale differs between panels.

Figure 4.S2: Genus identities of reads obtained from a mock community of DNA obtained from known-species root samples. Green dots show proportion of template DNA added to the mixture. Black bars show the proportion of reads obtained. Panels are technical replicates, each separately amplified and sequenced from the same aliquot of mixed DNA.

Figure C.2: Genus identities of reads obtained from a mock community of DNA obtained from known-species root samples. Green dots show proportion of template DNA added to the mixture. Black bars show the proportion of reads obtained. Panels are technical replicates, each separately amplified and sequenced from the same aliquot of mixed DNA.

Figure 4.S3: Species identities of reads obtained from (top row) DNA extracted from single-species root samples, and (second two rows) DNA from the Andropogon gerardii sample spiked with 1%, 5%, or 10% Elymus canadensis or Sorghastrum nutans DNA. Notice that the barcoding assignment identifies the dominant sequence from the Andropogon gerardii sample as Solidago, not a grass!

Figure C.3: Species identities of reads obtained from (top row) DNA extracted from single-species root samples, and (second two rows) DNA from the “*Andropogon gerardii*” sample spiked with 1%, 5%, or 10% *Elymus canadensis* or *Sorghastrum nutans* DNA. Notice that the barcoding assignment identifies the dominant sequence from the “*Andropogon gerardii*” sample as *Solidago*, not a grass!

Figure 4.S4: Relative abundance (fraction of reads from each sample) as a function of sample depth for each observed plant genus. Sequences were clustered at 99% similarity and identified to species according to the closest BLAST match against the Genbank nt database. Taxa were then collapsed by genus and groups with a mean abundance less than 1% per sample were removed for plotting.

Figure C.4: Relative abundance (fraction of reads from each sample) as a function of sample depth for each observed plant genus. Sequences were clustered at 99% similarity and identified to species according to the closest BLAST match against the Genbank nt database. Taxa were then collapsed by genus and groups with a mean abundance less than 1% per sample were removed for plotting.

Figure 4.S5: Observed species co-occurence rates versus the rates expected for independent, randomly distributed species of the same abundance, calculated separately for (a-c) shallow, medium, and deep soil layers, or (d) all samples from all depths. Each point represents one pair of species and the observed co-occurance rate is the number of root samples with at least 1% of reads attributed to each species in the pair. Colors indicate species pairs whose co-occurance rate differs significantly (p<0.05) from the null model.

Figure C.5: Observed species co-occurrence rates versus the rates expected for independent, randomly distributed species of the same abundance, calculated separately for (a-c) shallow, medium, and deep soil layers, or (d) all samples from all depths. Each point represents one pair of species and the observed co-occurrence rate is the number of root samples with at least 1% of reads attributed to each species in the pair. Colors indicate species pairs whose co-occurrence rate differs significantly (p<0.05) from the null model.