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Soil microbial communities with greater investment in resource acquisition have lower growth yield

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Authors

Malik, Ashish A
Puissant, Jeremy
Goodall, Tim
et al.

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Highlights

- Evidence for tradeoff in microbial resource acquisition and growth yield traits
- Growth yield patterns linked more to carbon than nitrogen enzyme activity
- Smaller stoichiometric than energetic constraints on community metabolism
- Community-aggregated trait tradeoffs have consequences for soil carbon cycling

1 **Soil microbial communities with greater investment in resource acquisition**
2 **have lower growth yield**

3

4 **Ashish A. Malik^{1,2}, Jeremy Puissant¹, Tim Goodall¹, Steven D. Allison^{2,3} and Robert I.**
5 **Griffiths¹**

6 ¹Centre for Ecology and Hydrology, Wallingford, UK

7 ²Department of Ecology and Evolutionary Biology, University of California, Irvine, USA

8 ³Department of Earth System Science, University of California, Irvine, USA

9

10 **Abstract**

11 Resource acquisition and growth yield are fundamental microbial traits that affect
12 biogeochemical processes and have consequences for ecosystem functioning. However, there
13 is a lack of empirical observations linking these traits. Using a landscape-scale survey of
14 temperate near-neutral pH soils, we show tradeoffs in key community-level parameters
15 linked to these traits. Increased investment into extracellular enzymes estimated using
16 specific potential enzyme activity was associated with reduced growth yield obtained using
17 carbon use efficiency measures from stable isotope tracing. Reduction in growth yield was
18 linked more to carbon than nitrogen acquisition highlighting smaller stoichiometric than
19 energetic constraints on community metabolism in examined soils.

20

21 **Keywords:** carbon; microbial communities; enzymes; carbon use efficiency; nitrogen; traits

22 Microorganisms are known to affect biogeochemical cycling of elements with consequences
23 for ecosystem functioning. Of particular interest is how microbial metabolic strategies affect
24 the fate of plant carbon (C) entering soils (Schimel and Schaeffer 2012, Gleixner 2013). Soil
25 microorganisms partition detrital carbon into biomass production and respiration, and this
26 partitioning is key in determining the amount of carbon stored in soil (Schimel 2013, Liang et
27 al. 2017). Microbial growth yield often measured in C units as carbon use efficiency (CUE),
28 is defined as the amount of new growth production per unit of resource consumed (Manzoni
29 et al. 2012, Roller and Schmidt 2015, Geyer et al. 2016). It determines the fraction of carbon
30 that is allocated to biosynthetic processes (excluding that excreted as metabolites and
31 enzymes) versus the fraction that is respired for cellular energy requirements. Thus, growth
32 yield integrates microbial physiology and is a measure of the energetic and material costs for
33 survival and growth. Resource limitation can reduce growth yield by increasing the
34 investment into metabolic machinery to degrade and take up complex substrates (Frank 2010,
35 Allison 2014, Lipson 2015). This investment to acquire energy- and nutrient-rich molecules
36 comes in the form of extracellular enzymes that depolymerise complex macromolecules to be
37 then taken up and assimilated. Extracellular enzyme activity is widely believed to reflect
38 cellular metabolism specifically regulated by resource availability in the environment
39 (Sinsabaugh et al. 2010). Although there is some theoretical support to verify tradeoffs in
40 growth versus resource acquisition, empirical validation of these tradeoffs in soil microbial
41 communities is lacking (Middelboe and Sndergaard 1993). Nutrient limitation, particularly
42 nitrogen (N), can also affect growth yield as cells need to maintain the elemental
43 stoichiometry of their biomass (Manzoni et al. 2012, Sinsabaugh et al. 2013, Geyer et al.
44 2016). Under such conditions where carbon availability exceeds growth requirements,
45 microbes may take up substrates in excess to meet nutrient requirements, leading to overflow
46 respiration. Thus, it is also crucial to resolve the energetic and stoichiometric constraints on

47 microbial growth yield in soil environments (Sinsabaugh et al. 2010).

48

49 We hypothesised that due to resource constraints, community-level tradeoffs exist between
50 growth yield and resource acquisition, and that nutrient limitation affects community
51 metabolism and reduces growth yield. To test this hypothesis, we assessed the empirical
52 relationships between key physiological traits of soil microbial communities sampled at a
53 landscape scale. Soil samples were collected in triplicate from 56 sites across Britain with
54 land uses ranging from more pristine species-rich grasslands to intensive grasslands and
55 arable croplands, which together represent a set of distributed samples encompassing a
56 gradient of soil organic carbon concentrations (Malik et al. 2018b). Resource acquisition
57 traits were quantified by assessing the biomass specific potential activities of the extracellular
58 enzymes β -1,4-glucosidase (BG), acetyl esterase (AE), leucine aminopeptidase (LAP) and β -
59 1,4-N-acetylglucosaminidase (NAG); BG and AE were used as a proxy for C acquisition and
60 LAP and NAG were used as a proxy for N acquisition. Microbial growth yield was estimated
61 as community CUE by tracing ^{13}C -labelled, plant-derived substrates into total microbial
62 DNA and respired CO_2 . Using DNA-C concentration as a proxy for microbial community
63 biomass could lead to its underestimation, however, measuring ^{13}C incorporation into
64 microbial DNA to measure growth is ideal as new DNA formation reflects microbial growth.
65 However, DNA accounts for a smaller proportion of the total cellular biomass and therefore
66 absolute value of microbial CUE measured here could be underestimated in comparison to
67 approaches that employ other biomarkers.

68

69 Following from our recent study comprehensively examining microbial community
70 physiology where we observed soil pH driven shifts in microbial CUE and its links to soil C
71 accumulation (Malik et al. 2018b), here we focus on the physiology of communities in near

72 neutral pH soils (38 sites). We excluded those from acidic ($\text{pH} < 6.2$) wet soils that exhibited
73 very slow growth rates and low CUE (Figure 1a, Supplementary information figure S1)
74 resulting from alternate physiological constraints (Malik et al. 2018b). From each of the
75 geographically distributed sites, 3 dispersed soil cores (5 cm diameter, 15 cm deep) were
76 sampled. After all visible roots were removed, aliquots of the homogenized soil were used for
77 the following functional analyses. For microbial respiration measurements, a soil aliquot (1
78 g) from each replicate was placed in a 10 mL glass vial, 100 μL of ^{13}C -labeled plant leaf litter
79 DOC solution (0.13 mgC) was added and incubated overnight (for ~ 16 h) in the dark at room
80 temperature (21°C). The filter-sterilised DOC solution was prepared from ^{13}C -labeled
81 powdered plant leaf litter that was produced by growing a temperate herb in a $^{13}\text{CO}_2$
82 atmosphere (Malik et al. 2015). Respired $^{13}\text{CO}_2$ collected in the headspace of incubation vials
83 was measured using a gas chromatography isotope ratio mass spectrometer (GC-IRMS,
84 Delta+ XL, Thermo Fisher Scientific, Germany) coupled to a PAL-autosampler (CTC
85 Analytics) with general purpose (GP) interface (Thermo Fisher Scientific, Germany). Soil
86 microbial total DNA was used as a proxy for biomass; DNA extraction was carried out on a
87 soil aliquot of 0.25 g from each replicate using PowerSoil-htp 96-well soil DNA isolation kit
88 following manufacturer instructions (MO BIO Laboratories, UK). Another set of identical
89 DNA extraction was performed following addition of 25 μL of the DO^{13}C solution and
90 overnight (16 h) incubation in dark. Both extracts with and without the tracer were analysed
91 in the size exclusion chromatography (SEC) mode on a liquid chromatography isotope ratio
92 mass spectrometer LC-IRMS (HPLC system coupled to a Delta+ XP IRMS through an LC
93 IsoLink interface; Thermo Fisher Scientific, Germany, Malik et al., 2015). This allowed us to
94 obtain DNA-C content and the proportion of DO^{13}C in microbial DNA. Microbial CUE was
95 estimated as $\text{DNA-}^{13}\text{C}/(\text{DNA-}^{13}\text{C} + \sum \text{CO}_2\text{-}^{13}\text{C})$, where $\sum \text{CO}_2\text{-}^{13}\text{C}$ is the cumulative DO^{13}C lost
96 during respiration. More analytical details are given elsewhere (Malik et al. 2015, 2018b).

97

98 Potential activity of the extracellular enzymes was estimated with the common assay protocol
99 using fluorogenic substrates (Puissant et al. 2015). β -1,4-glucosidase, acetyl esterase, leucine
100 aminopeptidase and N-acetyl glucosaminidase activity were assayed at saturated substrate
101 concentration (300 μ M). Briefly, we homogenized 1.5 g soil in 20 ml of deionized water. The
102 resultant slurry was used to perform enzyme activity assays using methylumbelliferyl (MUF)
103 and 7-amino-4-methylcoumarin (AMC) conjugated substrates. The reaction was performed
104 for 3 hours at 28°C, with one fluorometric measure every 30 minutes (BioSpa 8 Automated
105 Incubator). Fluorescence intensity was measured using a Cytation 5 spectrophotometer linked
106 to the automated incubator. Biomass specific enzyme activities were calculated using DNA-C
107 measures as biomass proxy. Visualisations and regression analyses were performed with R
108 software 2.14.0 (R Development Core Team 2013) using ggplot2 and lme4 packages,
109 respectively (Bates et al. 2015).

110

111 We linked biomass specific potential activities of a set of extracellular enzymes to
112 community metabolism in order to assess microbial resource demand and its impact on
113 microbial growth yield. We observed a negative linear-log relationship between community
114 CUE and C acquisition activity ($R^2=0.22$, $p<0.001$, figure 1b). BG catalyses a terminal
115 reaction in the hydrolysis of glucose from cellobiose (Sinsabaugh et al. 2010) and AE is
116 involved in non-specific deacetylation including that of xylans (Zhang et al. 2011). Both
117 cellulose and hemicellulose, targets of the two enzymes, do not contain N and hence can be
118 used as a proxy for C acquisition. Whereas, LAP catalyses the hydrolysis of proteins and
119 NAG is involved in the hydrolysis of chitin and peptidoglycan, these target compounds are
120 principle sources of N for microorganisms. LAP and NAG have thus been widely used as a
121 proxy for N acquisition (Burns and Dick 2002, Sinsabaugh et al. 2010). A similar negative

122 linear-log relationship was observed between community CUE and N acquiring enzyme
123 activity ($R^2=0.04$, $p=0.028$, figure 1c), and although statistically significant this relationship
124 was weaker relative to that between CUE and C acquiring enzyme activity. These
125 relationships were assessed using linear mixed models to account for within site variation
126 (three replicates per site) across the geographically distributed soils, while assuming
127 community CUE to be a dependent variable for statistical purposes. 30-40% of the variation
128 in CUE was explained by site which was added as a random factor in the mixed effect model
129 (Table 1). The distribution of these traits across the landscape was also related to the soil
130 organic carbon (SOC) concentration gradient (overlaid in figure 1a-d). We have previously
131 observed, in the same set of soils, that decreasing community CUE and biomass is related to
132 decreasing SOC concentration ($R^2=0.34$, $p<0.0001$; Malik et al. 2018b). Here we show that
133 decreasing SOC was also linked to increasing biomass specific C enzyme activity ($R^2=0.3$,
134 $p<0.0001$), and to a very small extent to increasing N enzyme activity ($R^2=0.06$, $p=0.02$). C
135 enzyme activity and to a smaller degree N enzyme activity was positively correlated to
136 biomass specific respiration and community aggregated growth rate (table S1). These
137 patterns suggest that in soils with lower SOC (usually intensive grasslands and arable
138 croplands), resource limitation drives microbial communities to invest heavily into resource
139 acquisition traits that trades off against growth yield. On the other hand, communities grow
140 efficiently in more resource-rich soils with higher SOM and more readily available precursor
141 molecules (usually “pristine” or less intensive grasslands) as they possess substrate uptake
142 mechanisms like ABC transporters and have lower biomass specific activity of extracellular
143 enzymes (Malik et al. 2018b, Zhalnina et al. 2018). Lower maintenance requirement of these
144 communities is corroborated by observations of lower biomass specific respiration in such
145 soils. It is also interesting to note that certain communities exhibited lower enzyme activity
146 per unit biomass and lower growth yield thus weakening the regression trends (Figure 1b-c).

147 Moreover, although the enzymatic C:N ratio increases with decreasing CUE as we
148 hypothesised ($R^2=0.17$, $p<0.001$, figure 1d, table 1), there was little evidence to suggest
149 stoichiometric constraints on microbial growth and metabolism. The stronger association of
150 C- relative to N-acquiring enzyme activity with CUE suggests that community-level
151 energetic constraints are greater than stoichiometric constraints (Sinsabaugh et al. 2010,
152 Mooshammer et al. 2014). Still, this result could also reflect the resource and nutrient status
153 of the temperate soils under investigation, which appeared to be C- and not N-limited. We
154 also observed that enzymatic C:N ratio and soil C:N ratio did not covary (Figure S2)
155 indicating that soil C:N ratio is not a good indicator of available resources (Mooshammer et
156 al. 2014).

157

158 Based on empirical relationships, we provide evidence for a clear tradeoff between
159 community-level growth yield and resource acquisition potential in near neutral pH soils.
160 Although the statistical power of these relationships is not strong (given the geographically
161 distributed nature of this survey and the high amount of variation explained by site), the
162 patterns in trait distribution demonstrate distinct life history strategies. The observed
163 tradeoffs are in line with those assumed or predicted by theoretical models (Allison 2014,
164 Manzoni et al. 2014). On the basis of the trade-off patterns observed in this study, we applied
165 a three-way microbial trait framework similar to Grime's competitor-stress tolerator-ruderal
166 (C-S-R) framework for plants (Grime 1977). Growth yield suffered in communities investing
167 in maintenance requirements like resource acquisition through regeneration of extracellular
168 enzymes (Figure 2, lower right). This tradeoff is reiterated by the absence of scenarios of
169 communities excelling in both traits (Figure 2, upper right). However, a large amount of
170 variation in community growth yield was explained by site thus it is plausible that either or
171 both of these traits trade-off with some other unmeasured trait linked to the soil environment,

172 likely stress tolerance (Schimel et al. 2007, Malik et al. 2018b, Wood et al. 2018). In support
173 of this interpretation, we previously found lower growth yield in acidic soils (Figure 1a;
174 Malik et al. 2018b) highlighting much higher maintenance costs of acid stress tolerance in
175 such soils. Thus, we demonstrate strong support for the growth-maintenance tradeoff
176 hypothesis and show trait tradeoffs have consequences for soil carbon dynamics. In line with
177 the empirical trends, we propose a microbial Y-A-S (high yield-resource acquisition-stress
178 tolerance) life history framework (Malik et al. 2018a), which suggests that tradeoffs in
179 resource allocation among traits linked to high yield, resource acquisition and stress tolerance
180 prevent microbes from excelling at multiple strategies such that different strategies are
181 favoured under different environmental conditions. However, more work is required in
182 estimating trait values for stress tolerance strategies and how they trade off with microbial
183 growth yield. We also show, in the temperate soils under study, that stoichiometric
184 imbalances have smaller impacts on microbial community growth yield in comparison to
185 energetic requirements. This finding suggests that C flow in cellular systems is a fundamental
186 constraint on microbial growth efficiency that affects the fate of plant and soil organic
187 carbon.

188

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195

196 **Author contributions**

197 AAM, JP and RIG designed research; AAM and TG performed the stable isotope analyses;
198 JP and TG performed the enzyme assays; AAM and JP performed statistical analyses; AAM
199 and SDA developed the conceptual framework, AAM drafted the manuscript and all authors
200 were involved in critical revision and approval of the final version.

201

202 **Figure legends**

203 **Figure 1: a)** Regression trends of microbial CUE with soil pH across the landscape scale
204 gradient of soils. Data from all 56 sites with three replicates at each site are presented here.
205 The threshold was determined at pH 6.2 below which microbial CUE was very low, hence
206 excluded from this study. **b-c)** Regression trends of community-aggregated growth yield or
207 carbon use efficiency-CUE (unitless) with biomass specific C and N acquiring enzyme
208 activity expressed as $\text{nmol min}^{-1} \mu\text{g-DNA-C}^{-1}$ (DNA as a biomass proxy) from 38 sites with
209 $\text{pH} > 6.2$. **d)** Relationship between growth yield and enzymatic C:N ratio. Overlaid in the
210 scatterplots is the variation in soil C concentration. The x-axes in b-d are on a \log_2 scale as a
211 means to transform a skewed variable into a more approximate normal distribution.

212 **Figure 2:** Conceptual framework assigning dominant life history strategies to microbial
213 communities superimposed on the observed trait distribution patterns.

214

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287

Table 1: Results of linear mixed effect models used to assess community CUE-enzyme activity relationship by analyzing the predictive power of enzyme measures to explain the variance in community CUE. Enzyme variables were used as fixed factors and site was used as a random factor in the mixed model. ICC (intraclass correlation coefficient) accounts for the variance explained by site. Marginal R^2 describes the proportion of variance explained by the fixed factor alone, whereas, conditional R^2 describes the proportion of variance explained by both the fixed and random factors. Number of observations: 114, number of sites: 38.

Predictor variable	C enzyme	N enzyme	Enzyme C:N
Intercept	0.14	0.11	0.15
Confidence interval	0.11 - 0.17	0.08 - 0.14	0.12 - 0.18
p	<0.001	0.028	<0.001
ICC _{site}	0.30	0.40	0.34
Marginal R^2	0.22	0.04	0.17
Conditional R^2	0.45	0.43	0.45

Figure 1

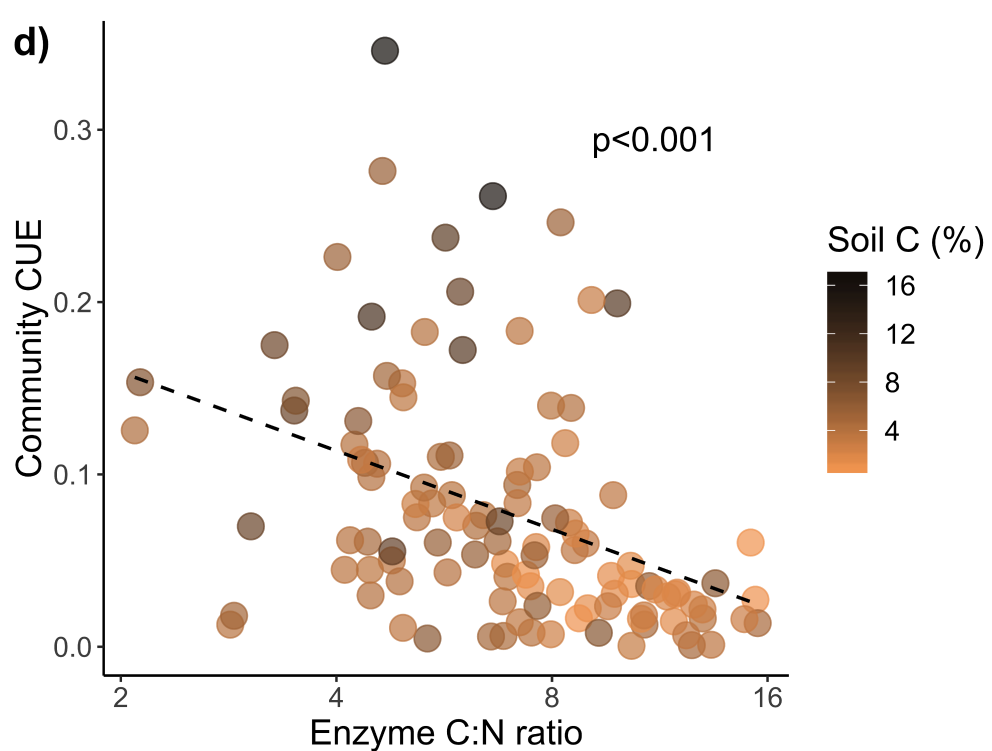
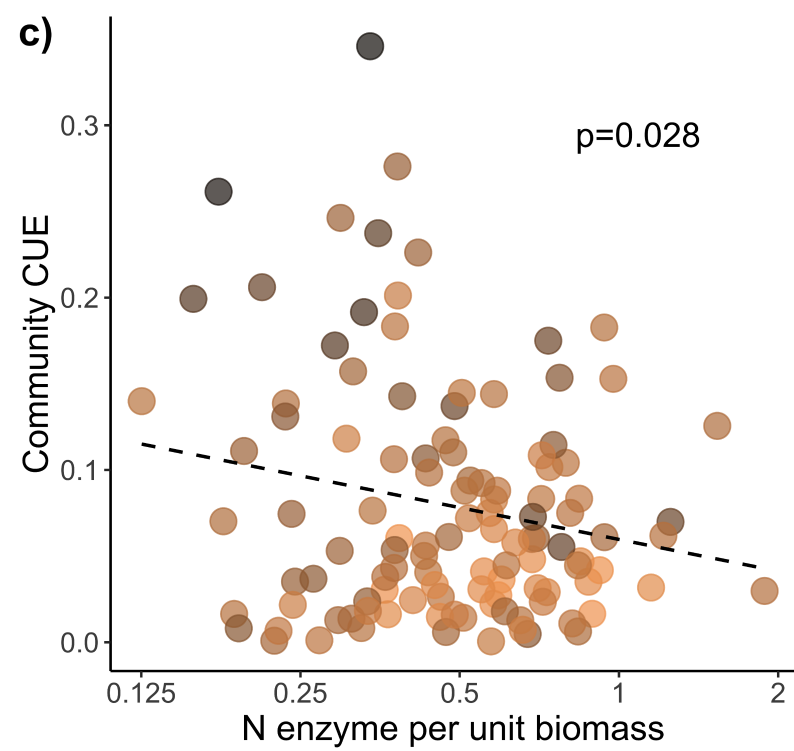
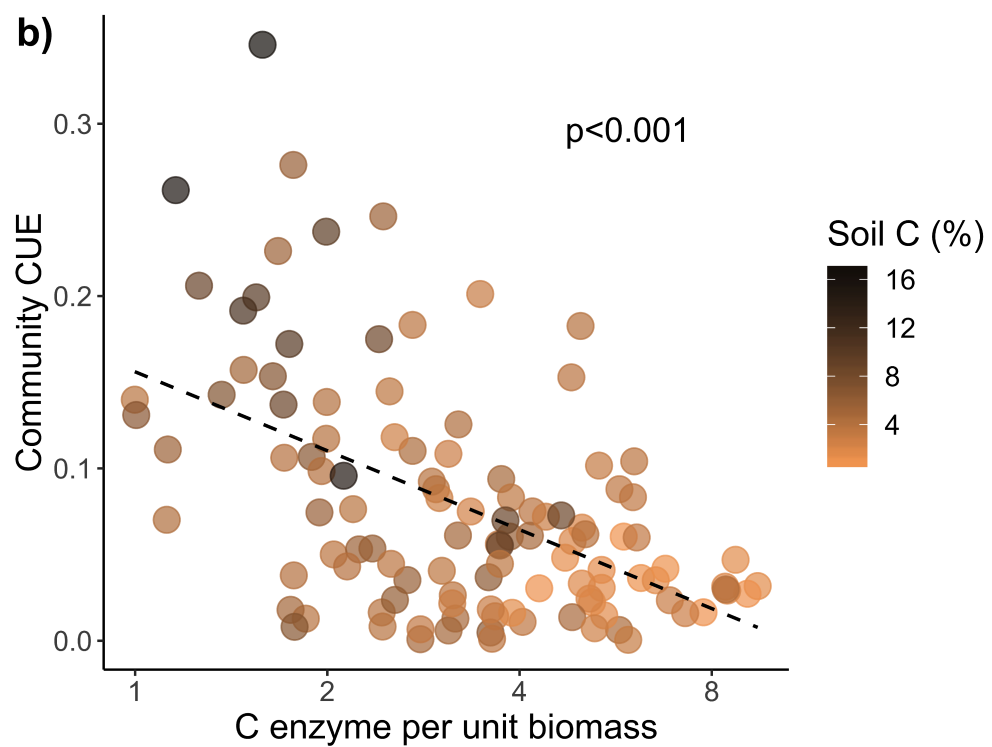
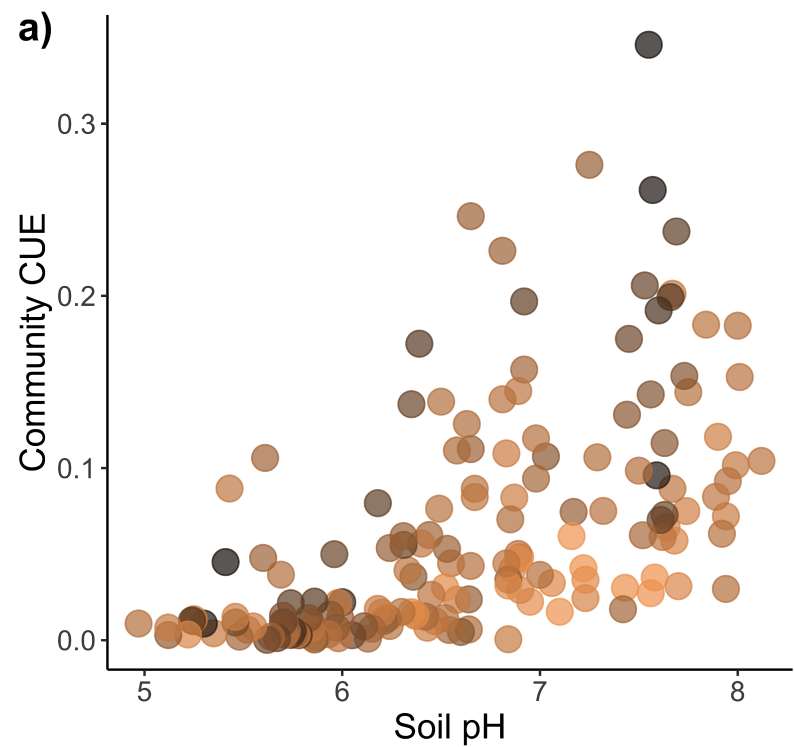


Figure 2

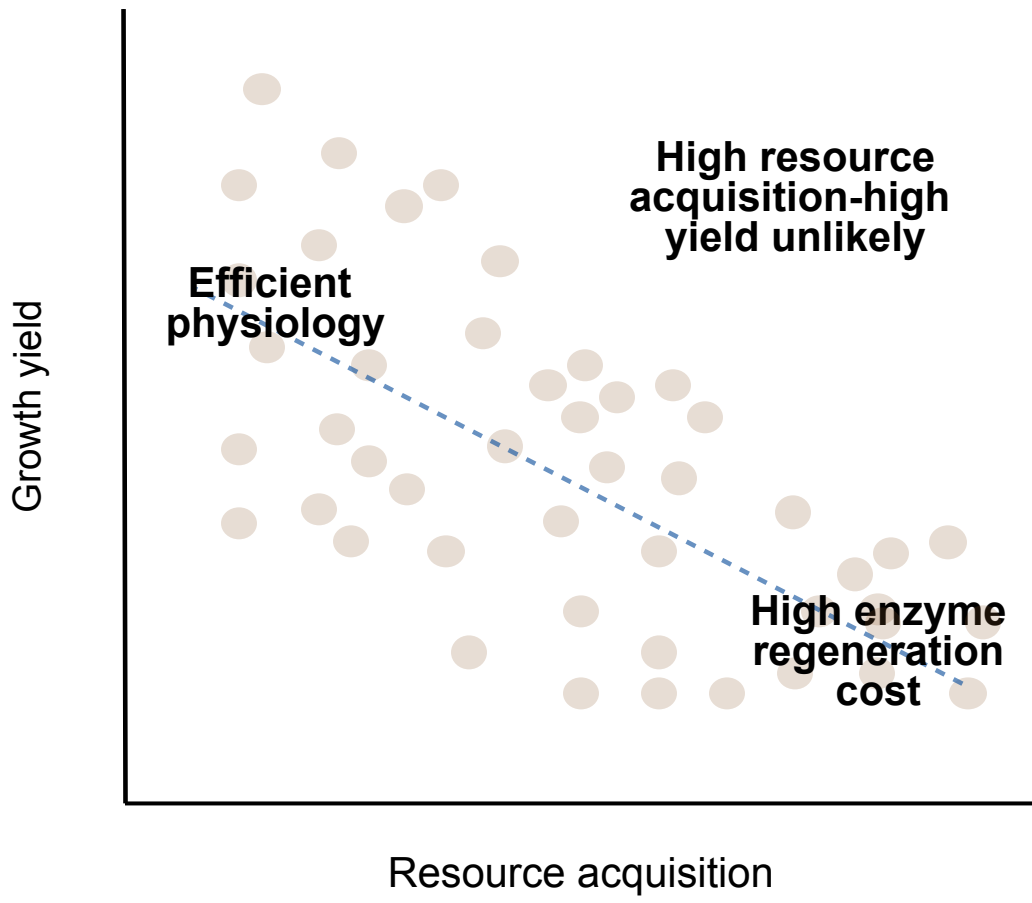


Figure 2