

1 **Title:** Rhizosphere microbial communities explain positive effects of diverse crop rotations on
2 corn and soybean performance

3 **Running title:** microbiome explain benefits of diverse rotations

4

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22 **Abstract**

23 In agricultural systems, crop rotation diversity influences soil microbial communities and often
24 increases crop productivity. Yet the specific contributions of microorganisms to crop rotation
25 benefits are unknown. We studied corn (*Zea mays* L.) and soybean (*Glycine max* L.) within a
26 two-year corn-soybean rotation and four, four-year, four-crop rotations with varying crop
27 sequences. We hypothesized that rhizosphere microbial communities would predict crop
28 productivity contingent on rotation diversity and previous crop legacy. Sampling at seedling and
29 flowering stages, we assessed rhizosphere bacterial and fungal communities, plant tissue
30 nutrients, aboveground biomass, and yield. Rhizosphere communities varied with rotation
31 diversity and previous crop legacy. Concurrently, corn and soybean yields and biomasses were
32 larger in more diverse rotations and with different crop legacies, but not tissue nutrients. Fungal
33 communities predicted the suppression of corn seedlings when following soybean, and soybean
34 seedlings when following corn, independently of rotation effects. This fungal effect ultimately
35 predicted suppressed corn yield in the corn-soybean rotation, while in more diverse rotations,
36 bacterial communities predicted corn would fully recover from a soybean legacy by flowering.
37 These results suggest that corn-soybean rotations select for yield-suppressive microbial
38 communities and highlight a microbial mechanism behind the benefits of diverse rotations.

39

40 **Introduction**

41 Microorganisms mediate essential ecological processes in agricultural ecosystems.
42 Agroecosystems depend on the activity of microorganisms to mineralize organic inputs and
43 sustain nutrient cycling, promote soil structure and stabilization of organic matter pools, and
44 support plants through symbioses (1). Microorganisms directly interact with plants, in particular
45 in the area physically closest to and under greater influence of the plant root, the rhizosphere (2).
46 Beyond acting as plant pathogens, rhizosphere microorganisms can stimulate plant growth
47 through different mechanisms, including nutrient cycling and increased nutrient availability to
48 the plant, synthesis plant growth promoting organic compounds, priming of plant resistance, and
49 antagonism of pathogen and pest activity (3–6). Hence, the diversity and function of rhizosphere-
50 associated microorganisms, which are intimately related to plant performance, are important
51 assets in the sustainable intensification of agriculture, with the goal of achieving increased crop
52 yields without compromising the environment (7–9).

53 In annual cropping systems, which typically contain monocultures of a single crop grown
54 per year, one way to alter the diversity and function of rhizosphere-associated microorganisms is
55 through the selection and sequencing of plants grown in a multi-year rotation. For instance,
56 incorporating additional crops into a continuous monoculture or a two-year rotation can help
57 manage both soil fertility and pathogen and pest pressure (9). This rotation effect happens at
58 multiple timescales. First, a plant species releases a variety of root exudates, which modulate
59 rhizosphere microorganisms in a plant species-specific manner (10,11). These changes may
60 directly impact the subsequent crop as a legacy effect. Legacy effects of crop history have been
61 described for crop health and soil processes (12,13), soil and rhizosphere microbial communities
62 (14–16) and individual microorganisms (17,18). This is followed by an effect observed on a

63 longer timescale wherein the overall diversity and plant species composition of a rotation impact
64 microbial communities. Generally, diversified rotations – those with more than two crops grown
65 in sequence across at least two years – have higher microbial diversity and altered microbial
66 activities than simple two-year rotations (19).

67 In parallel with microbial effects, diversified rotations can increase productivity and
68 stability over time under less favorable conditions and without additional inputs (20–22).
69 Additionally, shifting from low-diversity rotations such as corn-soybean to incorporate
70 additional crops can substantially reduce fertilizer use and greenhouse gas emissions, and
71 improve air quality, without compromising economic or agronomic performance (23). Therefore,
72 the careful design of cropping practices that enable crop diversification, such as crop rotations,
73 plays an important role in the development of sustainable agriculture (24). However, while a
74 number of microbial community changes and processes have been implicated in driving greater
75 crop productivity, the importance of microorganisms in mediating the effect of rotation diversity
76 on crop productivity is poorly understood (25). This knowledge gap hinders the monitoring and
77 development of crop rotations that promote key interactions leading to greater crop establishment,
78 vigor and yield (26).

79 Previously, we demonstrated that both the previous crop legacy and rotation sequence
80 composition impact rhizosphere-associated microbial communities in corn using soils from this
81 field study (12). In the current study we evaluate the in-field predictive power of microorganisms
82 on crop performance in response to the effects of crop rotation diversity and previous crop
83 legacy. We studied a 16-year old experiment comparing a two-year, corn and soybean rotation to
84 multiple four-year rotations. We have documented greater yield of both corn and soybeans in at
85 least one of the four-year rotations compared to the two year rotation (20,27). Hence, we

86 hypothesized that both the diversity of rotation and the legacy of the preceding crop
87 independently affected corn and soybean yield. Further, we hypothesized that rotational diversity
88 and legacy effects could be better predicted by concurrent changes in rhizosphere microbial
89 communities, in comparison to plant tissue nutrient contents. In testing these hypotheses, we a)
90 derive indicators of yield-supporting or yield-suppressing rhizosphere bacterial and fungal
91 communities and b) identify rotation characteristics that would discourage yield-suppressive
92 rhizosphere communities. These indicators and rotation characteristics are critical to facilitating
93 the design and monitoring of cropping systems that alter soil and rhizosphere microbial
94 communities to support sustainable intensification in agriculture.

95

96 **Materials and Methods**

97 **Site description**

98 A long-term research experiment was established in 2000 at the Eastern South Dakota Soil and
99 Water Research Farm in Brookings, South Dakota, USA (44°21' N; 96°48' W) to evaluate the
100 benefits of four-year rotation sequences. Thirty-year mean annual precipitation is 580mm and
101 mean annual temperature is 6.2°C. The Mollisol soils are a moderately drained, Barnes sandy
102 clay loam with organic carbon content of 18 g C kg⁻¹ soil (0–15 cm). Rotation treatments were
103 established in a randomized complete block design with four replications; each crop in a rotation
104 sequence was present each year. The plots were no-till, with 85% locally recommended nitrogen
105 fertilization based on fall soil tests and crop yield goals ((corn:7.84 Mg ha⁻¹; winter wheat: 4.03
106 Mg ha⁻¹; spring wheat: 3.36 Mg ha⁻¹; oat: 3.94 Mg ha⁻¹), phosphorus inputs of 17.6 kg P ha⁻¹ at
107 planting, and herbicide-based weed management as needed (28). Corn (*Zea mays* L.) and
108 soybean (*Glycine max* L. Merr.) in the following rotation sequences were examined: CS: corn –

109 soybean; CPWwS: corn - pea (*Pisum sativum* L.) - winter wheat (*Triticum aestivum* L.) –
110 soybean; COWwS: corn - oat (*Avena sativa* L.) - winter wheat – soybean; CSSwSf: corn -
111 soybean– spring wheat – sunflower (*Helianthus annuus* L.); and CSSwP: corn – soybean – spring
112 wheat – pea. CS is a two-year rotation; the others are four-year rotations. Corn follows soybean
113 in CS, CPWwS, and COWwS; and soybean follows corn in CS, CSSwSf, and CSSwP. See
114 Supplementary Methods.

115

116 **Sample collection and plant measurements**

117 Plant and soil samples were collected from corn and soybean plots within each rotation in 2016
118 and 2017, coinciding with the completion of four cycles of four-year rotations. At seedling
119 (vegetative stage 1-3), six corn and soybean plants were destructively sampled from each plot,
120 and roots with surrounding soils were collected to a depth of 15 cm with a hand trowel. Plants
121 were sampled again at flowering (corn – VT/R1, soybean – R2). Four plants per plot were cut at
122 the base and associated root and soil were sampled using golf cup cutters (10.8 cm diameter) to
123 15 cm depth. Sampling tools were disinfected with 70% ethanol between plots. Samples were
124 maintained on ice packs in the field and refrigerated (4°C) until processing. In the laboratory, the
125 root and associated rhizosphere soils (i.e. roots plus adhering soils after shaking), herein
126 collectively referred to as the rhizosphere, were collected for microbial community analyses and
127 stored at -80 °C.

128

129 Aboveground plant tissue was collected and dried at 60° C for biomass measurements and tissue
130 nutrient analysis. Dried tissue was ground to \approx 2 mm sieve and analyzed for plant nutrient
131 concentrations by inductively-coupled plasma emission spectrometry (AgLab Express, Sioux

132 Falls, SD). Yields were collected with a combine and corrected to standard moisture (corn – 155
133 g kg⁻¹; soybean – 130 g kg⁻¹).

134

135 **Amplicon sequencing of bacterial and fungal ribosomal gene markers**

136 Prior to DNA extraction, approximately 0.2 g of rhizosphere sample was freeze-dried and ground
137 with a bead beater for 30 s. Total rhizosphere DNA was extracted using Qiagen's DNeasy®
138 Plant-96 kit. Library preparation for amplicon sequencing in the Illumina MiSeq (San Diego, CA,
139 USA) platform was performed using a two-step PCR protocol (29), (30). The 16S rRNA gene
140 V4 region (16S) and the internal transcribed spacer 2 (ITS2) were used for bacterial and fungal
141 amplicon sequencing of rhizosphere samples using primers 515fm and 806rm (31,32); and
142 ITS3mix1-5,10 and ITS4 (33) that included an overhang tag for Nextera-kit indexing (Table S1) .
143 Gene-specific amplification was performed following Benitez et al. (12) for each individual plant
144 per plot, and individual PCR reactions were pooled by field plot prior to indexing. Indexed
145 amplicons were cleaned, quantified and pooled in equimolar concentrations for sequencing in a
146 2x 300 MiSeq sequencing run. In 2016, amplicon libraries were prepared in house and sequenced
147 at the University of Minnesota Genomics Center, Microbiome Sequencing Services (UMGC,
148 Saint Paul, MN, USA). In 2017, both library preparation and sequencing were performed at
149 UMGc.

150

151 **Read processing to amplicon sequence variants**

152 Primers and adapters were trimmed from pair-ended, de-multiplexed fastq reads using cutadapt
153 v1.8 (34). Truncated reads were processed to amplicon sequence variants (ASVs) in R ,3.6 (35)
154 following the DADA2 pipeline (36). Taxonomic assignment was based on the SILVA database

155 nonredundant training set version 132 (37) for bacteria and UNITE all eukaryotes v8.2 (38) for
156 fungi. Non-bacterial and fungal sequences were removed. Dataset statistics, including diversity
157 metrics, were calculated using *phyloseq* (38) (Table S2).-

158

159 **Statistical Analyses**

160 We planned a multi-step analysis to compare two explanations of differences in corn and
161 soybean yield across rotations: nutrient content or microbial community differences (Figure S1).

162 All analyses were performed in R (35) v3.6. Unless otherwise noted, analyses used base R
163 functions, figures were made with *ggplot2* (39), and structural equation models (SEM) used
164 *lavaan* (40). Permutations and bootstrapped SEM errors used 999 iterations.

165

166 *Yield responses to rotation and rotation contrasts*

167 First, we tested whether corn and soybean yields for these two years (2016-17) varied with
168 rotation, using the *Anova()* command from *car* (41). Then, pre-defined contrasts were used to
169 identify aspects of the five rotations that seemed to affect yield (Table S3). The three contrasts
170 included aspects of rotation diversity and crop legacy between rotations, and were partially
171 orthogonal: First, rotation diversity (two versus four species) compared the CS rotation with the
172 more diverse COWwS, CPWwS, CSSwSf, and CSSwP. Within the four-year rotations, we
173 further contrasted two types of attributes of the previous crop. The first was whether corn
174 followed soybean versus either pea or sunflower, or whether soybean followed corn versus
175 winter wheat. This contrast separated the legacy effect of the previous crop from the effect of
176 rotation diversity. The second previous crop attribute tested the effects of sunflower prior to corn,

177 based on the results from Benitez et al (12) and the effect of pea in a rotation in soybean. We
178 tested contrasts with *glht()* in *multcomp* after accounting for year effects (42).

179

180 *Plant vigor as yield predictors*

181 Next, we tested whether plant vigor at both seedling and flowering stages were predictive of each
182 crop yield using SEM. Plant vigor at seedling and flowering stages were indicated by biomass
183 and tissue nitrogen, phosphorus, and potassium concentrations. First, a definition of plant vigor
184 was tested using confirmatory factor analysis (43). This tested whether more vigorous plants had
185 greater tissue nutrient concentrations as well as greater biomass, which would indicate nutrient
186 limitation. This definition of plant vigor simplified to biomass as the sole indicator based on a
187 negative correlation between biomass and nutrient concentrations, as well as Akaike information
188 criteria (AIC) and χ^2 deviance (Figure S2). We tested this reduced model as an SEM.

189

190 *Microbial community responses to rotation and rotation contrasts*

191 In analyzing microbial communities, we employed a compositional analysis approach, which
192 mitigates many of the challenges of analyzing high-throughput sequencing data (44–46). We first
193 removed rare taxa, defined as ASVs that were present in fewer than 5% of total samples, and
194 sparse samples, defined as samples with fewer than three unique 16S or ITS2 ASVs. We also
195 excluded *Bradyrhizobium* from all 16S communities. Next, to enable logarithmic transformations
196 with minimal compositional data distortion, we replaced zeros in our community tables by
197 multiplicative replacement using the *cmultRepl()* command in *zCompositions* (47). Next, we
198 converted counts to relative abundances and transformed to centered-log-ratios with *CLR()* from
199 *easyCODA* (48). We then performed a weighted log-ratio analysis (LRA; (49)), analogous to

200 redundancy analysis, to test the effect of rotation on community structure after partialing year
201 effects, using the *pcwOrd()* function of *pcwOrd* (50). *pcwOrd* has been validated against both
202 *easyCODA* and *vegan* (48,51). Both samples and taxa were weighted to reflect certainty in
203 relative abundances of taxa across samples – taxa by mean relative abundance across samples,
204 and samples by $\log_{10}(\text{total reads})$. Without weighting, uncertainty of rare taxa or poorly-
205 sequenced samples dominates solutions of correspondence analysis and log-ratio analysis (44–
206 46,49). Finally, we tested whether communities responded to rotation using a permutational
207 multivariate analysis of variance (PERMANOVA; (52)).

208
209 This analysis was performed for each microbial amplicon (16S and ITS2) under each crop (corn
210 and soybean) at each sampling time (seedling and flowering). For those communities found
211 responsive to rotation, we then substituted rotation with the above-defined, significant contrasts
212 into the LRAs to test whether the community responded to rotation diversity or rotation sequence
213 (Table S3). These arranged samples along a single axis constrained by the contrast, which we
214 tested using with PERMANOVA.

215

216 *2.4.3 Microbial community predictors of biomass and yield*

217 If a community responded to the rotation contrast at 90% confidence, we extracted the
218 constrained axis score for each sample. We then tested whether the 16S or ITS2 community axes
219 that responded to the rotation contrast also mediated rotation effects on crop biomass by
220 comparing three classes of structural equation models (Figure S3). The first, a “no mediation”
221 model, hypothesized that the rotation contrast predicted the microbial community as defined by
222 the axis score, and also predicted crop biomass. The “full mediation” model hypothesized that

223 the rotation contrast predicted only the microbial community, and only the microbial community
224 predicted crop biomass. The “partial mediation” model hypothesized that the rotation contrast
225 predicted both the microbial community and crop biomass, and the community also predicted
226 biomass. In all models, year was included as a covariate predictor of biomass; seedling biomass
227 was also included as a predictor of flowering biomass. These models were compared using total
228 deviance (χ^2) and Akaike information criterion (AIC).

229
230 If either the full or partial mediation model were most parsimonious, we visualized the
231 relationship between the microbial community and crop biomass by plotting the marginal
232 biomass, i.e. after removing year, rotation, and seedling biomass effects, against the
233 community’s ordination axis score. We tested all ASVs’ responses to the rotation contrast using
234 multiple permutational ANOVAs, with adjusted p values to report the false discovery rate (53)
235 and identified the ASVs that contributed at least 1% of the community shift with rotation. For
236 fungi, we interpreted the potential function of contrast-responsive taxa using FunGUILD (54).

237
238 Finally, we constructed a full SEM that combined the vigor-predicting-yield SEM (Figure S2)
239 with rotation- and microbes-predicting-crop biomass SEM (Figure S3), which tested whether
240 microbial communities that predicted early- and mid-season crop biomass ultimately predicted
241 crop yield differences.

242

243 **Data Availability**

244 Data analyzed during this study are included in this article and its Supplementary Information.
245 Raw sequences generated in this work have been deposited in NCBI’s Sequence Read Archive

246 under BioProject numbers [PRJNA655937](#), [PRJNA655936](#), [PRJNA656563](#) for soybean, corn and
247 sequencing controls, respectively. Analysis code is available at
248 https://github.com/pmewing/brookings_rotation_rhizobiomes.

249

250 **Results**

251 **3.1 Corn**

252 Corn's rhizosphere bacterial and fungal communities varied with rotation. At the seedling stage,
253 rotation explained a credible amount of variance in both bacterial ($F_{5,34} = 1.14$; $R^2 = 0.11$; $p =$
254 0.06) and fungal ($F_{5,34} = 2.08$, $R^2 = 0.16$, $p = < 0.001$) communities (Figure 1; Table S4). Both
255 communities were different depending on whether they originated in long, diverse rotations
256 (bacteria: $F_{2,37} = 1.33$, $R^2 = 0.03$, $p = .04$; fungi: $F_{2,37} = 3.31$, $R^2 = 0.07$, $p < 0.001$). For fungi, the
257 soybean legacy was also important ($F_{2,37} = 1.83$, $R^2 = 0.04$, $p = 0.03$). Corn rhizosphere
258 communities also diverged among rotations at the flowering stage (bacteria: $F_{5,32} = 1.27$; $R^2 =$
259 0.13 , $p = 0.004$; fungi: $F_{5,34} = 1.60$, $R^2 = 0.14$, $p = 0.002$). However, only the diversity of rotation
260 emerged as a driver of these community responses (bacteria: $F_{2,35} = 1.33$, $R^2 = 0.03$, $p = 0.05$;
261 fungi: $F_{2,37} = 1.67$, $R^2 = 0.04$, $p = 0.03$).

262

263 Concurrently with rhizosphere responses, corn yields varied significantly with rotation ($F_{4,34} =$
264 276 ; $p < 0.001$; Figure 2; Table S5). Specifically, corn yielded significantly less in the two-year
265 (CS) rotation, by an average of 1400 ± 300 kg/ha ($t = -4.9$; $p < 0.001$) compared to the longer,
266 more diverse rotation (Table S6). The lower corn yield in the CS rotation was independent of a
267 soybean legacy, as within the four-year rotations corn following soybean did not result in lower
268 yields ($t = 0.2$; $p = 1.0$). A sunflower legacy reduced corn yields marginally compared to legacies

269 of other crops ($t = -2.4, p = 0.07$). Corn vigor at seedling and flowering stages predicted corn
 270 yield. However, corn tissue nutrient concentrations were not a driver of this, as they were
 271 negatively correlated with biomass and produced a less parsimonious model than biomass alone
 272 (final model $\chi^2 = 0.69, p = 0.41$; Figure S2).

273
 274 At both stages, biomass varied with rotation (seedling: $F_{4,34} = 4.36, p < 0.001$; flowering: $F_{4,34} =$
 275 $3.63, p = 0.01$; Figure 2; Table S5). Rotation diversity again emerged as an important driver of
 276 corn biomass, with corn growing in the two-year rotation being smaller than in four-year
 277 rotations (seedling: -0.06 ± 0.02 g/plant, $t = -2.8, p = 0.02$; flowering: -18.5 ± 5.7 g/plant, $t = -$
 278 $3.24, p = 0.007$; Table S5). Corn at the seedling stage also had a marginally lower biomass with a
 279 soybean legacy in four-year rotations (-0.05 ± 0.02 g/plant, $t = -2.95, p = 0.07$). The sunflower
 280 legacy did not affect corn biomass at either stage (seedling: $t = 1.56, p = 0.29$; flowering: $t = -$
 281 $1.18, p = 0.52$).

282
 283 Shifts in bacterial and fungal communities with rotation predicted corn biomass at both stages
 284 better than either rotation diversity or the previous crop's legacy (Figure 3). At the seedling stage,
 285 when corn was grown in a diverse rotation, the resulting shifts in both rhizosphere communities
 286 better predicted corn seedling biomass than rotation diversity alone (partial mediation: AIC =
 287 $221, \chi^2 = 0.0008$; Table S7). However, ignoring a microbial effect was most parsimonious (No
 288 mediation: AIC = 219; $\chi^2 = 1.62, p = 0.8$). On the other hand, the fungal community fully and
 289 parsimoniously explained the effect of a soybean legacy on corn seedling biomass (Full
 290 mediation: AIC = 149, $\chi^2 = 0.4, p = 0.8$; No mediation: AIC = 164, $\chi^2 = 15.2$). The taxa that were
 291 more prevalent with a soybean legacy include the likely pathogens, *Giberella acuminata* (Booth),

292 a member of *Diaporthe*, and a member of *Drechslera* (Table S8). Additionally, three variants of
293 *Olpidium brassicae* (Woronin) were associated with corn following either sunflower or wheat.
294 The relative proportions of groups of taxa together predicted a lower corn seedling biomass when
295 soybean preceded (standard coefficient = -0.38, $z = -3.9$, $p < 0.001$; Figure 3).

296
297 At the flowering stage, whether corn was grown in a two-year or four-year rotations shaped
298 bacterial communities that fully and parsimoniously mediated the effect of rotation diversity on
299 corn biomass (Full Mediation: AIC = 216, $\chi^2 = 2.32$, $p = 0.9$; No Mediation: AIC = 220, $\chi^2 =$
300 7.23; Figure 3; Table S7). Concurrent differences in fungal communities generally reduced
301 model quality versus the No Mediation model. Among the bacterial taxa that changed with
302 rotation diversity, various strains of the ubiquitous *Candidatus Udeobacter* were more prevalent
303 in the long, diverse rotations, while various *Proteobacteria* as well as a number of
304 *Actinobacteria* were more prevalent in the corn-soybean rotation (Table S8). This bacterial
305 community shift predicted lower corn biomass in the short rotation (standard coefficient = -0.28,
306 $z = -3.2$, $p = 0.001$) independently of corn biomass at the seedling stage (Figure 3).

307
308 Overall, the suppression of corn yield in the two-year, corn-soybean rotation relative to the
309 diverse, four-year rotations was best understood as resulting from the combined effects of a
310 soybean legacy and rotation diversity on rhizosphere microbial communities (fungi with soybean
311 legacy at seedling: standard coefficient = -0.05, $z = -1.9$, $p = 0.054$; bacteria with the simple
312 rotation at flowering: standard coefficient = -0.04, $z = -1.5$, $p = 0.13$; overall model $\chi^2 = 25.4$, $p =$
313 0.044; Figure 3).

314

315 3.2 Soybean

316 In contrast with corn, the structure of soybean's rhizosphere bacterial community was not
 317 significantly different among rotations (seedling: $F_{5,33} = 1.14$, $R^2 = 0.11$; $p = 0.16$; flowering:
 318 $F_{5,34} = 1.12$, $R^2 = 0.10$; $p = 0.23$; Figure 4; Table S4). Fungal communities, however, were
 319 different among rotations at both time points (seedling: $F_{5,33} = 2.32$, $R^2 = 0.20$, $p < 0.001$;
 320 flowering: $F_{5,33} = 1.62$, $R^2 = 0.16$, $p = 0.01$). At the seedling stage, the fungal community varied
 321 with crop legacy ($F_{2,36} = 3.14$, $R^2 = 0.07$, $p < 0.001$). At the flowering stage, fungal communities
 322 again differed with the legacy of corn ($F_{2,36} = 2.89$, $R^2 = 0.07$, $p = 0.004$) and with rotation
 323 diversity ($F_{2,36} = 1.22$, $R^2 = 0.03$, $p = 0.004$).

324

325 Concurrently with rhizosphere fungal communities, soybean yields varied significantly among
 326 rotations ($F_{4,28} = 8.72$, $p < 0.001$; Figure 5; Table S5). Soybean yields were 830 +/- 160 kg/ha
 327 lower in the two-year rotation than in the diverse, four-year rotations ($t = -5.2$, $p < 0.001$; Table
 328 S6). This result was independent of a legacy of corn, as when following corn in four-year
 329 rotations, soybean yields were 780 +/- 174 kg/ha smaller ($t = -4.5$, $p < 0.001$) than when
 330 following wheat. In contrast to our hypothesis, a rotation with pea did not affect soybean yields (t
 331 $= -0.65$, $p = 0.88$). Soybean vigor at seedling and flowering stages predicted soybean yield.
 332 However, as with corn, tissue nutrient concentrations were not a driver of this: they were
 333 negatively correlated with biomass and produced a less parsimonious model than biomass alone
 334 ($\chi^2 = 4.0$; $p = 0.05$; Figure S2).

335

336 At both stages, soybean biomass varied with rotation (seedling: $F_{4,33} = 6.0$, $p < 0.001$; flowering:
 337 $F_{4,33} = 16.2$, $p < 0.001$; Figure 5; Table S5). At the seedling stage, a corn legacy reduced soybean

338 biomass by 0.08 +/- 0.02 g/plant ($t = -3.53$; $p = 0.004$; Table S6). This response was maintained
339 through flowering, when the corn legacy reduced soybean biomass by 4.5 +/- 0.7 g/plant ($t = -6.2$,
340 $p < 0.001$). Rotation diversity reduced this biomass suppression soybean growing in the 4-year
341 rotations was 3.2 +/- 0.8 g/plant larger than in the two-year rotation ($t = -3.7$, $p = 0.002$). The
342 rotations with pea only affected soybean biomass at the seedling stage, increasing biomass by
343 0.07 +/- 0.02 g/plant (seedling: $t = 3.1$, $p = 0.01$; flowering: $t = 0.78$, $p = 0.8$).

344

345 Shifts in the fungal community predicted soybean biomass (Figure 6). At the seedling stage, the
346 fungal community fully and parsimoniously explained the corn legacy effect on soybean biomass
347 (Full mediation: AIC = 165; $\chi^2 = 0.60$, $p = 0.74$; No mediation: AIC = 168; $\chi^2 = 3.68$; Table S7).
348 A number of fungal taxa varied credibly with the previous crop under soybean seedlings but did
349 not follow clear functional patterns (Table S8). Nonetheless, these taxa together predicted lower
350 biomass of soybean seedlings when corn preceded (standard coefficient = -0.43, $z = -3.63$, $p <$
351 0.001 ; Figure 6).

352

353 At the flowering stage, differences in fungal communities resulting from rotation diversity
354 partially mediated the effect of rotation diversity on soybean biomass, moderately improving fit
355 (AIC = 73.6, $\chi^2 = 7.11$; Table S7). However, the no mediation model was more parsimonious
356 (AIC = 71.6 $\chi^2 = 7.16$, $p = 0.07$). Therefore, we did not attempt to identify taxa behind a fungal
357 effect on soybean flowering biomass. Although fungal communities did not credibly predict
358 yield (seedling fungi: standard coefficient = -0.04, $z = -1.4$, $p = 0.15$; model $\chi^2 = 6.8$, $p = 0.56$;
359 Figure 6), the lower soybean seedling biomass in the two-year rotation relative to the four-year,
360 diverse rotation was predicted by crop legacy effects on rhizosphere fungal communities.

361 **Discussion**

362 Soil and rhizosphere microbial communities are known to respond to crop rotation both
363 compositionally and functionally (12,55–57). Whether changes in microbial communities
364 explain concurrent increases in crop productivity in diverse rotations is less documented.
365 Consistent with other studies, we observed changes in bacterial and fungal community structure,
366 crop biomass, and crop yield between different rotations (e.g. (17,19,56,57). However, these
367 rotations differed in both the diversity of the rotation and the sequence of crop species, which
368 impact microbial communities and soil processes on different timescales. In general, we found
369 that crop legacy effects (i.e. previous crop effects) on rhizosphere communities were strongest at
370 the seedling stage, and rotation diversity effects were most consistent at flowering. The choice of
371 the previous crop in a rotation can shape the rhizosphere microbial communities of subsequent
372 crops – especially fungi – but this effect is transient as the following crop also influences
373 rhizosphere microorganisms. These crop influences happen within the context of more
374 permanent shifts in the rhizosphere microbial community with increased rotation diversity.

375
376 To facilitate monitoring soil biological processes that support vigorous and high yielding crops
377 we employed SEM to test whether microbial community responses to rotation diversity and crop
378 legacy predicted differential plant performance across rotations. Structural equation modeling
379 has gained popularity in recent years for its ability to both communicate and test complex
380 hypotheses of system dynamics as readily-understood graphs (58,59). Inferences from SEM are
381 most robust when comparing competing, positive hypotheses (60) as we did by a) testing
382 whether tissue nutrient concentrations explained crop performance; and b) whether knowledge of
383 the microbial communities improved prediction of crop performance. Our results provide strong

384 evidence that alterations of the rhizosphere-associated bacterial and fungal communities are
385 partially responsible for greater crop performance in more diverse rotations: we could better
386 predict crop performance when incorporating microbial communities to the analysis, compared
387 to crop rotation only. Overall, a) fungal communities shaped by the previous crop predicted the
388 biomass of corn and soybean seedlings, b) bacterial communities in long rotations predicted corn
389 biomass at tasseling, and c) neither bacterial nor fungal communities predicted soybean biomass
390 at flowering.

391

392 Just as crop health may affect the structure of rhizosphere communities, microbial communities
393 also impact crop health. Additionally, other factors might also contribute to crop vigor across
394 rotations. For example, differences in soil water usage by the previous crop can reduce water
395 availability the following season, inducing drought losses (61). Our site is rarely water limited,
396 and the Palmer Drought Severity Index was greater than 2.0 for the duration of the study,
397 suggesting moisture depletion was unlikely to be a major factor in crop performance (62).

398 Alternatively, while nutrient availability might affect crop performance (14,63,64), we found no
399 evidence for nutrient limitation as biomass was consistently negatively correlated with nitrogen
400 and phosphorus concentrations. Overall, our analysis suggests that crop resource use efficiency
401 was suppressed in the two-year rotation by elements of rhizosphere communities across contexts
402 of annual weather variation. Still, these microbial communities are conservatively understood as
403 indicators of overall changes in soil properties with diversified rotations that improve crop
404 performance.

405

406 We report putative identities and/or functions for the fungal (including plant pathogens) and
407 bacterial taxa (largely ubiquitous soil/plant-associated) that predicted crop responses to rotation,
408 while emphasizing caution when interpreting these assignments. This is due to the ambiguity of
409 precisely identifying taxa from ITS and 16S rRNA fragments, the relatively unknown roles of
410 those taxa that were identified at genus or species equivalents, and the difficulty of reproducing
411 exact matches to taxa across locations and years (54,65,66). Instead, we note that continuous
412 monocultures of various plant species often are characterized by the accumulation of plant
413 parasitic and pathogenic bacteria and fungi which suppress the growth of the monoculture plant
414 host (67–69). Moreover, a single year of rotation with a non-host crop is not sufficient to
415 meaningfully reduce some pathogen populations, such as *Fusarium verguliforme* (O’Donell & T.
416 Aoki), the causative agent of soybean sudden death syndrome (70). These corn-soybean plots
417 had grown only two species for 16 years, and in general, the US Corn Belt has been increasingly
418 dominated by two species across its 650,000 km² since World War II (71,72). This creates a
419 strong, persistent, and extensive selective pressure on crop-associated microbial communities
420 that are more likely detrimental than beneficial (55,73). Our results, especially for the identified
421 fungal taxa, are consistent with this hypothesis.

422
423 Whether this selection pressure on microbial communities in two-year rotations has practical
424 implications remains a pressing question. In natural systems, more diverse plant communities
425 support more diverse and higher-functioning microbial communities, which further support plant
426 growth (e.g. (74)) For corn grown in North America, the continuous cropping yield penalty is
427 4.3% versus a corn-soybean rotation (75). However, the corn-soybean yield penalty versus

428 longer rotations may be 6-fold larger (20). Understanding the mechanisms that underly these
429 benefits of diverse rotations on crop performance is an urgent need.

430
431 Our results identify communities of microbes that predict suppressed corn and soybean yield in
432 short rotations. To our knowledge, these are the first field results that directly implicate microbial
433 communities found in corn-soybean rotations with a corn-soybean yield penalty. This study lays
434 a foundation for monitoring microbial communities with the goal of manipulating crop rotation.
435 Further study is necessary to test whether the communities of potentially crop-suppressive taxa
436 we identified are recoverable across years or fields, and also reproduce predictions of crop
437 performance. Still, the microbial taxa identified in this work represent preliminary indicators of
438 crop-supportive and crop-suppressive rhizosphere communities which are sensitive to
439 management. Identification of these types of biological indicators is a major bottleneck in the
440 monitoring of soil health, and in the design and implementation of sustainable cropping systems
441 (25,76).

442

443 **Conclusion**

444 Continued innovation in agricultural management is necessary to reduce environmental impacts
445 of agriculture while continuing to meet global food demands (77). Microbial activity may
446 support these goals, but significant challenges remain, notably, quantifying the agronomic
447 significance of changes in microbial communities, and developing approaches to monitor these
448 communities such that outcomes can be predicted. We address these challenges by identifying
449 suites of bacterial and fungal taxa that are sensitive to management and predict meaningful
450 increases in the growth and performance of corn and soybean, independent of plant tissue

451 nutrient concentrations. These bacteria and fungi were altered by both crop sequencing and the
452 overall diversity of a rotation, which highlights that these rotation characteristics are
453 complimentary in designing sustainable and productive agricultural systems. These results will
454 facilitate the incorporation of microorganisms into cropping systems design and monitoring, and
455 ultimately support the sustainable intensification of agriculture.

456

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462 MSBenitez: Conceptualization, Data curation, Formal analysis, Investigation, Methodology,
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465 Writing original draft/review & editing

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467 RMLehman: Conceptualization, Funding acquisition, Project administration, Resources, Writing
468 review & editing, Supervision

469 **Competing Interests**

470 The author(s) declare no competing financial interests.

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474 **Disclaimer**

475 Mention of trade names or commercial products in this publication is solely for the purpose of
 476 providing specific information and does not imply recommendation or endorsement by the U.S.
 477 Department of Agriculture. USDA is an equal opportunity provider and employer.

478 **References**

- 479 1. Reid A, Greene SE. How microbes can help feed the world: Report on an American
 480 Academy of Microbiology Colloquium. Washington, DC: American Society for
 481 Microbiology; 2012. Available from: [https://www.ncbi.nlm.nih.gov/books/NBK559436/doi:](https://www.ncbi.nlm.nih.gov/books/NBK559436/doi:10.1128/AAMCol.Dec.2012)
 482 10.1128/AAMCol.Dec.2012
 483
- 484 2. Philippot L, Raaijmakers JM, Lemanceau P, van der P. Going back to the roots: the
 485 microbial ecology of the rhizosphere. *Nat Rev Micro*. 2013 Nov;11(11):789–99.
- 486 3. Stringlis IA, Proietti S, Hickman R, Van Verk MC, Zamioudis C, Pieterse CMJ. Root
 487 transcriptional dynamics induced by beneficial rhizobacteria and microbial immune
 488 elicitors reveal signatures of adaptation to mutualists. *The Plant Journal*. 2018
 489 Jan;93(1):166–80.
- 490 4. Kwak M-J, Kong HG, Choi K, Kwon S-K, Song JY, Lee J, et al. Rhizosphere microbiome
 491 structure alters to enable wilt resistance in tomato. *Nature Biotechnology*. 2018 Nov;
 492 36:1100-1109.
- 493 5. Jacoby R, Peukert M, Succurro A, Koprivova A, Kopriva S. The role of soil
 494 microorganisms in plant mineral nutrition-current knowledge and future directions.
 495 *Frontiers in plant science*. 2017 Sep;8:1617–1617.
- 496 6. Weller DM. Biological control of soilborne plant pathogens in the rhizosphere with bacteria.
 497 *Annual Review of Phytopathology*. 1988 Sep;26(1):379–407.
- 498 7. Pretty J, Bharucha ZP. Sustainable intensification in agricultural systems. *Annals of Botany*.
 499 2014 Dec;114(8):1571–96.
- 500 8. Pretty J. Intensification for redesigned and sustainable agricultural systems. *Science*. 2018
 501 Nov;362(6417): eaav0294.
- 502 9. Davis AS, Hill JD, Chase CA, Johanns AM, Liebman M. Increasing cropping system
 503 diversity balances productivity, profitability and environmental health. *PLOS ONE*. 2012
 504 Oct;7(10): e47149.
- 505 10. Haichar F el Z, Marol C, Berge O, Rangel-Castro JI, Prosser JI, Balesdent J, et al. Plant
 506 host habitat and root exudates shape soil bacterial community structure. *The ISME Journal*.
 507 2008 Dec;2:1221-1230.

- 508 11. Hu L, Robert CAM, Cadot S, Zhang X, Ye M, Li B, et al. Root exudate metabolites drive
509 plant-soil feedbacks on growth and defense by shaping the rhizosphere microbiota. *Nature*
510 *Communications*. 2018 Jul;9(1):1-3.
- 511 12. Benitez M-S, Osborne SL, Lehman RM. Previous crop and rotation history effects on maize
512 seedling health and associated rhizosphere microbiome. *Scientific Reports*. 2017 Nov
513 16;7(1):15709.
- 514 13. McDaniel MD, Grandy AS, Tiemann LK, Weintraub MN. Eleven years of crop
515 diversification alters decomposition dynamics of litter mixtures incubated with soil.
516 *Ecosphere*. 2016 Aug 1;7(8):e01426.
- 517 14. McDaniel MD, Tiemann LK, Grandy AS. Does agricultural crop diversity enhance soil
518 microbial biomass and organic matter dynamics? A meta-analysis. *Ecological Applications*.
519 2014 Apr;24(3):560–70.
- 520 15. Wattenburger CJ, Halverson LJ, Hofmockel KS. Agricultural management affects root-
521 associated microbiome recruitment over maize development. *Phytobiomes Journal*. 2019
522 Jan 1;3(4):260–72.
- 523 16. Somenahally A, DuPont JI, Brady J, McLawrence J, Northup B, Gowda P. Microbial
524 communities in soil profile are more responsive to legacy effects of wheat-cover crop
525 rotations than tillage systems. *Soil Biology and Biochemistry*. 2018 Aug 1;123:126–35.
- 526 17. Peralta Ariane L., Sun Yanmei, McDaniel Marshall D., Lennon Jay T. Crop rotational
527 diversity increases disease suppressive capacity of soil microbiomes. *Ecosphere*. 2018 May
528 15;9(5):e02235.
- 529 18. Jauri PV, Altier N, Pérez CA, Kinkel L. Cropping History Effects on Pathogen Suppressive
530 and Signaling Dynamics in *Streptomyces* Communities. *Phytobiomes Journal*. 2017 Dec
531 19;2(1):14–23.
- 532 19. Venter ZS, Jacobs K, Hawkins H-J. The impact of crop rotation on soil microbial diversity:
533 A meta-analysis. *Pedobiologia*. 2016;59(4):215–23.
- 534 20. Bowles TM, Mooshammer M, Socolar Y, Calderón F, Cavigelli MA, Culman SW, et al.
535 Long-term evidence shows that crop-rotation diversification increases agricultural
536 resilience to adverse growing conditions in North America. *One Earth*. 2020 Mar
537 20;2(3):284–93.
- 538 21. Gaudin ACM, Tolhurst TN, Ker AP, Janovicek K, Tortora C, Martin RC, et al. Increasing
539 crop diversity mitigates weather variations and improves yield stability. *PLoS ONE*.
540 2015;10(2):e0113261.
- 541 22. de Vries FT, Griffiths RI, Knight CG, Nicolitch O, Williams A. Harnessing rhizosphere
542 microbiomes for drought-resilient crop production. *Science*. 2020 Apr 17;368(6488):270.

- 543 23. Hunt ND, Liebman M, Thakrar SK, Hill JD. Fossil energy use, climate change impacts, and
544 air quality-related human health damages of conventional and diversified cropping systems
545 in Iowa, USA. *Environ Sci Technol*. 2020 Sep 15;54(18):11002–14.
- 546 24. Gurr GM, Lu Z, Zheng X, Xu H, Zhu P, Chen G, et al. Multi-country evidence that crop
547 diversification promotes ecological intensification of agriculture. *Nature Plants*. 2016 Feb
548 22;2(3):16014.
- 549 25. Hartman K, van der Heijden MGA, Wittwer RA, Banerjee S, Walser J-C, Schlaeppli K.
550 Cropping practices manipulate abundance patterns of root and soil microbiome members
551 paving the way to smart farming. *Microbiome*. 2018 Jan 16;6(1):1-4.
- 552 26. Dias T, Dukes A, Antunes PM. Accounting for soil biotic effects on soil health and crop
553 productivity in the design of crop rotations. *Journal of the science of food and agriculture*.
554 2015 Feb;95(3):447–54.
- 555 27. Lehman RM, Osborne SL, Duke SE. Diversified no-till crop rotation reduces nitrous oxide
556 emissions, increases soybean yields, and promotes soil carbon accrual. *Soil Science Society
557 of America Journal*. 2017 Feb;81(1):76–83.
- 558 28. Clark J. SDSU Extension: Fertilizer Recommendation Guidelines [Internet]. 2020.
559 Available from: <https://extension.sdstate.edu/fertilizer-recommendation-guide>
- 560 29. Illumina. Illumina.16S Metagenomic Sequencing Library Preparation: Preparing 16S
561 Ribosomal RNA Gene Amplicons for the Illumina MiSeq System. Technical Note
562 15044223. 2015.
- 563 30. Gohl DM, MacLean A, Hauge A, Becker A, Walek D, Beckman KB. An optimized
564 protocol for high-throughput amplicon-based microbiome profiling. 2016 25 July;
565 Available from: <http://dx.doi.org/10.1038/protex.2016.030>
- 566 31. Walters W, Hyde ER, Berg-Lyons D, Ackermann G, Humphrey G, Parada A, et al.
567 Improved bacterial 16S rRNA gene (V4 and V4-5) and fungal internal transcribed spacer
568 marker gene primers for microbial community surveys. *mSystems*. 2015 22;1(1). Available
569 from: <http://msystems.asm.org/content/1/1/e00009-15.abstract>
- 570 32. Apprill A, McNally S, Parsons R, Weber L. Minor revision to V4 region SSU rRNA 806R
571 gene primer greatly increases detection of SAR11 bacterioplankton. *Aquatic Microbial
572 Ecology*. 2015;75(2):129–137.
- 573 33. Tedersoo L, Bahram M, Polme S, Koljalg U, Yorou NS, Wijesundera R, et al. Fungal
574 biogeography. Global diversity and geography of soil fungi. *Science*.
575 2014;346(6213):1256688.
- 576 34. Martin M. Cutadapt removes adapter sequences from high-throughput sequencing reads.
577 *EMBnet.journal*. 2011;17(1):10–12.

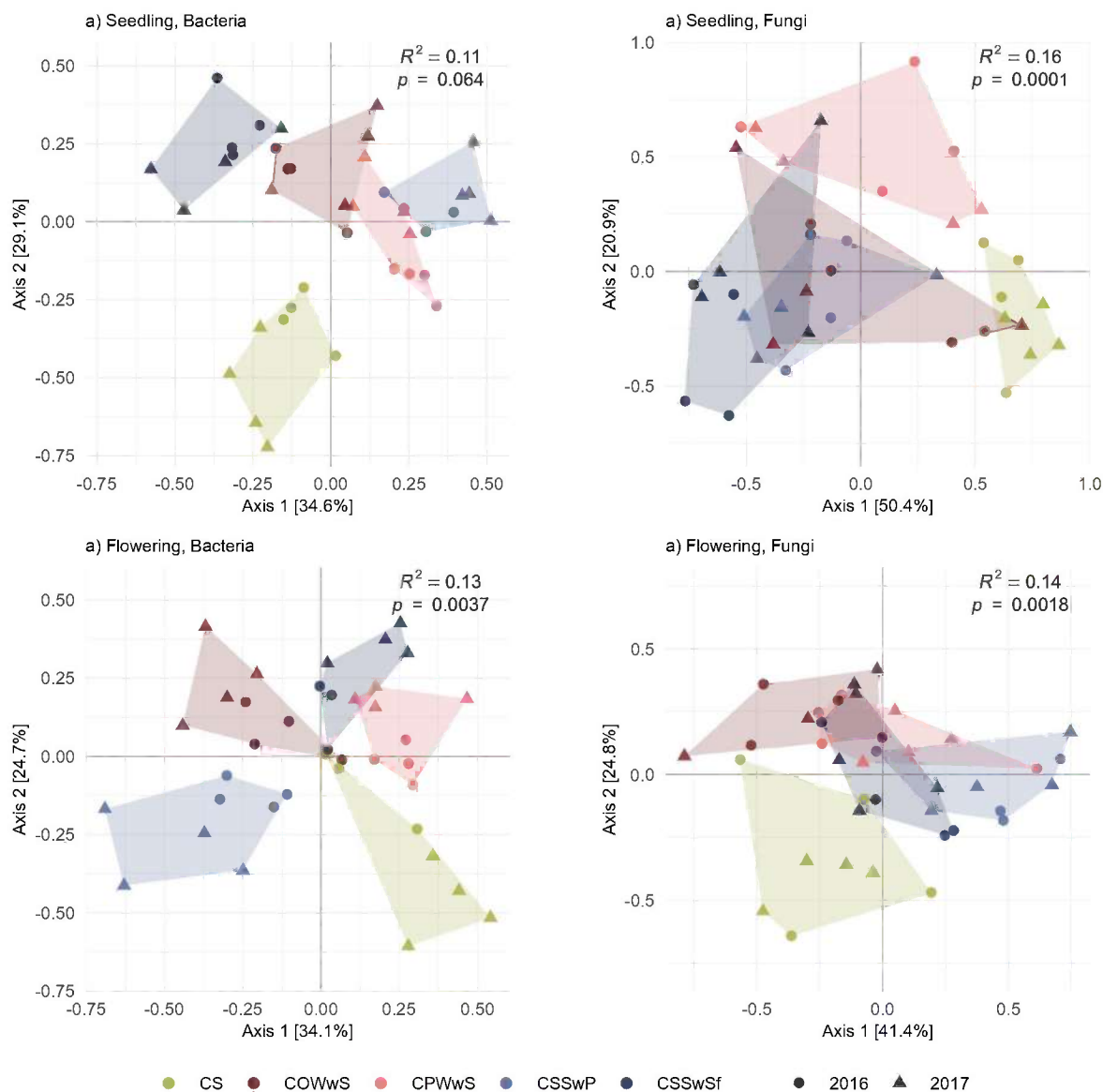
- 578 35. R Core Team. R: A Language and Environment for Statistical Computing [Internet].
579 Vienna, Austria: R Foundation for Statistical Computing; 2020. Available from:
580 <https://www.R-project.org/>
- 581 36. Callahan BJ, McMurdie PJ, Rosen MJ, Han AW, Johnson AJA, Holmes SP. DADA2:
582 High-resolution sample inference from Illumina amplicon data. *Nature Methods*. 2016 May
583 23;13:581.
- 584 37. Quast C, Pruesse E, Yilmaz P, Gerken J, Schweer T, Yarza P, et al. The SILVA ribosomal
585 RNA gene database project: improved data processing and web-based tools. *Nucleic Acids*
586 *Res*. 2013;41(Database issue):D590-6.
- 587 38. Abarenkov K, Nilsson RH, Larsson K-H, Alexander IJ, Eberhardt U, Erland S, et al. The
588 UNITE database for molecular identification of fungi - recent updates and future
589 perspectives. *New Phytol*. 186(2):281–5.
- 590 39. Hadley Wickham. *ggplot2: Elegant Graphics for Data Analysis* [Internet]. Springer-Verlag
591 New York; 2016. Available from: <https://ggplot2.tidyverse.org>
- 592 40. Rosseel Y. lavaan: An R Package for Structural Equation Modeling. *Journal of Statistical*
593 *Software, Articles*. 2012;48(2):1–36.
- 594 41. Fox J, Sanford Weisberg. *An {R} Companion to Applied Regression* [Internet]. Third.
595 Thousand Oaks CA: Sage; 2019. Available from:
596 <https://socialsciences.mcmaster.ca/jfox/Books/Companion/>
- 597 42. Hothorn T, Bretz F, Westfall P. Simultaneous inference in general parametric models.
598 *Biometrical Journal: Journal of Mathematical Methods in Biosciences*. 2008;50(3):346–363.
- 599 43. Brown T, Moore MT. Confirmatory factor analysis. In: *Handbook of structural equation*
600 *modeling*. The Guilford Press; 2012. p. 361–79.
- 601 44. Gloor GB, Wu JR, Pawlowsky-Glahn V, Egozcue JJ. It's all relative: analyzing microbiome
602 data as compositions. *AnnEpidemiol*. 2016;26(5):322–9.
- 603 45. Knight R, Vrbanac A, Taylor BC, Aksenov A, Callewaert C, Debelius J, et al. Best
604 practices for analysing microbiomes. *Nature Reviews Microbiology*. 2018 Jul;16(7):410–22.
- 605 46. McLaren MR, Willis AD, Callahan BJ. Consistent and correctable bias in metagenomic
606 sequencing experiments. *Elife*. 2019 Sep 10;8:e46923..
- 607 47. Palarea-Albaladejo J, Martín-Fernández JA. zCompositions — R package for multivariate
608 imputation of left-censored data under a compositional approach. *Chemometrics and*
609 *Intelligent Laboratory Systems*. 2015 Apr;143:85–96.
- 610 48. Greenacre M. *Compositional data analysis in practice*. CRC Press; 2018.

- 611 49. Greenacre M, Lewi P. Distributional equivalence and subcompositional coherence in the
612 analysis of compositional data, contingency tables and ratio-scale measurements. *Journal of*
613 *Classification*. 2009 Apr 1;26(1):29–54.
- 614 50. Ewing, P, Lehman, M. pcwOrd [Internet]. 2020. Available from:
615 <https://github.com/pme1123/pcwOrd>
- 616 51. Oksanen J, Blanchet FG, Friendly M, Kindt R, Legendre P, McGlinn D, et al. *vegan*:
617 *Community ecology package*. R package version 25-6 [Internet]. 2019; Available from:
618 <https://CRAN.R-project.org/package=vegan>
- 619 52. Legendre P, Oksanen J, ter Braak CJF. Testing the significance of canonical axes in
620 redundancy analysis: Test of canonical axes in RDA. *Methods in Ecology and Evolution*.
621 2011 Jun;2(3):269–77.
- 622 53. Benjamini Y, Hochberg Y. Controlling the false discovery rate: A practical and powerful
623 approach to multiple testing. *Journal of the Royal Statistical Society: Series B*
624 (Methodological). 1995 Jan 1;57(1):289–300.
- 625 54. Nguyen NH, Song Z, Bates ST, Branco S, Tedersoo L, Menke J, et al. FUNGuild: An open
626 annotation tool for parsing fungal community datasets by ecological guild. *Fungal Ecology*.
627 2016 Apr 1;20:241–8.
- 628 55. Dick RP. A review: long-term effects of agricultural systems on soil biochemical and
629 microbial parameters. *Agriculture, Ecosystems & Environment*. 1992 May;40(1–4):25–36.
- 630 56. Soman C, Li D, Wander MM, Kent AD. Long-term fertilizer and crop-rotation treatments
631 differentially affect soil bacterial community structure. *Plant Soil*. 2017 Apr;413(1–2):145–
632 59.
- 633 57. D’Acunto L, Andrade JF, Poggio SL, Semmartin M. Diversifying crop rotation increased
634 metabolic soil diversity and activity of the microbial community. *Agriculture, Ecosystems*
635 *& Environment*. 2018 Apr;257:159–64.
- 636 58. Smith RG, Davis AS, Jordan NR, Atwood LW, Daly AB, Grandy AS, et al. Structural
637 equation modeling facilitates transdisciplinary research on agriculture and climate change.
638 *Crop Science*. 2014;54(2):475–483.
- 639 59. Eisenhauer N, Bowker MA, Grace JB, Powell JR. From patterns to causal understanding:
640 Structural equation modeling (SEM) in soil ecology. *Pedobiologia*. 2015 Mar;58(2–3):65–
641 72.
- 642 60. Pearl J. Chapter 5: The causal foundations of structural equation modeling. In: *Handbook of*
643 *Structural Equation Modeling*. New York, NY: Guilford Press; 2012.
- 644 61. Kirkegaard J, Christen O, Krupinsky J, Layzell D. Break crop benefits in temperate wheat
645 production. *Field Crops Research*. 2008 Jun;107(3):185–95.

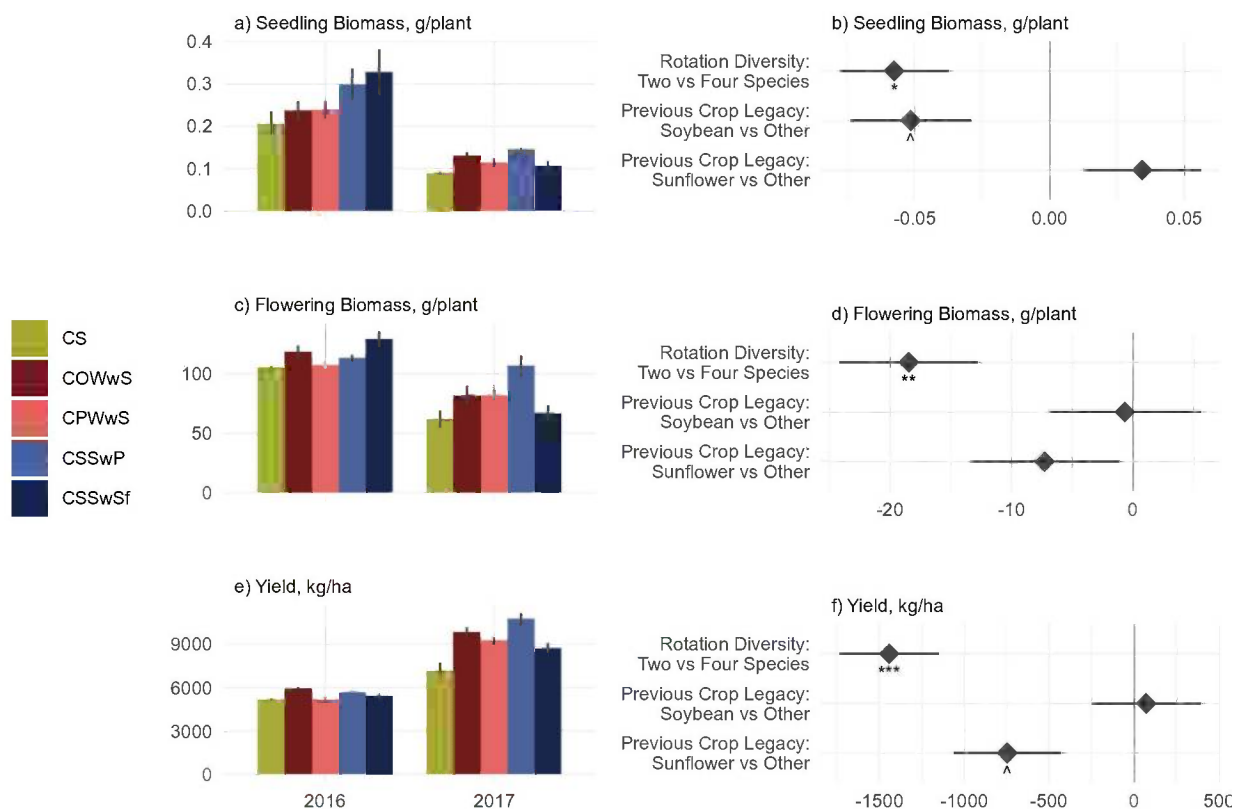
- 646 62. NOAA. Palmer Drought Severity Index January 2016 - October 2017 [Internet]. Historical
 647 Palmer Drought Indices. 2020 [cited 2020 Aug 10]. Available from:
 648 <https://www.ncdc.noaa.gov/temp-and-precip/drought/historical-palmers/psi/201601-201710>
- 649 63. Riedell WE, Osborne SL, Pikul JL. Soil Attributes, Soybean mineral nutrition, and yield in
 650 diverse crop rotations under no-till conditions. *Agronomy Journal*. 2013;105:1231–6.
- 651 64. Riedell WE, Pikul JL, Jaradat AA, Schumacher TE. Crop rotation and nitrogen input effects
 652 on soil fertility, maize mineral nutrition, yield, and seed composition. *Agronomy Journal*.
 653 2009 Jul 1;101(4):870–9.
- 654 65. Nguyen NH, Smith D, Peay K, Kennedy P. Parsing ecological signal from noise in next
 655 generation amplicon sequencing. *New Phytol*. 2015;205(4):1389–93.
- 656 66. Douglas GM, Maffei VJ, Zaneveld JR, Yurgel SN, Brown JR, Taylor CM, et al. PICRUSt2
 657 for prediction of metagenome functions. *Nature Biotechnology*. 2020;1–5.
- 658 67. Lou Y, Clay SA, Davis AS, Dille A, Felix J, Ramirez AHM, et al. An affinity–effect
 659 relationship for microbial communities in plant–soil feedback loops. *Microb Ecol*. 2014
 660 May;67(4):866–76.
- 661 68. Lupwayi NZ, Kennedy AC. Grain legumes in northern great plains: impacts on selected
 662 biological soil processes. *Agron J*. 2007 Nov;99(6):1700–9.
- 663 69. Johnson NC, Copeland PJ, Crookston RK, Pflieger FL. Mycorrhizae: possible explanation
 664 for yield decline with continuous corn and soybean. *Agron J*. 1992 May;84(3):387–90.
- 665 70. Leandro LFS, Eggenberger S, Chen C, Williams J, Beattie GA, Liebman M. Cropping
 666 system diversification reduces severity and incidence of soybean sudden death syndrome
 667 caused by *Fusarium virguliforme*. *Plant Disease*. 2018 Sep;102(9):1748–58.
- 668 71. Hart JF. Change in the Corn Belt. *Geographical Review*. 1986 Jan;76(1):51.
- 669 72. Green TR, Kipka H, David O, McMaster GS. Where is the USA Corn Belt, and how is it
 670 changing? *Science of The Total Environment*. 2018 Mar;618:1613–8.
- 671 73. Bennett AJ, Bending GD, Chandler D, Hilton S, Mills P. Meeting the demand for crop
 672 production: the challenge of yield decline in crops grown in short rotations. *Biological
 673 Reviews*. 2012;87(1):52–71.
- 674 74. Zak DR, Holmes WE, White DC, Peacock AD, Tilman D. Plant diversity, soil microbial
 675 communities, and ecosystem function: Are there any links? *Ecology*. 2003;84(8):2042–50.
- 676 75. Seifert CA, Roberts MJ, Lobell DB. Continuous corn and soybean yield penalties across
 677 hundreds of thousands of fields. *AgronJ*. 2017;109(2):541–8.
- 678 76. Bünemann EK, Bongiorno G, Bai Z, Creamer RE, De Deyn G, de Goede R, et al. Soil
 679 quality – A critical review. *Soil Biology and Biochemistry*. 2018 May;120:105–25.

- 680 77. Hunter MC, Smith RG, Schipanski ME, Atwood LW, Mortensen DA. Agriculture in 2050:
681 Recalibrating Targets for Sustainable Intensification. *BioScience*. 2017 Apr 1;67(4):386–91.

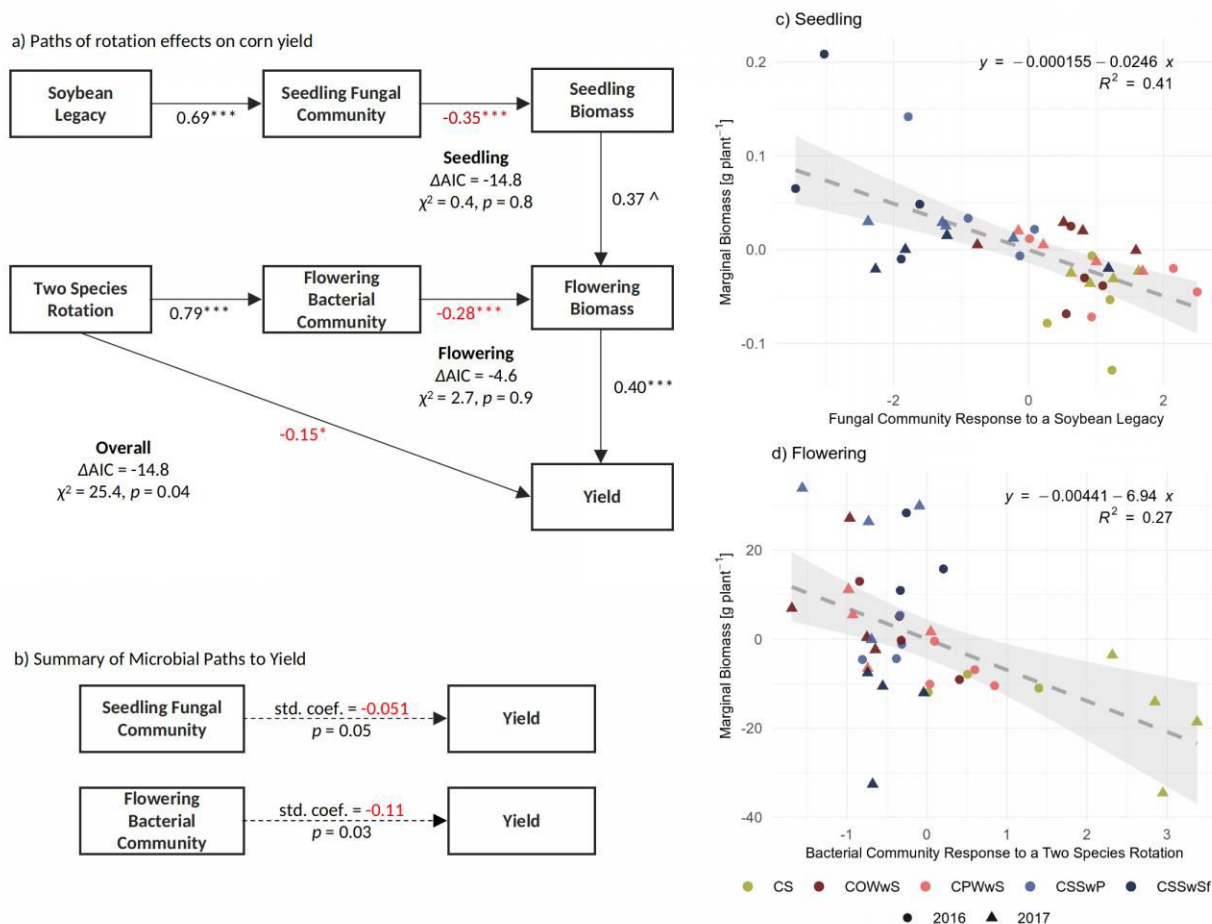
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683 **Figures**

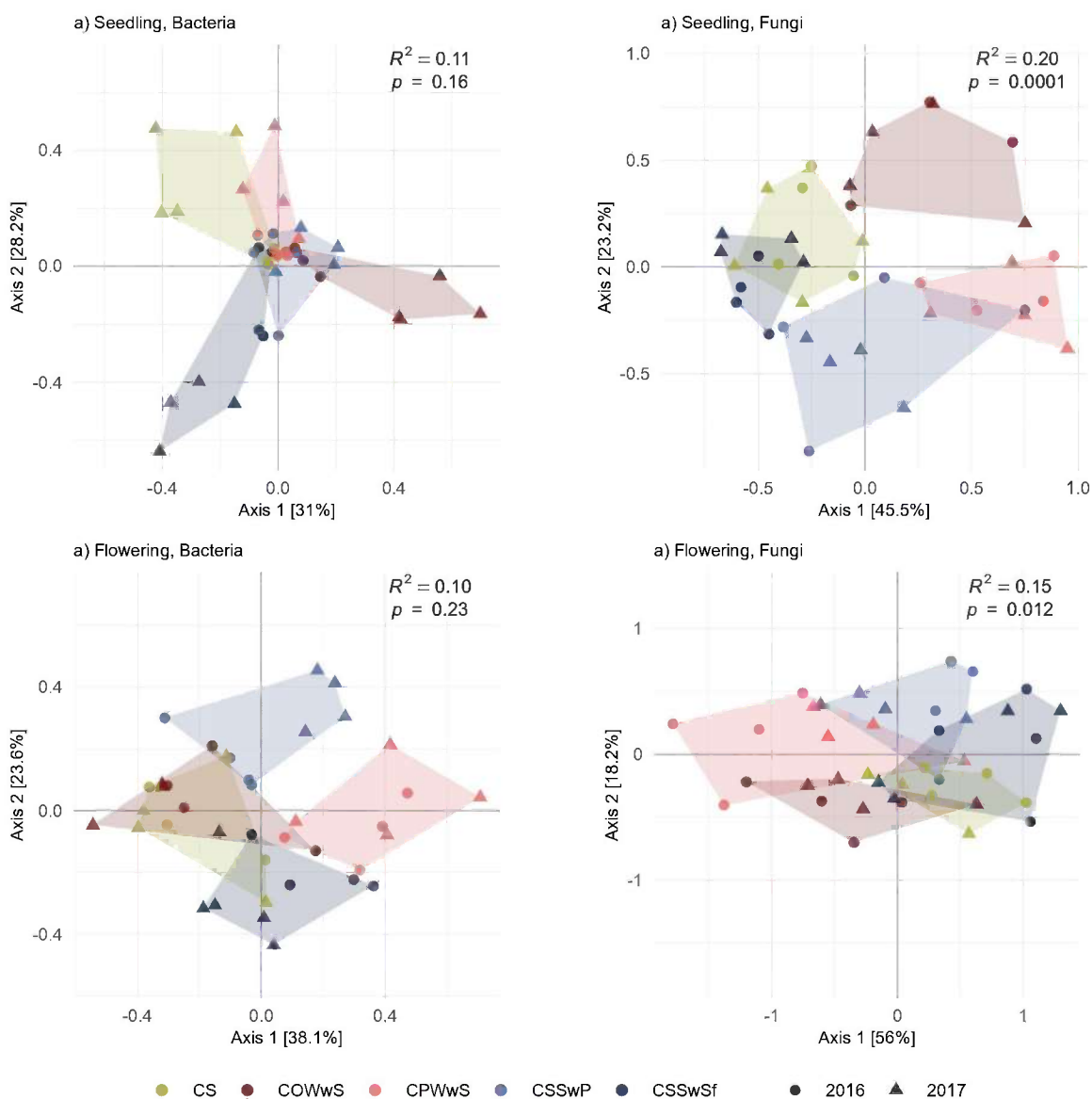
684
 685 Figure 1: Constrained log-ratio analysis of bacterial (16S) and fungal (ITS) communities at the
 686 seedling and flowering stages of corn. Data points are shaped by sampling year and colored by
 687 rotation. Additionally, the two-year rotation is yellow, and a soybean legacy in 4-year rotations
 688 are shades of red. Rotations: CS, Corn-Soy; COWwS, Corn-Oats-Winter wheat-Soy; CPWwS,
 689 Corn-Pea-Winter wheat-Soy; CSSwP, Corn-Soy-Spring wheat-Pea; CSSwSf, Corn-Soy-Spring
 690 wheat-Sunflower. Axis variances refer to the proportion of constrained variance shown along
 691 each axis. R^2 refers to the Pearson correlation coefficient. p -values are based on a pseudo- F
 692 test across 9999 permutations.
 693



694
 695 Figure 2: Corn vigor in response to rotation and rotation characteristics. a, b) biomass at seedling;
 696 c, d) biomass at flowering; e, f) yield in each year of study. In a), c), and e), colors represent
 697 rotation as in Figure 1. Panels b), d), and f) show mean effects of rotation characteristics on the
 698 measured parameters across years. Rotation characteristics correspond to the following contrasts:
 699 Rotation diversity, gold (2-yr) versus red and blue bars (4-yr); Previous Crop Soybean, red
 700 versus blue bars (other previous crop except soybean); Previous Crop Sunflower, dark blue vs
 701 light blue and red bars (other previous crop except sunflower). Significance of contrasts are: ^ - p
 702 < 0.1 ; * - $p < 0.05$; ** - $p < 0.01$; *** - $p < 0.001$. Errors are standard errors.
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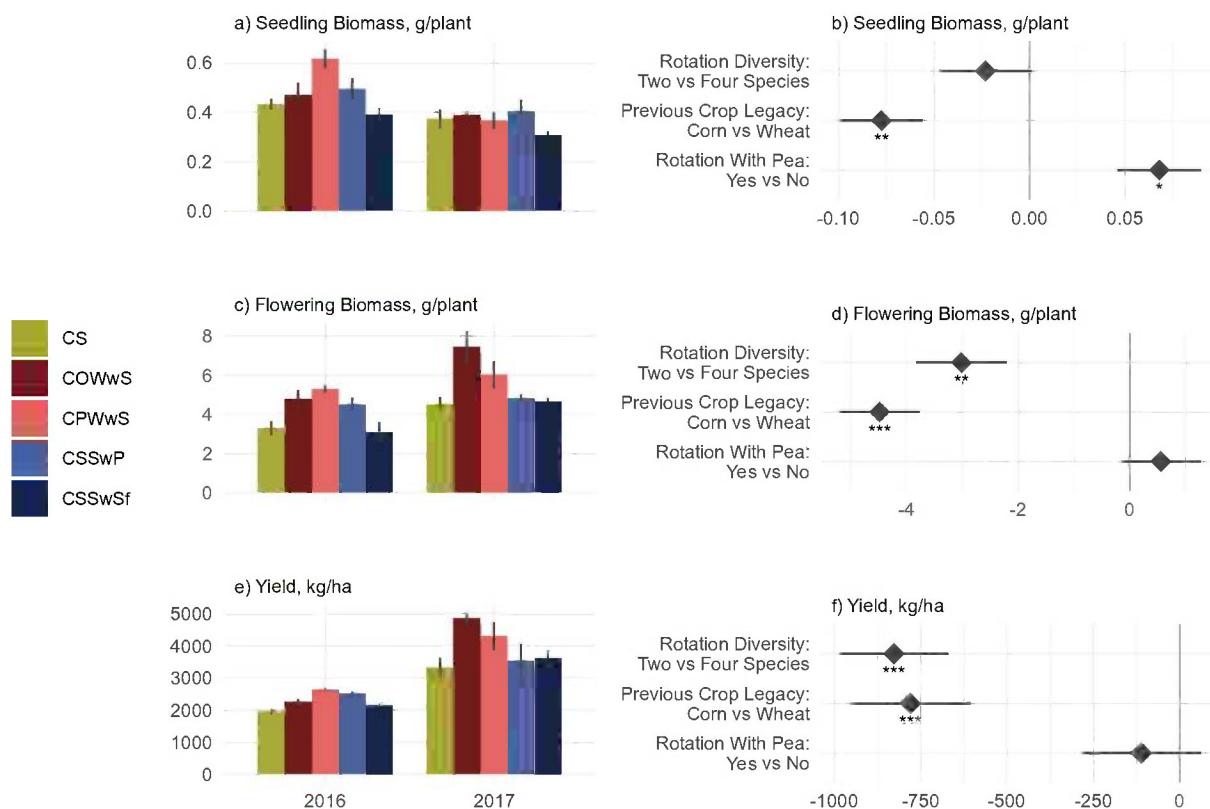


704
 705 Figure 3: Role of microbial communities in mediating effects of rotation on corn vigor and yield.
 706 a) Structural equation model describing these relationships. ΔAIC refers to the change in Akaike
 707 information criterion by including the microbial community as a predictor for corn biomass at
 708 either the seedling or flowering stage versus just using rotation information. Contrasts are as in
 709 Figure 2. The χ^2 statistics and the corresponding p values for each biomass sub-model and the
 710 full model are also indicated. Values adjacent to arrows are standardized regression coefficients;
 711 red are negative relationships, black are positive. Bootstrapped significance of paths are as in
 712 Figure 2; gray arrows were not significant at $p < 0.1$. Year was included as a covariate for
 713 biomass and yield measurements (not shown). b) Summary of paths between the indicated
 714 microbial community and corn yield, as mediated by biomass. c) Partial plot of the response of
 715 corn seedling biomass to the seedling fungal community as shaped by following soybean. The
 716 horizontal axis are principal sample scores along the first axis of an ordination constrained by the
 717 indicated rotation contrast after removing year effects. The vertical axis is marginal biomass after
 718 removing year effects. Shapes and colors are as in Figure 1. The gray shaded area indicates the
 719 standard error. R^2 is the Spearman correlation coefficient. d) Effect of the bacterial community
 720 shaped by rotation diversity on corn biomass at tasseling. Marginal biomass is after removing
 721 effects of year and seedling biomass. All symbology is as in c).

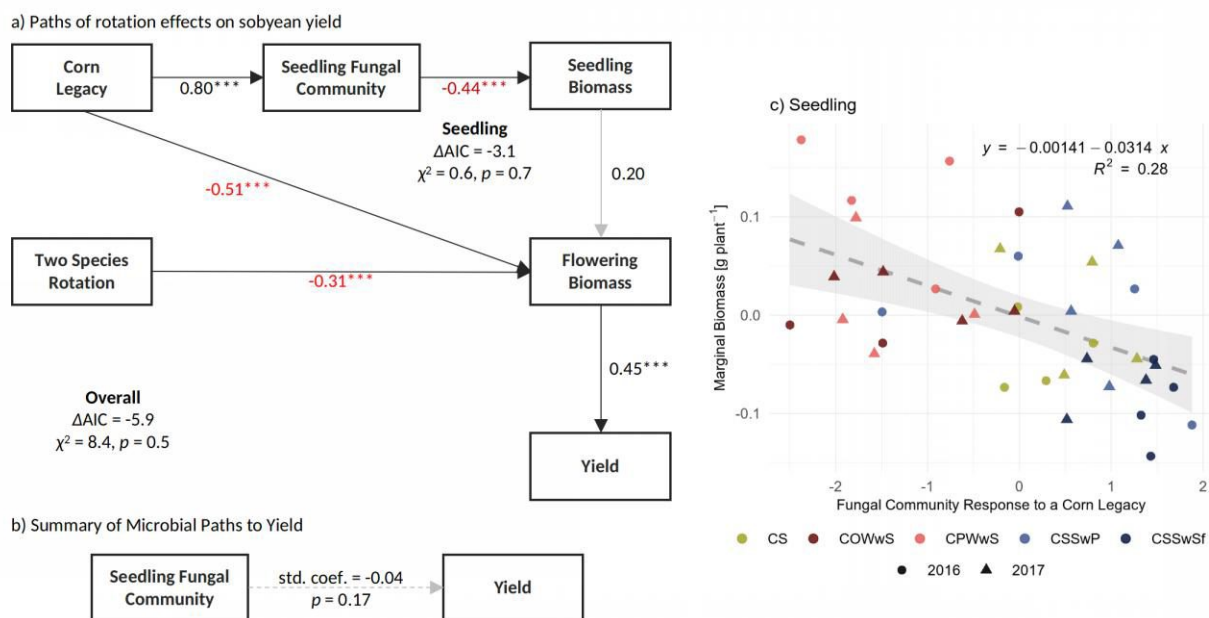


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Figure 4: Constrained log-ratio analysis of bacterial (16S) and fungal (ITS) communities at the seedling and flowering stages of soybean. Symboly is as in Figure 1. Additionally, a legacy of corn in 4-year rotations is indicated by shades of blue.



727
 728 Figure 5: Soybean vigor in response to rotation and rotation characteristics. a, b) biomass at
 729 seedling; c, d) biomass at flowering; e, f) yield in each year of study. In a), c), and e), colors
 730 represent rotation as in Figure 1. Panels b), d), and f) show mean effects of rotation
 731 characteristics on these parameters across years. Rotation contrasts are as follows: Rotation
 732 diversity, gold (two-yr) versus red and blue bars (four-yr); Previous Crop Corn, blue versus red
 733 bars (other previous corn, except corn); Rotation with pea: light blue versus dark blue and red
 734 bars (rotation does not include pea). Significance of contrasts are: ^ - $p < 0.1$; * - $p < 0.05$; ** - p
 735 < 0.01 ; *** - $p < 0.001$. Errors are standard errors.
 736



737
 738 Figure 6: Role of microbial communities in mediating effects of rotation on soybean vigor and yield. a)
 739 Structural equation model describing these relationships. Year was included as a covariate for biomass
 740 and yield measurements (not shown). b) Summary of paths between the indicated microbial community
 741 and corn yield, as mediated by biomass. c) Partial plot of the response of corn seedling biomass to the
 742 seedling fungal community as shaped by following soybean. Symbology for each panel is as in Figure
 743 3 and contrasts are as in Figure 5.
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