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# Root production in a subtropical pasture is mediated by cultivar and defoliation severity

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31 **Abstract**

32

33 **Background.** Grasslands occupy significant land area and account for a large proportion of the  
34 global soil carbon stock, yet the direct effects of grazing and genotypic composition on  
35 relationships between shoot and root production are poorly resolved. This lack of understanding  
36 hinders the development of models for predicting root production in managed grasslands, a  
37 critical variable for determining soil carbon stocks.

38 **Methods.** We quantified the effects of season-long defoliation treatments on both shoot and root  
39 production across four cultivars of a widely-planted pasture grass species (*Paspalum notatum*  
40 Fluegge) in a common garden setting in South Florida, USA.

41 **Results.** We found that infrequently applied (4 week) severe defoliation (to 5 cm) substantially  
42 enhanced shoot production for all cultivars, while severe defoliation reduced root production  
43 across cultivars, regardless of frequency. Overall, cultivars varied substantially in root  
44 production across the range of defoliation treatments in our study. However, there was no  
45 significant relationship between shoot and root production.

46 **Conclusions.** Our results find that aboveground and belowground productivity are only weakly  
47 coupled, suggesting caution against use of simple aboveground proxies to predict variations in  
48 root production in grasslands. More broadly, our results demonstrate that improved modeling and  
49 management of grasslands for belowground ecosystem services, including soil carbon  
50 sequestration/stocks, will need to account for intraspecific genetic variations and responses to  
51 defoliation management.

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## 57 **Introduction**

58

59           Grassland ecosystems occupy more than a fifth of earth's land area and account for a  
60 large proportion of the global SOC stock (1,2). However, there is considerable uncertainty in  
61 predictions of net ecosystem exchange, and hence carbon sequestration services from grasslands  
62 (3,4). One significant source of uncertainty is that while large herbivore grazing is known to  
63 mediate patterns of plant species composition, diversity, and aboveground primary productivity  
64 (5–7), the effects of grazing on belowground processes and soil carbon is less clear (8–11). In  
65 particular, there are limited field studies where the impact of grazing on root production in  
66 grassland systems has been directly measured (e.g., via root ingrowth cores or minirhizotron  
67 technology, but see Ziter and MacDougall (12) Balogianni et al. (11) and Cooley et al. (13)).  
68 Since belowground production may be the largest component of total NPP for many grasslands  
69 (14,15), determining how grazing affects root production will help to predict if and when  
70 grassland ecosystems will behave as carbon sinks, and whether grazing is likely to promote or  
71 inhibit carbon sequestration services.

72           Root carbon inputs may constitute a disproportionate amount of the total SOC stock  
73 compared with shoot carbon (16–18), and are especially critical in grassland ecosystems where  
74 aboveground tissue is susceptible to frequent removal by fire and grazing (19). Current  
75 understanding of how grazing affects root production is ambiguous. For example, one temperate  
76 mesocosm study showed that intense defoliation inhibited root production and accelerated the  
77 loss of SOC (20), whereas some field studies have documented greater belowground allocation  
78 and root production under grazing (Hafner et al. (21) in the Tibetan plateau; Wilson et al. (22) in  
79 subtropical pasture).. Augustine et al. (23) found that defoliation reduced belowground carbon  
80 allocation in one grazing-adapted North American grass species (*Pascopyrum smithii*, western

81 wheatgrass) but not in another (*Bouteloa gracilis*, blue grama), highlighting interspecific  
82 variations in response to a given defoliation regime. In general, laboratory and mesocosm studies  
83 have found that frequent grazing/defoliation leads to declines in standing root biomass over the  
84 long term (24), whereas a global synthesis of data comparing grazed and ungrazed grasslands  
85 found a mix of positive and negative effects on standing root biomass (25). Overall, this  
86 discordance suggests that variations in plant composition, underlying environmental factors,  
87 grazing intensity, or some combination of these factors significantly mediate the effect of grazing  
88 on root production.

89         Grazing effects on belowground production may not only vary based on plant species, but  
90 also on the genotypic composition of a grazed stand, given the increasing evidence of the  
91 importance of intraspecific variation in driving ecosystem structure and function (26,27). In  
92 general, some literature suggests that reduced root allocation (and increased shoot allocation)  
93 following grazing may represent an evolutionarily adaptive trait for grazing tolerance (28). For  
94 instance, Carman (1985) (29) noted that short-leaved genotypes of *Schizachyrium scoparium*,  
95 selected from a long-term grazed site, exhibited lower rates of root elongation post-grazing than  
96 longer-leaved genotypes from a long-term grazing excluded site. Planted pasture grasses also  
97 have been shown to exhibit genotypic variability in shoot and root production in response to  
98 grazing (e.g. Dawson et al. (30)). For example, Interrante et al. (31) observed significantly less  
99 plant cover in recently selected, upright-growing *Paspalum notatum* (bahiagrass) cultivars in  
100 response to severe, frequent defoliation, but did not observe less cover with the same defoliation  
101 treatments applied to widely naturalized cultivars, suggesting significant intraspecific variability  
102 in grazing tolerance and belowground allocation.

103           Although root production is a critical component of predicting the carbon cycle in  
104 grassland ecosystems, it is difficult to monitor or predict over large spatial scales. Thus, regional-  
105 scale grassland models have been developed that predict total NPP and/or greenhouse gas  
106 exchange on the basis of aboveground canopy characteristics estimated from remote sensing  
107 (32–34). Similarly, some previous work has sought to predict BNPP on the basis of readily  
108 obtained aboveground measurements in both grasslands (14) and forests (35). Recently,  
109 concerted efforts have been made to link fine root traits with other plant traits, across species and  
110 environments, by compiling and analyzing global-scale big datasets (36). The goal is to have  
111 reliable aboveground proxies for predicting critical belowground root processes (37). However,  
112 given the evidence for potentially significant genotypic and defoliation effects on belowground  
113 carbon allocation, it is unclear whether aboveground proxies can ever reliably approximate root  
114 production. Given the central importance of root system carbon inputs to maintaining SOC,  
115 especially in grasslands, we need more data from experimental systems where genotypic  
116 composition and grazing management have been manipulated, and the relationship between  
117 above and belowground allocation have been quantified.

118           In this study, we tested the independent and combined effects of defoliation intensity and  
119 frequency, and cultivar on root production of a widely utilized pasture grass species of the  
120 southeastern United States, *Paspalum notatum* Flüegge (bahiagrass). For Bahiagrass, we can  
121 broadly delineate cultivars on the basis of growth habit where historically older, widely  
122 naturalized cultivars tend to have a more prostrate growth pattern, whereas recently selected  
123 cultivars tend to have a more upright growth pattern, reflecting selection for improved forage  
124 growth characteristics (38). Previous work, and considerable producer experience, suggests that  
125 bahiagrass has a remarkable resilience to intense grazing, wherein forage growth and quality is

126 maximized with severe defoliation (close to ground level) so long as regrowth intervals are  
127 adequate (39,40). However, the impact of defoliation severity on root production across  
128 cultivars, and their associated growth habits, has not been directly studied, reflecting a general  
129 lack of information on belowground growth responses in warm season subtropical pasture (13).  
130 To redress this gap in knowledge we conducted an experiment in a common garden setting under  
131 realistic conditions of limited soil fertility to isolate the effects of defoliation intensity, frequency  
132 and cultivar on belowground production, and to evaluate the relationship between aboveground  
133 and belowground growth.

134 Consistent with the literature on compensatory growth responses from natural and  
135 planted pastures (40–42), and the literature on genotypic variability (e.g. Dawson et al. (30)) we  
136 hypothesized that:

- 137 1) Severe defoliation, applied infrequently, would stimulate increases in  
138 aboveground primary productivity (via compensatory response mechanisms),  
139 but would have neutral effects on root productivity across all cultivars;
- 140 2) Severe defoliation, applied frequently, would significantly suppress root  
141 production across all cultivars as a consequence of plant requirements to  
142 prioritize photosynthate allocation to regrowing shoots;
- 143 3) Widely naturalized, decumbent cultivars would show proportionally greater  
144 reductions in root production under severe defoliation compared to the more  
145 upright cultivars, reflecting a beneficial adaptation for increased shoot  
146 allocation following severe defoliation events; and
- 147 4) Despite alterations to belowground allocation on the basis of cultivar and  
148 defoliation treatment, shoot production and root production would positively

149 correlate at the plot level reflecting variations in underlying soil factors  
150 determining total productivity.

151

## 152 **Materials & Methods**

153

154 To evaluate the independent and potential interactive effects of defoliation intensity and  
155 plant cultivar on root production, we established 32 3 m x 7 m experimental plots at the  
156 University of Florida Range Cattle Research and Education Center, Ona, FL (27°26' N,  
157 82°55'W) in 2009. The soils were uniform and classified as Pomona fine sand (sandy, siliceous,  
158 hyperthermic Ultic Alaquod). First, we seeded plots with one of four bahiagrass cultivars  
159 (Argentine, Pensacola, Tifton-9, and UF-Riata). Bahiagrass is a perennial C4 pasture grass with  
160 improved germplasm that was introduced to Florida in the 1920s from South America and  
161 constitutes the primary forage for the Florida cow-calf industry (43). 'Argentine' and 'Pensacola'  
162 are widely-distributed, naturalized cultivars in the state of Florida with a decumbent growth  
163 habit, whereas 'Tifton-9' and 'UF-Riata' are recently-released cultivars selected for improved  
164 agronomic characteristics including more upright growth habits and less photoperiod sensitivity  
165 (31,38). Plots were fully established by the onset of the 2010 summer growing season with  
166 complete, uniform plant cover. More details, including soil fertility characteristics can be found  
167 in Vendramini et al. (38). Site weather data for this period were accessed from the Florida  
168 Automated Weather Network (FAWN, <http://fawn.ifas.ufl.edu/data/>), including temperature,  
169 precipitation, and evapotranspiration, and all fell within normal ranges (Table A1).

170 We initiated defoliation treatments on June 13<sup>th</sup> 2013 and concluded field sampling 16  
171 weeks later on October 5<sup>th</sup> 2013. Although we did not measure soil moisture, the soils were all  
172 visibly waterlogged from July until the end of the experiment, as is typical in Florida Spodosol

173 soils (43). We therefore assumed that plant growth was not limited by water availability during  
174 the sampling period, or at the very least that water availability was essentially constant across  
175 plots. Each plot ( $n = 32$ ) was randomly assigned to either a frequent (2 week) or infrequent (4  
176 week) defoliation treatment to simulate grazing stress. Each plot was divided in half and received  
177 two defoliation intensities (a severe defoliation to 5 cm residual height, and a mild defoliation to  
178 15 cm residual height) resulting in  $n = 64$  experimental units (Figure A1). Thus, our design was  
179 effectively split-plot with two main-plot treatments (cultivar and defoliation frequency), while  
180 our subplot factor was defoliation intensity. Overall, each cultivar X defoliation severity X  
181 defoliation frequency treatment was replicated 4 times.

182 We harvested a 0.92-m<sup>2</sup> quadrat from each subplot during each defoliation treatment with  
183 a rotary mower (Sensation Mow-Blo Model 11F4-0) at the target cutting heights: 5 cm for the  
184 severe defoliation, 15 cm for the mild defoliation, values chosen based on personal observation  
185 (C.H. Wilson, L.E Sollenberger, J.M. Vendramini) to represent the extremes of pasture  
186 defoliation under grazing by beef cattle in Florida. To quantify aboveground production,  
187 harvested material was oven-dried at 60°C to constant mass and weighed on an analytical scale.  
188 During the final harvest, all subplots were harvested at 5 cm. Total aboveground production was  
189 determined by summing values for each subplot across all dates including the final harvest.  
190 Aboveground production values are presented in gm<sup>-2</sup> (dry biomass).

191 To quantify root primary production in response to the defoliation treatments, we  
192 installed 2-mm mesh root in-growth cores (44) on June 7<sup>th</sup>, 2013, prior to imposing the  
193 defoliation treatments. Cores were 7.5 cm diameter x 25 cm deep and constructed of fiberglass  
194 mesh. They were installed by first excavating a cylinder of soil with a soil auger to target  
195 dimensions, placing the mesh bags into the cylinder so that the upper edge of the bags was just



196 below the soil surface, and then re-filling the cores with sieved, root-free soil from the same plot.  
197 We retrieved the cores at the end of the growing season on October 5th 2013, 16 weeks after  
198 installation. The final volume of soil contained in each core was quantified prior to washing the  
199 roots free of soil on a 250- $\mu$ M sieve. Root samples were then oven-dried at 60°C to constant  
200 mass and weighed on an analytical scale. To correct for variation in core volume, root biomass  
201 was multiplied by a correction factor determined as the inverse of the ratio of each core volume  
202 to a reference core (a cylinder of 7.5 cm diameter and 25 cm depth). Finally, we visually  
203 determined that almost all root biomass was contained within the depth we evaluated (i.e. 25 cm  
204 depth) by digging several test pits around our study area. We note from personal observation that  
205 wet pastures tend to result in shallower root distribution, consistent with early literature such as  
206 (45). Therefore, we multiplied root biomass by a constant ( $10000/(\pi \cdot 3.75^2)$ ) to convert our  
207 measures to g/m<sup>2</sup>, putting them on an easily interpretable scale.

208

## 209 Statistical Analysis

210 Response variables for analyses were shoot and root production, and a measure of root  
211 allocation defined as:

$$212 \frac{\textit{Root production}}{\textit{Root production} + \textit{Shoot production}}$$

213 To analyze among-cultivar variability in response to our treatments, we parameterized a  
214 varying-intercept/varying-slope Bayesian hierarchical model that we applied to both of our  
215 response variables. In this model, we estimate intercept and slope (i.e., treatment effects)  
216 coefficients for each cultivar, where each batch of coefficients is modeled as a draw from a  
217 normal distribution with an estimated variance component (46). We included binary predictor  
218 variables using a -0.5/0.5 “effect coding” for our experimentally imposed treatments: lenient (15

219 cm) and infrequent (4 wk) defoliation were assigned -0.5 values, while frequent (2 wk) and  
220 severe (5 cm) defoliation were assigned 0.5 values. Under this coding, the model intercept  
221 represents the grand mean, and the coefficients for defoliation severity and frequency represent  
222 the main effects of severe and/or frequent defoliation across both levels of the other treatment  
223 (see e.g. Schabenberger et al. (47)). We also included a term for the interaction of severe and  
224 frequent defoliation treatments and a random effect of plot to allow for correlation in  
225 observations from the same plot. Our varying-intercept/varying-slope model therefore included  
226 four separate estimates of grand means (one for each cultivar), each of which represents an  
227 estimate of performance for that cultivar across all defoliation treatment conditions, and four  
228 treatment effect estimates (one for each cultivar) for frequent defoliation, severe defoliation, and  
229 their interaction. Since these coefficients were drawn from distributions with estimated variance  
230 components, the separate estimates were partially pooled towards their common mean, which  
231 also was estimated from the data, a property that built in an automatic correction for multiple  
232 comparisons among cultivars and obviated the need for arbitrary post-hoc adjustments such as  
233 the Bonferonni correction (48). Finally, because growth data are naturally constrained to be  
234 positive only and because we observed a pattern of variance increasing with the mean, we used a  
235 gamma distribution to model our data, which naturally accounts for this nearly universal pattern  
236 in biomass data. We used the standard log-link in our parameterization of the gamma regression  
237 model, and thus our model coefficients represent multiplicative effects, and are reported on the  
238 log link scale (46). Values greater than zero indicate positive effects on the response variable,  
239 whereas values less than zero indicate negative effects. As in all cases where the log-link is used,  
240 exponentiation of these regression coefficients returns the multiplicative effect which can be  
241 naturally interpreted as a % effect.

242 We display treatment effects graphically by first plotting estimated fixed effect  
243 coefficients (i.e. frequency, severity and frequency X severity) centered on the median, and  
244 include both a 50% (thick) and a 95% (thin line) uncertainty (credible) interval. These  
245 coefficients represent the overall average effects of treatment or the interaction effect across all  
246 cultivars. In addition, we graphically present the varying intercepts portion of our model, which  
247 represents the overall average deviation of each cultivar from the grand mean across all cultivars,  
248 and is thus naturally centered at zero. Here again, we include both 50% (thick) and a 95% (thin  
249 line) credible intervals. The proportion of the credible interval above or below zero can be  
250 interpreted as the Bayesian probability of that cultivar differing in response from the average  
251 across all cultivars. In the case of root allocation, we further analyze all the pairwise contrasts  
252 among cultivars (n=6 contrasts), by taking the difference between each coefficient at each  
253 iteration of the MCMC sampler. These pairwise contrasts thus represent the differences between  
254 each pair of cultivars in their overall root allocation, averaged across all treatment conditions.

255 We estimated these models in a Bayesian framework via Hamiltonian Monte Carlo in the  
256 packaged “rstanarm” (v2.18.2) called from R (v3.5.3) via Rstudio (v1.1.463). Prior to analysis,  
257 shoot and root production responses were standardized by dividing by their mean, resulting in  
258 this case with response variables with scale  $\sim O(1)$  to facilitate faster sampling, and to help  
259 specify weakly-regularizing Normal(0,1) priors for all treatment effects. For all models we  
260 sampled the target (posterior) distribution with four chains of 2000 iterations each. Model  
261 convergence was assessed via use of the  $\hat{R} < 1.01$  criterion (46) as well as by visual  
262 inspection for chain blending and stability, and monitoring of the powerful diagnostics built into  
263 rstanarm (i.e. divergent transitions and E-BFMI, citation).

264 To understand the relative importance of defoliation treatment and cultivar compared  
265 with shoot production for predicting root production, we first fit a simple univariate regression  
266 model using only aboveground biomass from each subplot (n=64) as a continuous covariate. We  
267 then refit our varying-intercepts/varying-slopes model while including shoot production as a  
268 continuous covariate alongside treatment and cultivar effects. We compare a Bayesian  $R^2$  metric  
269 between the models (49). Because the visual and  $R^2$  comparisons were so clear, we had no need  
270 to evaluate additional metrics of model predictive performance.

271

## 272 **Results**

### 273 *Shoot production model*

274 Average shoot production across all cultivars and treatment combinations in our study  
275 was  $290 \text{ gm}^{-2}$ , with the highest values observed in the infrequent severe defoliation treatment,  
276 which averaged  $384 \text{ gm}^{-2}$  (Fig 1). The fixed main effect estimate (on log-link scale, and reported  
277 as posterior median +/- posterior standard error) for severe defoliation was positive [ $0.28 \pm$   
278  $0.07$ , Fig 2a], while the estimate for frequent defoliation was negative [ $-0.18 \pm 0.08$ , Fig 2a];  
279 however, the interaction was negative as well [ $-0.25 \pm 0.15$ , Fig 2a], consistent with readily  
280 observable pattern (Fig 1) that it is the combination of severe + infrequent (4 wk) defoliation that  
281 leads to over-yielding. Overall, we did not estimate substantial variability in shoot production  
282 among cultivars across all treatments, although the upright cultivars (UF-Riata and Tifton-9) had  
283 slightly higher production than the decumbent cultivars Argentine and Pensacola (Fig. 3a).

284 **Fig. 1: Raw data ( $\text{gm}^{-2}$ ) plotted as circles (shoots) and triangles (roots).** Error bars show  
285 mean biomass ( $\text{gm}^{-2}$ ) +/- 1 SE for shoots (purple error bars) and roots (brown error bars). The  
286 panels are faceted by treatment combinations: intensity of defoliation on top (lenient 15 cm or  
287 severe 5 cm on top), and frequency of defoliation labeled on the right hand side (2 wk or 4 wk).  
288 The x-axis groups responses by cultivar: A = Argentine, P = Pensacola, T9 = Tifton-9, and UF-R  
289 = UF-Riata.

290

291 **Fig. 2: Fixed effects from varying-intercepts/varying-slopes Gamma regression model.**  
292 Coefficients are plotted on the log-link scale and include a median (point), 50% (thick line) and  
293 95% (thin line) credible intervals for a) shoot production, b) root production and c) root  
294 allocation. Where the entire 95% credible interval falls above or below zero, we can interpret  
295 that as a 97.5+% Bayesian probability of that coefficient having a positive or negative effect on  
296 the response, respectively.

297  
298 **Fig. 3: Varying-intercepts from the Gamma regression model for root production.**  
299 Coefficients represent deviations of each cultivar (A = Argentine, P = Pensacola, T9 = Tifton-9,  
300 and UF-R = UF-Riata) from the overall mean (fixed effect coefficient), and are thus naturally  
301 centered at 0, where negative values represent lower than average performance, and positive  
302 values higher than average performance. Plots include a median (point), and 50% (thick line) and  
303 95% (thin line) credible intervals. Where the entire 95% credible interval falls above or below  
304 zero, we can interpret that as a 97.5+% Bayesian probability of the cultivar having a higher or  
305 lower overall root production compared to the mean among all cultivars.

306

### 307 *Root production model*

308 We observed an average root production of 224 gm<sup>-2</sup>, where mild defoliation treatments  
309 were the highest with 262 gm<sup>-2</sup> averaged across 2 wk and 4 wk defoliation frequencies,  
310 compared with severe defoliation with an average of 186 gm<sup>-2</sup> (Fig 1). The fixed main effect  
311 estimate for severe defoliation was negative (-0.33 +/- 0.12, Fig 2b), with >97.5% of posterior  
312 probability below 0, while the main effects of frequent defoliation and the interaction of frequent  
313 X severe defoliation were highly uncertain, with 95% credible intervals spanning a similar range  
314 above and below zero. Average root production across all treatment groups varied by cultivar  
315 more substantially than shoot production (Fig 3b), with the decumbent cultivars Argentine and  
316 Pensacola having greater root production than the upright cultivars UF-Riata and Tifton-9 (Fig  
317 3b, Fig. 4). The greatest contrast was between Argentine and UF-Riata, which had a median  
318 posterior difference of -0.36 on the log-link scale (Fig. 4), which represents a 30% lower root  
319 production.

320 **Fig. 4: Pairwise contrasts among each cultivar for the varying intercepts of the root**  
321 **allocation model.** Key: A = Argentine, P = Pensacola, T9 = Tifton-9, and UF-R = UF-Riata.  
322 Plots include a median (point), and 50% (thick line) and 95% (thin line) credible intervals.  
323 Where the entire 95% credible interval falls above or below zero, we can interpret that as a  
324 97.5+% Bayesian probability of the first cultivar having a higher root allocation than the second  
325 cultivar.

326  
327 *Root allocation*

328 The fixed main effect estimate for severe defoliation on root allocation proportion was -  
329 0.34 +/- 0.09 (Fig 2c), a very similar median estimate to that for root production, although with a  
330 smaller uncertainty (SE = 0.09 versus 0.12). This result represents a median estimate of 29%  
331 reduced allocation proportion to roots overall among cultivars and across both frequencies of  
332 defoliation with severe defoliation. Variation among cultivars was also similar to that observed  
333 for root production (Fig 3c versus 3b), and thus we did not repeat the pairwise analysis since it  
334 would convey redundant information.

335  
336 *Root production predictions*

337 The univariate regression between shoot and root production revealed a very weak ( $R^2 =$   
338 0.09) relationship (Fig 5a). The full model that included treatment indicators and cultivar identity  
339 (as in the analyses above), yielded a median  $R^2$  of 0.45 (Fig 5b). After removing the varying  
340 intercepts/slopes by cultivar, this  $R^2$  value declined to 0.21 (see supplement), indicating that  
341 accounting for cultivar identity doubles model fit. Close examination of Fig 5b reveals that the  
342 full model accounted for observed variations in root production quite well in the range of 100-  
343 300  $\text{gm}^{-2}$  but severely underpredicted root production  $> 300 \text{ gm}^{-2}$ .

344 **Fig. 5: Shoot production does not predict root production.** a) Predicted versus observed  
345 scatterplot for root production as predicted by shoot production as an aboveground proxy, and b)  
346 predicted versus observed scatterplot for root production as predicted by defoliation treatment,

347 cultivar identity, and shoot production. For reference, the 1:1 line of “perfect fit” is plotted along  
348 with an in-sample median Bayesian  $R^2$  for both predictive models.

349

## 350 **Discussion**

351

352       Severe defoliation resulted in substantially greater shoot production when applied  
353 infrequently, but reduced root production among the bahiagrass cultivars. Averaged across all  
354 defoliation treatments, root production was also more strongly variable among cultivars than was  
355 shoot production. Thus, our results suggest that severe defoliation can trigger a tradeoff between  
356 aboveground and belowground allocation in managed subtropical pastures, and that the extent of  
357 this tradeoff depends in part on cultivar identity. Contrary to Georgiadis et al. (50) and Briske  
358 and Richards (28) who suggested that overcompensation is only likely to occur under water-  
359 limitation, or given concomitant fertilization, we found significantly greater shoot production in  
360 response to severe defoliation under limited fertility and abundant soil water. Compared with  
361 mild defoliation, all cultivars exhibited this compensatory aboveground growth response to  
362 severe defoliation, but only when defoliation was applied infrequently (similar to Gates et al.  
363 (51)). However, the severe, but infrequent defoliation treatment that led to aboveground  
364 compensatory growth also suppressed root production. Thus, under low-input conditions,  
365 manipulating defoliation intensity and frequency to enhance forage production could evoke a  
366 tradeoff between shoot and root production.. Given the substantial literature demonstrating the  
367 importance of root carbon for maintenance of soil carbon pools (17,18,22), these altered  
368 allocation patterns may have significant consequences for carbon cycling, and hence soil carbon  
369 sequestration services, in managed subtropical pastures. Moreover, use of simple aboveground  
370 proxies, such as leaf area/biomass, are unlikely to help constrain predictions of root production  
371 over large spatial scales.

372 Our results differ from the short-term responses measured by Ziter and Macdougall (12)  
373 and Hamilton III et al. (52) where a single defoliation event stimulated root production and root  
374 exudation, respectively. Moreover, the results reported here appear to conflict with  
375 measurements of standing root biomass, root exudation rates, and their connections to microbial  
376 biomass and soil carbon, across a system of long-term grazing exclosures on a similar pasture  
377 site, as reported in Wilson et al. (22). These discrepancies suggest that root responses to short-  
378 term grazing/defoliation events can strongly differ from season-long responses to grazing  
379 regimens where both intensity and frequency of defoliation are expected to mediate plant  
380 regrowth strategies (28). Moreover, long-term impacts of grazing exclusion in bahiagrass-  
381 dominated subtropical pasture appear to involve pronounced phenotypic shifts in root:shoot  
382 ratios, whereby absence of grazing favors lower root:shoot ratios, even when holding species  
383 composition constant (22). On the other hand, Thornton and Millard (53) found that greater  
384 severity of defoliation resulted in lower root mass (but greater N uptake per unit of root mass),  
385 which is consistent with our findings. Meanwhile, Dawson et al. (30) report that weekly  
386 defoliation over a growing season reduced root biomass compared with no defoliation, but  
387 infrequent defoliation (every 8 weeks) had no effect. Our ambivalent findings on the role of  
388 frequency of defoliation were thus somewhat surprising. Although we observed marked  
389 suppression of variability of production under our severe + frequent treatment (see e.g., Fig 1),  
390 root production was not markedly lower than in our severe + infrequent treatment. Overall, it  
391 appears that in our system, severity, not frequency, of grazing is the more important determinant  
392 of grass root production.

393 We observed substantial overall variability in root production among the grass cultivars.  
394 However, it does not appear possible to predict cultivar-level belowground responses to specific



395 grazing regimens based on observations of aboveground compensatory growth responses. As we  
396 hypothesized, the cultivars selected for enhanced upright growth habit (Tifton 9, UF-Riata, (31))  
397 exhibited less overall root production, especially Tifton-9, compared with the widely naturalized  
398 decumbent types (Argentine, Pensacola), especially Argentine. On the other hand, all cultivars  
399 responded equally negatively to severe defoliation *per se*, and we observed similar total root  
400 production among all cultivars in the severe + frequent defoliation treatment, a scenario  
401 reasonably representative of overstocked pastures. These results contradict the theory that more  
402 grazing-tolerant genotypes, in our case Argentine and Pensacola, will have lower root production  
403 as a consequence of greater post-grazing allocation to shoot regrowth (28,30). Instead, it appears  
404 that cultivars simply vary in root growth potential, but that severe defoliation, especially when  
405 applied frequently, overwhelms this variability.

406         Contrary to hypothesis, our study revealed that shoot and root production are decoupled  
407 at fine spatial scales, at least in our experimental plots, with shoot production explaining only 8%  
408 of the in-sample variation in root production. By contrast, defoliation treatment and especially  
409 cultivar identity appear to be very important for predicting root production in this system,  
410 together accounting for roughly half the observed variance in root production. Gill et al. (14)  
411 reported some success in predicting belowground NPP using an algorithm based only on  
412 aboveground biomass and climate. However, their model consistently under-predicted root  
413 production in more productive sites. Interestingly, we observed a similar severe underprediction  
414 of root production in our more productive plots. Thus, we caution against using aboveground  
415 proxies to predict belowground production, even within uniform and homogeneous ecosystems,  
416 such as the planted pasture system where we worked. Our results suggest that knowledge of  
417 grazing management and cultivar identity (in addition to species-level variations in composition,

418 (54,55)) are critical for generating accurate predictions of BNPP. Moreover, half of the variance  
419 in belowground production was unexplained, even in our best model, suggesting significant  
420 spatial heterogeneity in root system productivity that should be further investigated. Given recent  
421 calls highlighting the importance of plant roots to future progress in biogeochemical modeling  
422 and the quest to find reliable, scalable aboveground proxies to indirectly infer root processes  
423 (36,37), our results are a sobering reminder of the challenges inherent to linking production  
424 above and belowground. Accordingly, we suggest that a high priority for future research is to  
425 study belowground root-rhizosphere processes using spatially-explicit sampling protocols  
426 designed to maximize insight into heterogeneity at various spatial and temporal scales.

427         At the large scale, McNaughton (1998) (8) found that grazing intensity is uncorrelated  
428 with standing root biomass or productivity in the Serengeti. However, in speciose natural  
429 grasslands plant diversity may confer a stabilizing influence on root production (55,56). By  
430 contrast, monoculture pasture systems may respond more like mesocosm systems where high  
431 defoliation intensity is associated with reduced root biomass (24). Moreover, since a large  
432 proportion of managed grasslands are dominated by single species, variation in root production  
433 among cultivars may represent an especially important component of diversity. Grazing  
434 management may need to be matched to cultivar-level characteristics to optimize both forage and  
435 root production, and establishment of planted pastures with multiple cultivars or genotypes may  
436 be a viable, yet underappreciated, strategy for enhancing functional diversity. For instance,  
437 combining upright and decumbent cultivars may introduce beneficial genotypic diversity that  
438 could maximize utilization of both above and belowground resources via niche complementarity  
439 (57,58). Additionally, cultivar-level variability suggests the potential for ecologists to collaborate

440 with plant breeders to improve the sustainability of grassland agroecosystems by development of  
441 improved forage cultivars selected for superior belowground traits.

442 Overall, our results suggest that intermittent severe defoliation can elicit much greater  
443 shoot growth, but have neutral or negative effects on root production. It is possible that a more  
444 moderate defoliation intensity than we tested would have led to similar stimulation of  
445 aboveground compensation without the negative consequence for root production, a possibility  
446 our study was not designed to test. Neither did our study consider impacts of defoliation on  
447 rhizome biomass, but we note that our intent was to focus on root production since it appears to  
448 be of greater relevance for soil carbon sequestration than other compartments of plant biomass  
449 (17). Likewise, it is also possible that the lower fine root production we measured may have been  
450 compensated for by greater rhizodeposition/root exudation. However, this possibility seems  
451 unlikely given that rates of root exudation generally correlate to fine root surface area (22,59).

452

## 453 **Conclusions**

454

455 Root production is critical for maintaining and increasing soil carbon pools in grassland  
456 ecosystems, yet findings on the immediate and long-term effects of grazing on root production  
457 remain variable. We hypothesized that severe defoliation, if applied infrequently, might lead to  
458 overyielding of shoots, but would have only small impacts on root production. Moreover, we  
459 hypothesized that cultivars selected for an upright growth habit would show less root production  
460 overall, and would be more sensitive to defoliation stress. Overall, we found that severe  
461 defoliation *per se*, regardless of frequency, suppressed root production, even as infrequently  
462 applied severe defoliation increased shoot production. Thus, it appears that manipulating timing  
463 and intensity of grazing to optimize forage production might evoke a negative tradeoff with root

464 production. We did find support for the hypothesis that recently developed upright cultivars have  
465 lower root production, and a lower root:shoot ratio, than widely naturalized decumbent cultivars.  
466 The main limitation of our work is that realistic animal grazing management can differ from  
467 experimentally imposed defoliation in two major ways: 1) grazing impacts will fall along a  
468 spectrum of timing and intensity with more intermediate values than can be tested in a  
469 randomized factorial experiment, and 2) grazers will return a certain fraction of consumed  
470 carbon and nutrients in the form of manure and urine, creating heterogeneous patches of varying  
471 nutrient availability. Moreover, we also caution that year-year variability in growing conditions  
472 can induce variability in experimental effects. Ideally, we recommend long-term (3+ year) field  
473 studies of controlled grazing (or defoliation) to begin to properly estimate the random effects of  
474 such year-year environmental fluctuations.

475         In addition to recommending greater future consideration of intraspecific variations in  
476 belowground responses to grazing, our work supports the need to perform season-long measures  
477 of belowground productivity to obtain reliable estimates of belowground production that can be  
478 used to parameterize soil carbon models. Our data also suggest that reliance on aboveground  
479 proxies is, unfortunately, not justified at least for subtropical pastures. In addition, given the  
480 limitations of observational and comparative work, we suggest that longer-term field  
481 manipulations are necessary to evaluate a suite of grazing management scenarios across plant  
482 composition treatments. Such experiments will significantly improve our ability to inform the  
483 design and management of grassland agroecosystems for meeting aboveground (forage)  
484 production goals while also optimizing belowground production, and thus soil carbon  
485 sequestration and other soil carbon mediated ecosystem services such as nutrient retention and  
486 water cycling (2).

487

488

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648

## 649 SUPPORTING INFORMATION

650

651 **S1 Fig. Diagram showing layout of plots.** North is top of the page. Legend: Defoliation  
652 severity- Red = Severe Defoliation (5 cm), Blue = Lenient Defoliation (15 cm). Defoliation  
653 frequency - 2wk = Defoliated every 2 weeks, 4wk = Defoliated every 4 weeks. Bahia cultivar  
654 identity - A = Argentine, P = Pensacola, T9 = Tifton 9, R = UF-Riata.

655

656 **S1 Table. Meteorological data from our study site during study season.** Ona Range Cattle  
657 Research and Education Center. Accessed from the Florida Automated Weather Network  
658 (FAWN), <http://fawn.ifas.ufl.edu/>.

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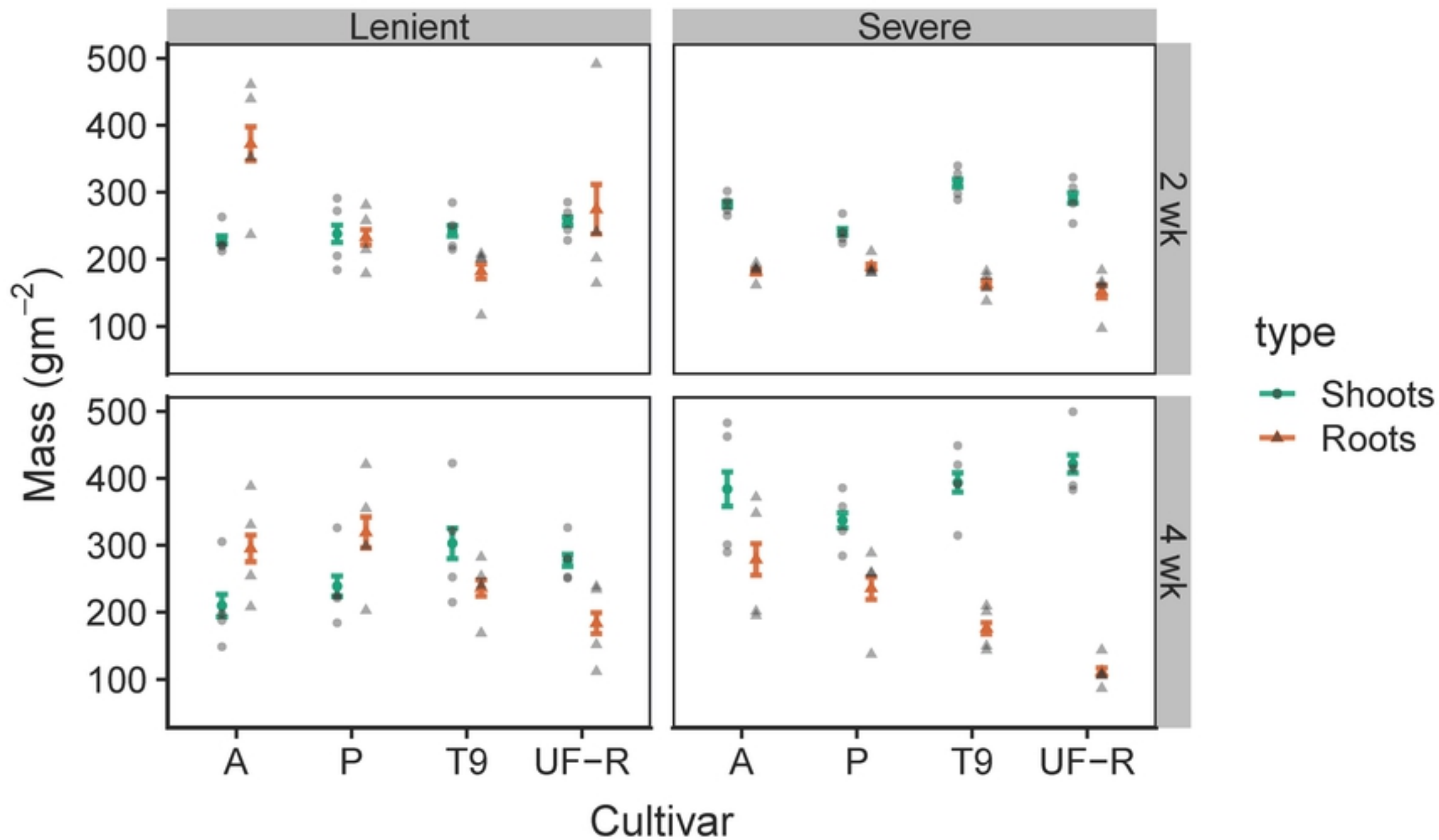
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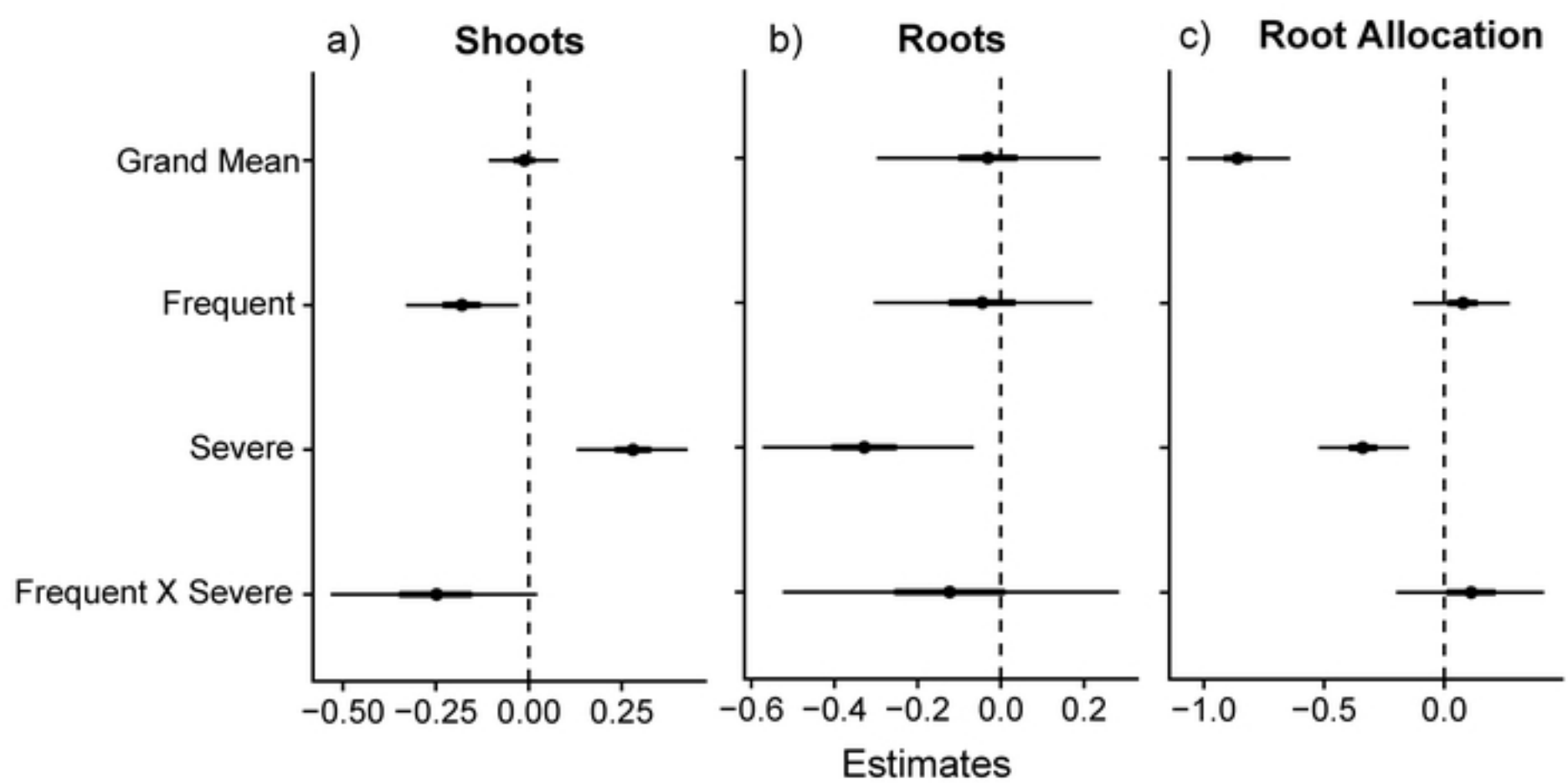
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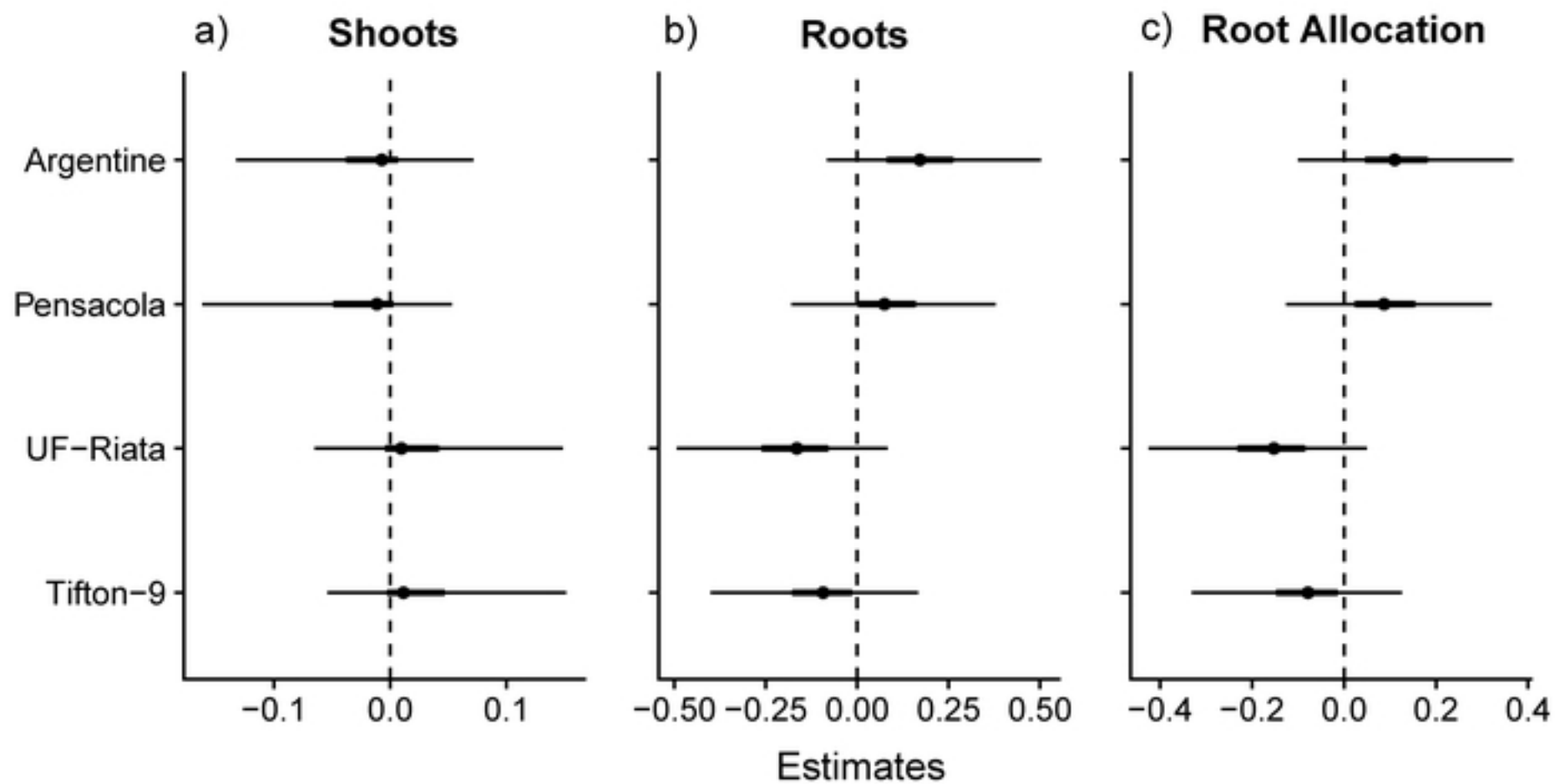
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Figure



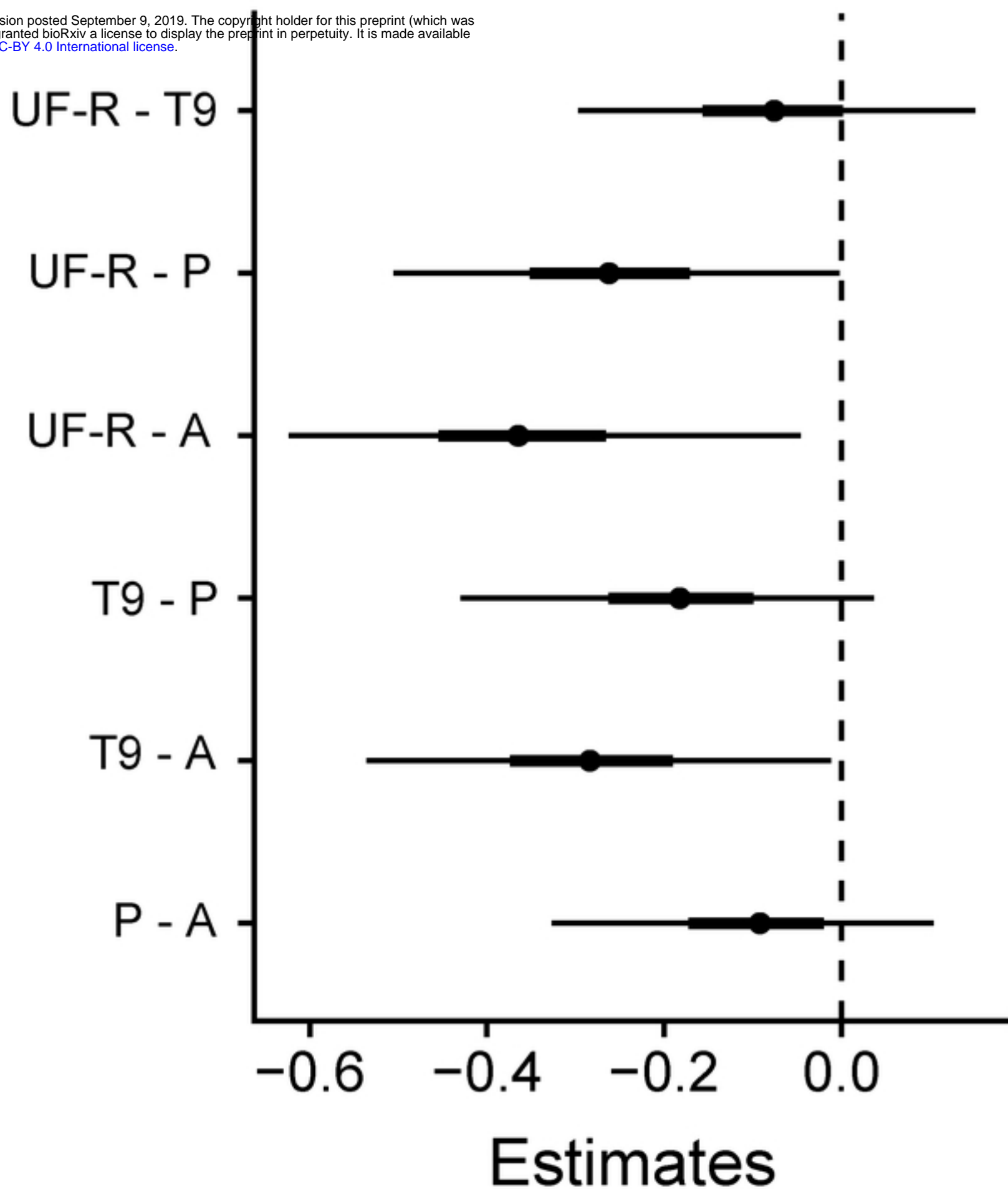
Figure



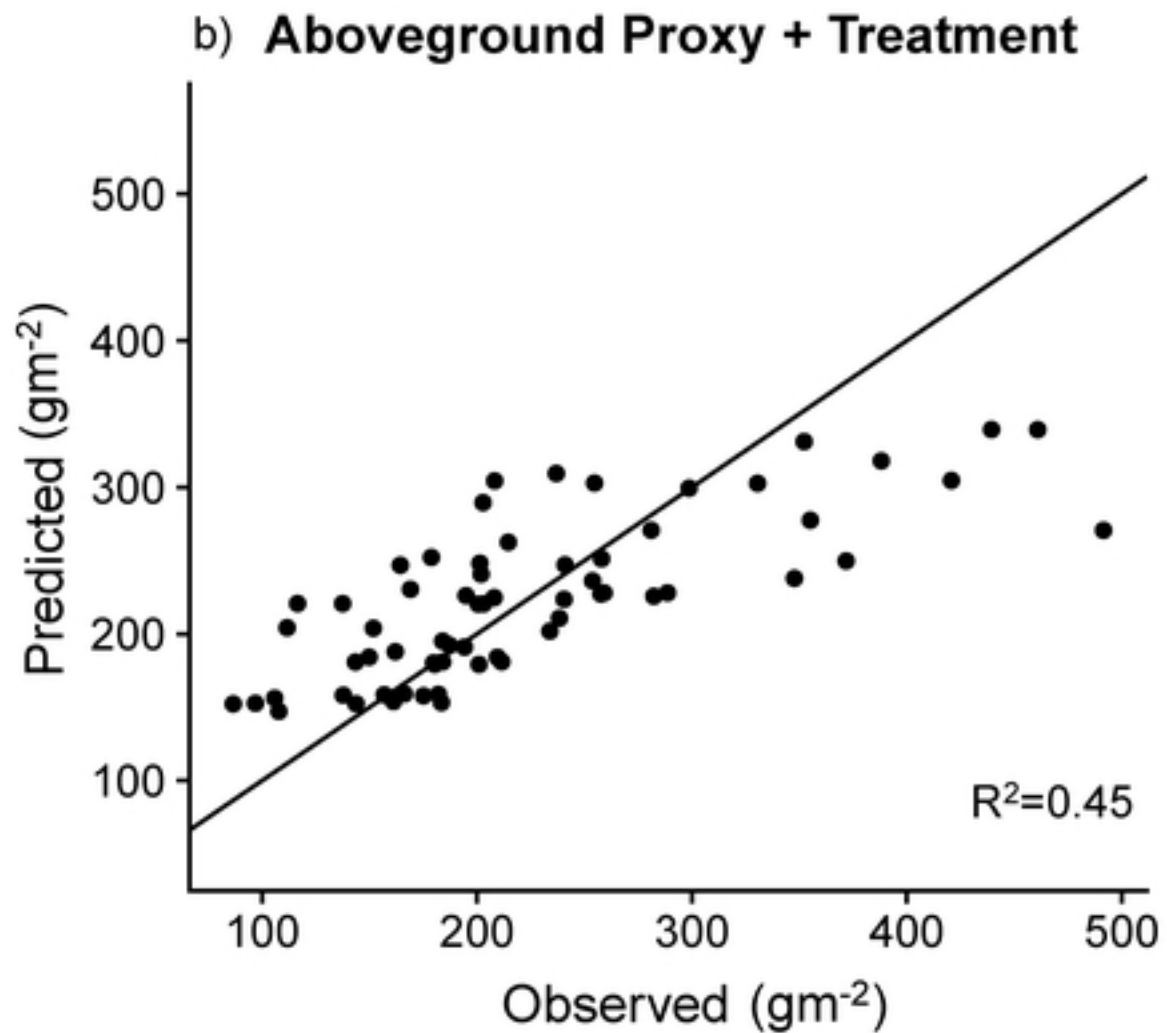
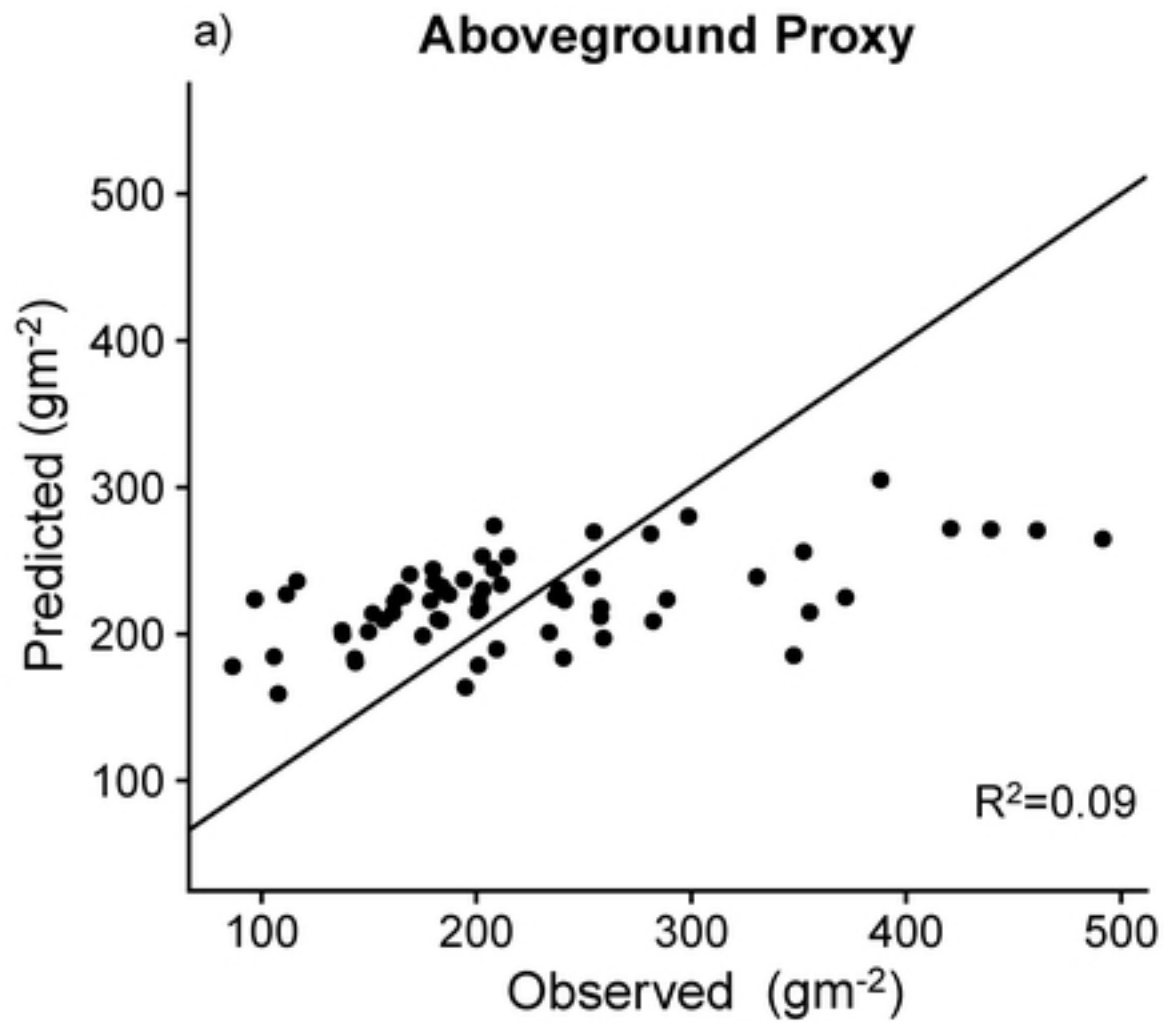
Figure

# Pairwise Differences

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Figure



Figure