

Time will tell: the temporal and demographic contexts of plant–soil microbe interactions

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1 **Abstract**

2 Soil microorganisms can have profound impacts on plant community dynamics and have received
3 increasing attention in the context of plant–soil feedback. The effects of soil microbes on plant
4 community dynamics are classically evaluated with a two-phase experimental design that consists
5 of a conditioning phase, during which plants modify the soil microbial community, and a response
6 phase, during which the biomass performance of plants is measured as their response to the soil
7 modification. Predicting plant community-level outcomes based on these greenhouse experimen-
8 tal results implicitly assumes that plant–soil microbe interactions remain constant through time.
9 However, a growing body of research points to a complex temporal trajectory of plant–soil microbe
10 interactions, with microbial effects varying with the conditioning duration, plant development,
11 and time since conditioning. Most previous studies also implicitly assume that measuring plant
12 biomass performance alone adequately captures the most critical impacts soil microbes have on
13 plant population dynamics, neglecting that soil microbes also govern other key demographic
14 processes over the plant life cycle. Here, we discuss the relevance of these temporal and demo-
15 graphic dimensions of plant–soil microbe interactions when extrapolating experimental results
16 and propose modeling frameworks that can incorporate the new empirical evidence. By integrat-
17 ing empirical and theoretical approaches, we provide a roadmap for more nuanced predictions of
18 the long-term consequences of plant–soil microbe interactions in nature.

19 **Keywords**

20 conspecific negative density dependence, demographic models, Janzen–Connell hypothesis, mi-
21 crobial community, patch occupancy model, plant–soil feedback

22 I. Introduction

23 Plants interact with a diverse array of soil microbes, including mutualists, decomposers, and
24 pathogens. These interactions can be bidirectional, with plants altering the composition of the soil
25 microbial community, and the resulting changes in microbial community impacting subsequent
26 plant performance in the conditioned soil (Bever, 1994, Bever et al., 1997, Bever, 2003). The study
27 of plant–soil microbe interactions has its origin in agricultural science (Huang et al., 2013, van der
28 Putten et al., 2013) and has been integrated into community ecology under the framework of
29 plant–soil feedback (PSF). Since its introduction by Bever et al. (1997), studies have extensively
30 discussed how plant–soil microbe interactions influence plant coexistence (Bever et al., 2010, Ke
31 and Miki, 2015, Bever et al., 2015, Kandlikar, 2024). The PSF framework has also been used to
32 explore how soil microbes affect patterns in the relative abundance of plant communities (Mangan
33 et al., 2010, Reinhart et al., 2021), restoration success (Wubs et al., 2016, Koziol et al., 2018), plant
34 invasion (Callaway et al., 2004, Suding et al., 2013), and the biodiversity–productivity relationship
35 (Kulmatiski et al., 2012, Forero et al., 2021).

36 To characterize the direction and strength of plant–soil microbe interactions, most studies
37 follow a two-phase experimental design aimed at capturing the two-way interactions between
38 plants and soil microbes (Bever et al., 1997). The classic greenhouse experiment consists of a
39 “conditioning” phase during which plants modify the soil microbial community, directly followed
40 by a “response” phase during which plants of the same or other species respond to the conditioned
41 soil community (Bever et al., 2010, Brinkman et al., 2010). This distinct two-phase design elegantly
42 captures the necessary information for parameterizing the key terms in the classic plant–soil
43 feedback model (Bever et al., 1997, 2012) and has enabled a strong empirical foundation of PSF
44 research across ecosystems (Crawford et al., 2019, Yan et al., 2022). However, this approach implies
45 a number of assumptions about the nature of plant–soil microbe interactions that do not align
46 with our contemporary understanding of their dynamics. In particular, a growing number of
47 studies have highlighted the importance of accounting for different temporal and demographic
48 dimensions of plant–soil microbe interactions (Kardol et al., 2013, Gundale and Kardol, 2021,
49 Chung, 2023). Such evidence should reshape both the design of experiments (e.g., how long
50 should the conditioning phase last?) and the interpretation of their results (e.g., how do microbial

51 effects on early-life stage plant performance translate to population-level consequences?). In this
52 paper, we focus on two key assumptions: first, the temporal assumption that microbial effects
53 develop quickly during the conditioning phase and maintain constant strength over time; and
54 second, the demographic assumption that plant biomass performance during the response phase
55 reflects microbial impact on plant population growth.

56 The conditioning and response phases in two-phase experiments are typically conducted
57 over short time frames (e.g., a few months), with the same time frame applied across all species
58 despite potential life history and growth trajectory differences between the focal species. Field-
59 based studies may also source conditioned soil microbial communities by collecting soil from
60 individuals growing in the field, but the age of the conditioning plant is generally unknown. Both
61 approaches implicitly assume that microbial effects develop relatively quickly and, perhaps more
62 importantly, that these effects maintain constant strength throughout different plant developmental
63 stages (Fig. 1a). This assumption is at odds with growing evidence that within a single plant
64 generation, microbial communities undergo a continuous turnover (e.g., Edwards et al., 2018,
65 Gao et al., 2019), and that their resulting effects on plant performance can vary based on the
66 duration of plant conditioning and response phases (e.g., Hawkes et al., 2013, Bezemer et al., 2018,
67 Lepinay et al., 2018; Fig. 1b). Moreover, it is often assumed that greenhouse-measured microbial
68 effects manifest both spatially (i.e., affecting concurrently growing plants) and temporally (i.e.,
69 carrying over through time with little change in its impact; Ke and Levine, 2021). However,
70 predictions made based on studies that conduct the response phase immediately following the
71 conditioning phase neglect the potential consequences of time lags that occur in nature (Ou
72 et al., 2024). Therefore, while experiments are understandably constrained by feasibility, explicit
73 examination of the system's temporal context is critical to better predict how soil microbes shape
74 natural plant communities.

75 The short-term nature of most experiments also constrains researchers to focus on a sin-
76 gle plant demographic response that presumably reflects the most critical impact of the mi-
77 crobial community (Ke and Wan, 2023). The most frequently measured performance proxy is
78 plant biomass, which is then used to calculate theoretically derived metrics to infer how soil
79 microbes influence plant coexistence. For instance, the biomass of plants in conspecific- and

80 heterospecific-conditioned soils can be used to calculate the pairwise feedback metric that quanti-
81 fies the frequency-dependent feedback loops generated by plant–soil microbe interactions (Bever
82 et al., 1997). Negative frequency-dependence arises when both plants condition their soil microbes
83 in a way that favors heterospecifics over conspecifics, thereby promoting plant coexistence (Craw-
84 ford et al., 2019). In the context of the classic PSF model, where soil microbes drive plant community
85 dynamics by changing plants’ intrinsic growth rates (Bever et al., 1997), these metrics operate under
86 the assumption that plant biomass performance is a proxy for plant population growth. However,
87 soil microbes can also affect other demographic processes across the plant life cycle that are not
88 captured simply by measuring plant biomass (e.g., changing seed and seedling survival rates or the
89 nature of density-dependence among plants), potentially with opposing effects at different plant
90 ontogenetic stages that lead to different coexistence predictions (Dudenhöffer et al., 2018, Dostálek
91 et al., 2022). Integrating these different impacts, instead of making predictions based on microbial
92 effects on any one life stage, is another challenge when predicting the long-term demographic
93 consequences of soil microbes.

94 Here, we discuss the two critical assumptions regarding temporal and demographic aspects
95 of plant–soil microbe interactions in nature. We aim to highlight the relevance of these assumptions
96 when extrapolating greenhouse results, and outline future empirical and theoretical avenues to
97 incorporate them. In particular, we advocate for a shift from using biomass-based performance
98 indices to parameterizing patch occupancy models and plant demographic models with microbial
99 effects. While these biologically important complications make experiments more logistically
100 challenging, we argue that integrating the temporal and demographic details can better predict
101 the outcome of plant–soil microbe interactions in their natural context.

102 **II. Significant consequences of overlooking the temporal and demo-** 103 **graphic aspects of plant–soil microbe interactions**

104 To motivate our thesis that explicitly evaluating the variation in microbial effects across time and
105 across different life stages is important for predicting their consequences in nature, we first present
106 a simple plant demographic model that illustrates the potential consequences of ignoring these

107 temporal dynamics. Specifically, we consider two annual plant species, N_1 and N_2 , with dynamics
 108 described by the Beverton–Holt annual plant model:

$$N_{i,t+1} = \overbrace{s_i (1 - g_i) N_{i,t}}^{\text{Survival of ungerminated seeds}} + \frac{\overbrace{\lambda_i g_i N_{i,t}}^{\text{Intrinsic fecundity of germinated seeds}}}{\underbrace{1 + \alpha_{ii} g_i N_{i,t} + \alpha_{ij} g_j N_{j,t}}_{\text{Effect of neighbors}}},$$

109 with subscripts i and j indicating species 1 or 2. The first term represents the survival of ungermi-
 110 nated seeds, with g_i and s_i representing seed germination and survival rate, respectively (circular
 111 loop in Fig. 2A). The second term represents seed production and density-dependent interactions
 112 among germinated seeds, with λ_i , α_{ii} and α_{ij} representing intrinsic plant fecundity, intraspecific
 113 and interspecific competitive impact experienced by N_i , respectively (rightward arrows in Fig. 2A).
 114 As opposed to biomass-based metrics, this demographic model provides the opportunity to study
 115 microbial effects on five different demographic parameters (i.e., g_i , s_i , λ_i , α_{ii} , and α_{ij}). For short-
 116 term greenhouse studies comparing these demographic processes in conditioned versus sterilized
 117 soil, this model offers a way to predict the long-term effect of soil microbes on plant competitive
 118 outcomes.

118 As a case study, consider a scenario in which pathogenic microbes operate by harming one of
 119 these demographic processes for a given species. If a short-term greenhouse study were to suggest
 120 that the primary effects of the soil pathogen is to reduce species 1’s seed survival (s_1) by 10% while
 121 leaving s_2 unaffected, the model would predict negligible impacts of the soil microbes on long-
 122 term plant community dynamics. This is illustrated in the left panel of Fig. 2B, as the grey lines
 123 (indicating species abundance under no pathogenic impact) and blue lines (indicating a pathogenic
 124 impact on species 1’s seed survival) almost overlap completely. If instead the greenhouse study
 125 were to find that the pathogen decreases plant 1’s intrinsic fecundity (λ_1) by 10%, the model
 126 predicts substantially lower population sizes for species 1 in the long-term ($\approx 18\%$ reduction in
 127 equilibrium abundance). This exercise highlights the importance of understanding where in the
 128 plant demographic cycle microbial effects arise, an aspect of plant–soil microbe interactions that
 129 is often overlooked when assuming a single performance measurement can predict demographic
 130 outcomes.

131 Further suppose that the pathogenic effects measured in the short-term greenhouse aggravate
132 over time in the field, for example due to the gradual accumulation of soil pathogens across multiple
133 generations (Diez et al., 2010, Day et al., 2015). The right panel of Fig. 2B depicts the competitive
134 outcomes caused by different microbial effects assuming that the 10% decrease in s_1 and λ_1 after one
135 generation intensified to an 80% decrease by the end of eight generations (i.e., 10% decrease after
136 every generation). While the temporally-intensifying pathogenic effect on s_1 (blue lines) remained
137 relatively insignificant, the pathogenic effect on λ_1 (orange lines) became so strong that it resulted
138 in the exclusion of N_1 . This simulation exercise demonstrates the consequence of neglecting the
139 temporal dynamics of plant–soil microbe interactions, a realistic concern in nature that is often
140 replaced by the simplifying assumption of a constant microbial effect in greenhouse experiments.

141

142 **III. Dissecting different temporal dimensions of microbial effects**

143 Studies on the temporal patterns of plant–soil microbe interactions have classically focused on its
144 variation along plant succession, which typically involves plants with different traits or shifts in
145 the external environment (Kardol et al., 2006, 2013, Bauer et al., 2015). However, temporal variation
146 in plant–microbe interactions also occurs across shorter time scales because the conditioned soil
147 microbial community and plant response both vary over time (Fig. 1B). Recognizing that plant–
148 soil microbe interactions are not constant through time directly influences the experimental design
149 and how we interpret experimental results. Moreover, this temporal variability may be a key
150 mechanism behind the effects of phenological mismatch between plants and soil microbes (Peay,
151 2018, Rudgers et al., 2020). In this section, we review evidence of temporal variability and discuss
152 mechanisms by which the impact of microbial communities on plant biomass performance varies
153 with the duration of the conditioning and response phases (subsection III.1), as well as the time lag
154 between consecutive generations (subsection III.2). We then discuss how to design experiments
155 that tackle the temporal complexities observed in nature (subsection III.3). Note that for this section
156 we focus on studies that measure plant biomass as the key performance proxy; we will discuss
157 other demographic responses in section IV.

158 III.1 Temporal development during the conditioning and response phases

159 As the strength and direction of plant–soil microbe interactions depend on the timing of interac-
160 tions, the duration of the conditioning and response phases influences the greenhouse-measured
161 interaction strength. By compiling information on the experimental duration of studies included
162 in two prominent meta-analyses (Crawford et al., 2019, Yan et al., 2022), we showed that the length
163 of conditioning and response phases are short in most studies (Fig. 3). The median conditioning
164 length is 3.5 months ($n = 59$ studies, after excluding 47 studies with field-collected soils) while that
165 of the response phase is 3 months ($n = 106$ studies). Extrapolating from these experiments to predict
166 the long-term consequences of soil microbes is based on the assumption that the relative impact of
167 conspecific- and heterospecific-conditioned soils remains constant throughout plant development.
168 The significance of overlooking the temporal development of plant–soil microbe interactions is
169 exemplified when one considers plants with different life histories. For example, 20% of studies
170 (21 out of 106) in Fig. 3 evaluated microbially mediated stabilization between plant species pairs
171 comprised of one annual and one perennial species while implementing the same (usually short)
172 experimental duration. This overlooks the potential for short- and long-lived plants to condition
173 microbial communities at different rates, such that the same duration of soil conditioning may
174 correspond to different developmental stages and microbial effects (Kulmatiski et al., 2017): the
175 species-specific microbiome of a short-lived annual plant may be fully conditioned by the end of
176 an experiment, whereas that of a long-lived perennial may require a longer conditioning time.
177 Similarly, a short response phase may capture the full physiological response of an annual plant,
178 while that of a perennial may vary with its ontogeny. This mismatch in temporal development
179 patterns highlights the challenge of interpreting experimental results in the context of the focal
180 system’s natural history.

181 Compared to the classic two-phase design with a single fixed duration of soil conditioning
182 (Fig. 4A), a few studies have grown plants in soils that were conditioned for different duration
183 (red vertical arrow (i) in Fig. 4B). Studies have shown that the relative impact of conspecific- and
184 heterospecific-conditioned soil on the responding individual can vary with the duration of soil
185 conditioning. For example, Lepinay et al. (2018) found that after a brief conditioning period of
186 two weeks, heterospecific soil had a more negative impact on *Rorippa austriaca* performance than

187 its conspecific soil. However, a longer duration of soil conditioning resulted in the opposite re-
188 lationship: conspecific soil had an increasingly stronger negative impact peaking at six weeks
189 of conditioning, whereas the negative effect of heterospecific soils diminished after four to eight
190 weeks of conditioning. In a more natural setting, Ke et al. (2021) studied how the microbial impact
191 varied with soil conditioning length by transplanting seedlings into field-conditioned soil collected
192 under plant individuals of different ages. They found that the soil microbial community under-
193 went continuous successional dynamics over the span of 20 years and three out of four species
194 experienced negative microbial effects that intensified with longer conditioning time. Importantly,
195 these results have crucial implications on the design of two-phase experiments: arresting soil
196 conditioning at different time points causes the responding plant to encounter microbial commu-
197 nities with different compositions and functions, thereby giving rise to different plant–soil microbe
198 interactions.

199 Previous experimental studies on the temporal dynamics of plant–soil microbe interactions
200 have largely focused on the development of microbial effects across the lifespan of the responding
201 individual, which is typically achieved by harvesting responding plants at various time intervals
202 (Kardol et al., 2013, Gundale and Kardol, 2021; red diagonal arrow (ii) in Fig. 4B). For example,
203 by sequentially harvesting seedlings at four time points spanning 19 months, Hawkes et al. (2013)
204 showed that the microbial effect experienced by native plants became more negative through time,
205 whereas the development patterns for invasive plants were more variable. Recent studies have
206 also highlighted that other factors can modify the temporal pattern of microbial effects during
207 the response phase (Dostál, 2021, Bezemer et al., 2018). For instance, harvesting twice every week
208 for 11 weeks, Bezemer et al. (2018) showed that the negative effect of conspecific-conditioned soil
209 experienced by *Jacobaea vulgaris* attenuated as plants became older; however, when grown together
210 with a heterospecific competitor, the negative effect instead aggravated over time (but see Dostál,
211 2021 for a nonlinear pattern for three harvests spanning 13 months). Together, this empirical
212 evidence provides a strong impetus to consider temporal variability in the response phase since
213 harvesting an experiment at different endpoints can alter our understanding of the microbial
214 effect.

215 The temporal development of plant–soil microbe interaction likely occurs due to shifts in the

216 composition and/or functionality of microbial communities as plants mature or enter different de-
217 velopmental stages (Chaparro et al., 2013, Dombrowski et al., 2016, Edwards et al., 2018, Hannula
218 et al., 2019). Mechanisms underlying these shifts in soil microbial communities include physio-
219 logical changes in nutrient allocation or root exudation across plant ontogenetic stages (Chaparro
220 et al., 2013, Zhalnina et al., 2018), as well as an increase in immunity and antibiotic defense against
221 pathogens as plants mature (Bulgarelli et al., 2013, Chaparro et al., 2013). Furthermore, alterations
222 prompted by plants can lead to shifts in microbe–microbe interactions and the processes governing
223 microbial community assembly (Barret et al., 2015, Herrera Paredes and Lebeis, 2016, Bittleston
224 et al., 2021), all of which may trigger further responses in plant physiology via a complex interplay
225 between mechanisms. Importantly, as conditioning and response processes operate simultane-
226 ously in nature, the same set of mechanisms apply to explain temporal patterns in both phases.
227 For example, strengthening of immunity as plants mature can reduce pathogen abundance as
228 the conditioning phase progresses (Bulgarelli et al., 2013); it can also reduce plant susceptibility
229 to pathogens and alleviate negative microbial effects experienced by the plant as the responding
230 individual matures. Similarly, mechanisms that reduce the abundance of beneficial microbes after
231 soil conditioning (e.g., mature plants becoming less reliant on mutualistic partners) also act upon
232 the responding individual to diminish the observed positive microbial effect. We will elaborate
233 on necessary experiments to tease apart different temporal dimensions and mechanisms in the
234 subsection III.3.

235 **III.2 Alterations of microbial effects after plant death**

236 One common implicit assumption in plant–soil feedback studies is that greenhouse-measured
237 microbial effects manifest similarly on plants neighboring the focal individuals as on individuals
238 that arrive and grow in the conditioned soil after the focal plant. However, whether microbial
239 effects carry over through time and how long they persist remains an understudied temporal aspect
240 of plant–soil microbe interactions. This question is especially important for systems with discrete
241 growing seasons or dispersal limitation, where a temporal lag exists between the senescence of
242 one plant (the conditioning individual) and the growth of another (responding) individual. This
243 introduces a lag phase during which the conditioned soil is left unoccupied for an extended period

244 of time; processes such as litter decomposition, abiotic filtering, and stochastic drift may restructure
245 the microbial community during such lags. Studies growing seedlings in soils collected from dead
246 individuals (red vertical arrow (iii) in Fig. 4B) suggest that such lags can have distinct effects across
247 different systems. For example, Esch and Kobe (2021) showed that the negative effects of soil from
248 live *Prunus serotina* on the survival of conspecific seedlings faded away within one year after tree
249 removal. Conversely, Bennett et al. (2023) showed that microbial communities from soils collected
250 under dead and live adult *Populus tremuloides* trees had similar effects on conspecific seedlings. As
251 an alternative to collecting soil from naturally occurring dead individuals, Ou et al. (2024) modified
252 the two-phase experiment to include a six-month delay between the conditioning and response
253 phase; their results suggest that the seasonal lag in Mediterranean annual plant systems changes
254 the microbial community and their corresponding impact on plant coexistence. Below, we discuss
255 the mechanisms that could either maintain or alter microbial effects when a temporal lag exists
256 between consecutive generations.

257 Microbial effects could persist after active plant conditioning ceases due to the continued
258 survival and functioning of the conditioned microbial community in the soil (Lennon and Jones,
259 2011, Pepe et al., 2018, Esch et al., 2021, Hannula et al., 2021). For example, Esch et al. (2021)
260 found that the persisting pathogenic oomycetes collected from live versus dead tree stumps have
261 similar negative effects on conspecific seedling survival. Similarly, Pepe et al. (2018) showed that
262 arbuscular mycorrhizal fungi remain active and can spread from roots after host shoot removal.
263 The maintenance of microbial activity can occur if root systems remain active after the removal
264 of aboveground tissues or if the release of nutrients from dead belowground tissues mirrors
265 exudates from living plants (Johansen and Jensen, 1996, Müller et al., 2013). Additionally, trophic
266 flexibility (e.g., saprotrophic ability of certain pathogens; Bonanomi et al., 2010) and dormancy
267 of soil microbes can allow the microbial communities to persist after the death of their host,
268 enabling microbes to wait for the arrival of a new host (Lennon and Jones, 2011, Shade et al.,
269 2012, Shemesh et al., 2023). In these cases, the succeeding (response) individual will experience a
270 similar microbial effect despite the temporal lag in arrival timing, and predictions from immediate
271 transplant experiments are relevant to natural systems.

272 However, various processes can cause the microbial community to change after plants stop

273 actively conditioning the soil, such that subsequent responding individuals encounter a different
274 soil microbial community than that obtained in an immediate transplant scenario (Grove et al., 2015,
275 Veen et al., 2019, Ou et al., 2024). The process of litter decomposition can introduce phyllosphere
276 microbes to the soil (Fanin et al., 2021, Minás et al., 2021) and release chemicals and nutrients
277 that shift microbial communities (Veen et al., 2021). Additionally, different causes of plant death
278 (e.g., herbivory, fire, and disease) are often associated with further changes in abiotic factors,
279 with potential effects on the composition and function of microbial communities. For example,
280 canopy gaps caused by wind disturbances modify nearby light and moisture levels in a way that
281 suppresses pathogens (Augsburger, 1984, Reinhart et al., 2010, Nagendra and Peterson, 2016).
282 Finally, stochastic drift could decouple microbial community from plant conditioning influence if
283 the soil remains uncolonized over an extended period of time due to plant propagule limitation. In
284 these scenarios, immediate transplant experiments fail to capture the microbial effects experienced
285 by the responding plant in nature.

286 **III.3 Implications for experimental design**

287 While an increasing number of studies have recognized the temporal dimensions of plant–soil
288 microbe interactions, synthesizing the factors contributing to this variability, e.g., the life history of
289 plants and functional groups of microbes involved, requires more targeted studies. Here, we rec-
290 ommend a path forward for understanding these context dependencies. First, the temporal settings
291 of the experiment should guide our interpretation of the results. For instance, in Mediterranean
292 plant communities where the growing season only lasts a few months, traditional experiments in
293 which a short-term conditioning phase is immediately followed by the response phase may ade-
294 quately reflect potential microbial effects on concurrently growing neighbors that unfold within
295 one growing season. However, such a design may not be adequate to project microbial effects on
296 population dynamics across years because it overlooks the temporal lag associated with the clear
297 seasonality of plant growth in nature (Ou et al., 2024). Second, we encourage modification of the
298 classic two-phase design (Fig. 4A) to reflect the temporal aspects of a focal plant–soil system in
299 nature. For Mediterranean annual plant communities, mirroring the temporal dynamics of the
300 natural system by incorporating a decay phase during which the conditioned soils are exposed

301 to a prolonged drought with no vegetative growth (red vertical arrow (iii) in Fig. 4B) may pro-
302 vide a better understanding of how soil microbes shape plant community dynamics across years
303 (Ou et al., 2024). Moreover, researchers can build on long-term monitoring plots and historical
304 information to account for variation in conditioning duration, host plant age, or time since host
305 tree death. This approach may be especially applicable in studies that focus on long-lived plants,
306 which often source field-conditioned soils for greenhouse experiments (44%; 47 out of 106 studies
307 in Fig. 3). For example, Ke et al. (2021) estimated plant age with historical aerial photos and
308 employed a chronosequence approach to study the influence of soil conditioning length. Other
309 examples include using host tree size as a proxy of conditioning time (Chen et al., 2019) and uti-
310 lizing chronosequences of abandoned fields or agricultural harvest times to study the persistence
311 of microbial effects (van de Voorde et al., 2012, Esch and Kobe, 2021).

312 One can also design experiments that isolate a particular facet of temporal variability to help
313 disentangle the mechanisms behind observed temporal patterns. Current studies on the temporal
314 development of microbial effects typically employ sequential harvesting, where the observed
315 temporal changes result from the combination of varying plant physiological responses and any
316 changes to the soil community that are due to the effects of the responding plant itself (red diagonal
317 arrow (ii) in Fig. 4B). To isolate the effects associated with changing soil microbial communities
318 during soil conditioning, studies could plant seedlings of the same age in soils with different
319 conditioning duration (red vertical arrow (i) in Fig. 4B). Alternatively, if the goal is to isolate the
320 effects caused by changing plant physiology, an experiment could instead grow plants of different
321 ages/sizes (kept in a relatively sterilized environment such as a Magenta box before transplanting)
322 in soils with identical conditioning duration (red horizontal arrow (iv) in Fig. 4B). A recent study
323 by Liu et al. (2024) utilized such experimental design to illustrate the importance of conditioning
324 and response duration as well as the underlying mechanisms. In addition, mutants or cultivars
325 with different developmental rates can also be used to separate the effects of plant developmental
326 stage (e.g., vegetative growth or flowering) and age *per se* (Dombrowski et al., 2016). While the
327 above scenarios are deliberately artificial, such experiments can provide important mechanistic
328 insights into the observed temporal patterns of plant–soil microbe interactions.

329 While we have focused on changes happening over the course of a single plant-to-plant

330 replacement, these dynamics are closely related to other temporal patterns. One direction of re-
331 search is how microbial effects build up over generations through multiple rounds of conditioning
332 and response. A wealth of literature has explored the microbial changes underpinning reduced
333 crop yield following repeated planting (i.e., soil sickness; reviewed in Huang et al., 2013) and the
334 strengthening of conspecific microbial effects experienced by non-native plants after their intro-
335 duction (Diez et al., 2010, Dostál et al., 2013; but see Day et al., 2015). The temporal scale of these
336 studies typically spans hundreds of years. While this temporal pattern has been demonstrated
337 by experiments using soils with conditioning histories that span multiple generations, few studies
338 have generalized the traditional focus of single species to multiple species. In a unique greenhouse
339 experiment consisting of two rounds of soil conditioning by different combinations of six plant
340 species, Wubs and Bezemer (2018) demonstrated the complicated patterns arising from multiple
341 rounds of soil conditioning. Future work can expand upon Wubs and Bezemer (2018) to study
342 how the unique sequences of soil conditioning result in different plant–soil microbe interactions.
343 Another tightly interconnected aspect is the demographic facet of plant–soil microbial interactions:
344 as the responding individual matures, soil microbes can influence various demographic processes
345 in addition to varying biomass responses. We elaborate on this in the next section.

346 **IV. Assessing multiple demographic consequences of soil microbes**

347 Most two-phase studies of plant–soil microbe interactions are designed to evaluate how different
348 soil microbial contexts influence plant biomass performance. Experimentally, the implicit assump-
349 tion is that individual biomass at the end of the experiment integrates all critical impacts of the
350 microbial community and that variation in individual biomass growth is predictive of variation
351 in population growth rates. This assumption corresponds well with the classic feedback model
352 of Bever et al. (1997), where microbes regulate the intrinsic growth rate of an exponentially grow-
353 ing plant population. However, soil microbes can also alter other key demographic processes
354 throughout the plant life cycle that are not directly correlated with biomass accumulation (e.g.,
355 seed germination and pollinator visitation in Dudenhöffer et al., 2018). Dostálek et al. (2022)
356 demonstrated that it can be difficult to predict plant coexistence by using the microbial effect mea-
357 sured at a single life stage – while biomass performance suggests self-limitation of both *Bromus*

358 *erectus* and *Inula salicina*, including microbial effects on seed germination and fruit production sug-
359 gests that both species in fact benefited from self-conditioned soil. Here, we highlight key studies
360 that provide insights into microbial control over non-biomass plant demographic processes, with
361 a particular focus on early life stage transitions.

362 **IV.1 Microbial regulation of seed-to-seedling transition**

363 Soil microbes can have drastic consequences on the early life stages of plants. While these effects
364 can arise from microbial effects on distinct life history processes (i.e., seed survival, germination,
365 and early seedling survival; Fig. 5), empirical studies often group them together given the logistical
366 challenges of separating these effects in field settings. For example, when studying long-lived
367 plants such as forest trees, repeated demographic censuses are often used to monitor seed-to-
368 seedling transitions (e.g., Harms et al., 2000, Swamy et al., 2011). A large body of evidence
369 for microbial effects on plant early life stages comes from field studies finding that fungicide
370 applications alter patterns of seed and seedling demography (e.g., Bell et al., 2006, Bagchi et al.,
371 2014, Krishnadas et al., 2018, Song and Corlett, 2022). Many of these studies are conducted
372 to evaluate soil microbes as potential drivers of the Janzen–Connell hypothesis (Janzen, 1970,
373 Connell, 1971)) and conspecific negative density-dependence (CNDD). These hypotheses suggest
374 that the aggregation of host-specific enemies around adult plants reduces the survival probability
375 of seedlings that disperse close to adults and under high conspecific densities. While evaluating
376 the compound microbial effect across multiple early life stages can yield important insights, studies
377 that isolate microbial effects on specific underlying demographic transitions (Fig. 5) can enable a
378 nuanced and mechanistic understanding of microbial effects on plant population dynamics.

379 Soil-borne pathogens can cause substantial mortality at the seed stage across biomes (e.g.,
380 Kotanen, 2007, Sarmiento et al., 2017, Li et al., 2019). One system where the impact of fungal seed
381 pathogens has been systematically dissected is that of pioneer tree species in neotropical forests,
382 especially those in the genus *Cecropia*. As pioneer species whose seeds need to germinate quickly
383 in response to new gap openings, these species produce seeds that can persist in the soil until the
384 formation of nearby gaps. These seeds are vulnerable to pathogen attack during their time in the
385 soil seed bank, and as a result, fungicide treatments can nearly double their survival and emergence

386 (Dalling et al., 1998, Gallery et al., 2010). Moreover, Dalling et al. (1998) found that seeds were more
387 susceptible to pathogen attack in soils close to conspecific adults than in soils far from conspecifics,
388 implicating soil pathogens as potential drivers of Janzen–Connell dynamics. Furthermore, recent
389 advances have employed molecular methods toward understanding longstanding questions about
390 pathogen host specificity. Zalamea et al. (2021) found that seeds of closely related *Cecropia* species
391 harbor vastly distinct fungal communities, with species identity explaining substantially more
392 variation than the seeds' location or their viability. Working with a more diverse group of pioneer
393 tree species, Sarmiento et al. (2017) showed that while many fungi can grow on seeds of multiple
394 plant species, their effects on seed mortality are highly species-specific. Together, this series of
395 studies has highlighted soil-borne fungal seed pathogens as key microbial players in the dynamics
396 of pioneer trees in tropical forests. While quantifying microbial effects on seed survival requires
397 laborious methods (e.g., tetrazolium staining for testing seed viability; Sarmiento et al., 2017), a
398 better understanding of these effects is critical given that seed limitation can be a bottleneck on
399 plant population dynamics (Harper, 1977, Clark et al., 2007).

400 Soil microbes can also affect the rates and timing of germination. Such regulation primarily
401 arises due to the production and/or metabolism of key germination-related phytohormones like
402 gibberellins (reviewed in Keswani et al., 2022 and Bottini et al., 2004) or ethylene (reviewed in
403 Ravanbakhsh et al., 2018 and Ishaq, 2017). While studies of how soil microbes regulate germination
404 have historically focused on managed settings, evidence that microbes also affect germination
405 in natural settings is now accumulating. In one of the few two-phase experiments focused on
406 pairwise feedback effects on germination, Miller et al. (2019) found species-specific effects of
407 conditioned microbes on germination. Specifically, the legume *Desmodium illinoense* achieved lower
408 germination rates in conspecific-conditioned soils than in sterilized or heterospecific-conditioned
409 soils, while germination of *Bromus inermis* and *Solidago canadensis* was unaffected by soil microbes.
410 Across a large-scale microcosm experiment, Eldridge et al. (2021) found that soil bacterial and
411 fungal communities help explain substantial variation in patterns of seed germination across nine
412 plant species, suggesting a relationship between soil microbes and plant germination that is not
413 explained simply by their shared responses to abiotic soil properties. Even when soil microbes do
414 not affect overall rates of germination, they can alter the phenology of germination (Keeler and

415 Rafferty, 2022) which could either harm (e.g., if later germination reduces seedlings' performance
416 due to competition; Orrock and Christopher, 2010) or benefit (e.g., if later germinants escape
417 severe competition at the seedling stage or avoid abiotic stress; Leverett et al., 2018) population
418 growth.

419 Finally, soil microbes also play a key role in determining the survival of seedlings after
420 germination. The widespread role of mycorrhizal symbioses in promoting seedling survival and
421 the potential for soil-borne pathogens to cause mortality among seedlings have been studied for
422 decades and reviewed elsewhere (e.g., Gilbert, 2002, Horton and van der Heijden, 2008). Recent
423 advances have focused on elucidating the relative role of harmful and beneficial soil microbes in
424 driving seedling survival and establishment across different environmental contexts, including
425 abiotic conditions (Bingham and Simard, 2011), the relative abundance of conspecific and het-
426 erospecific adults (Teste et al., 2017), and the functional groups of mycorrhizal fungi (Liang et al.,
427 2016, Bennett et al., 2017). In addition to studies that directly track the fate of newly germinated
428 seedlings in specific microbial contexts, studies that monitor the fate of older plant individuals
429 also often speculate soil microbes as the underlying mechanism (e.g., CNDD studies on the sur-
430 vival of larger individuals; Comita et al., 2010). While, in comparison, the effect of soil microbes
431 on seedling survival has rarely been the target variable in biomass-focused greenhouse experi-
432 ments, recent studies have also started to quantify the contribution of this demographic process to
433 microbe-mediated coexistence (Dudenhöffer et al., 2022, Chung et al., 2023, Pajares-Murgó et al.,
434 2024).

435 **IV.2 Microbial effects beyond early life stages**

436 As seedlings establish and grow into reproductive adults, the soil microbial community continues
437 to affect their performance in various ways not captured by experiments that focus only on plant
438 biomass. While an exhaustive review of all such effects of soil microbes is beyond the scope of
439 this study, we briefly highlight soil microbial regulation of flowering phenology and susceptibility
440 to herbivores. Over the past decade, evidence of microbial regulation of flowering phenology
441 across systems has become widespread (Lau and Lennon, 2012, Wagner et al., 2014, Igwe et al.,
442 2021). Although the consequences of such phenological shifts at the population level are seldom

443 quantified, the few-day differences reported in these studies could in principle have drastic con-
444 sequences for plant fitness, especially under abiotic stress when earlier flowering can be crucial to
445 reproductive success and fitness (reviewed in Kazan and Lyons, 2016, O'Brien et al., 2021). The soil
446 community can also regulate plant susceptibility to invertebrate herbivores (e.g., Howard et al.,
447 2020, Pineda et al., 2020, Kalske et al., 2022), with such effects likely arising due to soil microbe-
448 induced changes in leaf metabolomes or volatile organics (Kalske et al., 2022, Huberty et al., 2022).
449 The consequences of microbe-mediated shifts in plant–herbivore interactions on insect population
450 dynamics are becoming increasingly well-studied (reviewed in Shikano et al., 2017), but whether
451 these changes affect plant population dynamics is less well established. Soilborne pathogens can
452 also contribute to inter-specific and spatial variability in rates of adult tree mortality (Das et al.,
453 2016). The integration of these microbial effects remains an ongoing challenge. In light of this, we
454 propose that a promising approach is to combine experiments with system-specific models that
455 can assess their long-term consequences on plant population dynamics.

456 **IV.3 Implications for experimental design**

457 While incorporating all aforementioned demographic impacts of soil microbes is logistically chal-
458 lenging, we also see a path forward. Current experimental studies of plant–microbe interactions
459 often transplant pre-germinated seeds into conditioned soils, thereby neglecting the impact of soil
460 microbes on seed survival and germination. Accordingly, a first step in enhancing our under-
461 standing of this phenomenon is for two-phase studies to plant ungerminated seeds and report
462 germination rates along with the biomass performance and survival rates of germinated plants.
463 Studies can employ statistical approaches (Dudenhöffer et al., 2022, Chung et al., 2023) or other
464 population demographic models (David et al., 2019, Dostálek et al., 2022) to integrate the impact
465 of microbes on multiple early stage transitions (see also section V.). Moreover, for short-lived
466 plants, one can aim to follow the entire plant life cycle. For example, Dostálek et al. (2022) doc-
467 umented seedling establishment and biomass dynamics for two growing seasons, and recorded
468 final fruit production of plants in different soil microbial backgrounds. While such an experiment
469 is more challenging, the matrix population model parameterized by Dostálek et al. (2022), where
470 soil microbes modulate transition probabilities across states, enables a more nuanced estimate of

471 microbial impact compared to solely relying on biomass-based metrics.

472 Compared to greenhouse-based plant–soil feedback studies that focus on biomass perfor-
473 mance, CNDD studies using field census data are arguably more directly linked to population
474 growth due to their emphasis on individual survival. However, observational CNDD studies
475 can be limited as it can be challenging to attribute demographic patterns to soil microbes, and
476 the impact of heterospecifics, which are necessary to infer coexistence outcomes, is sometimes
477 overlooked. We propose that controlled experiments could complement census data for more
478 mechanistic insights. For example, field-based biocide experiments have been used to identify soil
479 microbes as key drivers of Janzen–Connell effects in seed and seedling mortality (Bell et al., 2006,
480 Bagchi et al., 2010, Song and Corlett, 2022, Krishnadas and Comita, 2018). Furthermore, adding a
481 reference treatment in randomly located field soil allows one to estimate frequency-independent
482 microbial impacts on survival, aligning with recent studies that emphasize plant–soil microbe
483 interactions within modern coexistence theory (Kandlikar et al., 2019, Ke and Wan, 2020). Green-
484 house experiments can also be adapted to capture the density-dependent microbial effects implicit
485 in CNDD studies. To this end, one can use field-conditioned soil from locations with varying adult
486 densities or perform a pot experiment with varying seedling densities (Ke and Wan, 2023). These
487 modifications in study design can help bridge the gap between microbial impacts inferred from
488 experiments and field census data.

489 Finally, we argue that researchers should identify the demographic process that acts as a
490 bottleneck for plant population growth in the focal system and prioritize studying the microbial
491 impact on that specific demographic process. For example, in communities dominated by species
492 with persistent seed banks, the microbial effect on seed survival may be particularly important.
493 In systems where plant germination is highly constrained by soil-borne pathogens, germination
494 success in soils with different conditioning histories should be measured. We also recognize
495 that in some plant communities, individual biomass growth indeed correlates well with critical
496 demographic processes. For annual plants, individual biomass at the time of peak flowering may
497 reflect fecundity (Neytcheva and Aarssen, 2008, Younginger et al., 2017). For forest trees, since
498 seedling survival beneath the forest canopy is often size-dependent (Chang-Yang et al., 2021),
499 microbial effects that reduce seedling biomass lead to higher mortality and thus have a clear

500 demographic consequence on plant populations. However, while individual biomass can serve
501 as a proxy for population growth in these particular systems, it is crucial to recognize that the
502 underlying demographic process enabling this interpretation varies among systems.

503 **V. Modeling frameworks for incorporating temporal and demographic** 504 **aspects of plant–soil microbe interactions**

505 As reviewed in the above sections, the strength and direction of plant–soil microbe interactions
506 vary along different temporal dimensions and can influence various demographic processes. While
507 empirical studies are essential for growing our understanding of these aspects, predicting their
508 long-term consequences requires an integration of data with models of plant population dynamics.
509 Therefore, we encourage studies to go beyond biomass-based inferences to demographic models
510 that directly incorporate microbial effects. Developing suitable theoretical models for the focal
511 plant–soil system and connecting them with empirical data is a pressing research direction. Below,
512 we discuss two theoretical frameworks that are especially well-suited to incorporate the temporal
513 and demographic components of plant–soil microbe interactions and highlight studies that have
514 parameterized them with empirical data.

515 **V.1 Patch occupancy models**

516 Patch occupancy models represent a relatively straightforward framework for studying plant–soil
517 microbe interactions (Pacala and Tilman, 1994, Mouquet et al., 2002). In this group of models,
518 plants compete for unoccupied sites (patches) and the probability that a particular plant species
519 establishes in a local site depends on the site’s microbial legacy (Stump and Comita, 2018, Miller
520 and Allesina, 2021, Ke and Levine, 2021). Such models can either be spatially implicit, which
521 assumes that the landscape can be divided into an infinite number of patches and tracks the
522 proportion of different plant–soil microbe states (e.g., Miller and Allesina, 2021, Ke and Levine,
523 2021), or spatially explicit, which considers a fixed-size arena and allows one to consider spatial
524 proximity when modeling microbial impact (e.g., the diffusion of microbial effects from live indi-
525 viduals nearby; Bever et al., 1997, Mack and Bever, 2014, Bauer et al., 2015). Detailed formulation

526 aside, a common assumption in such models is that plants only indirectly influence each other by
527 modifying soil microbial legacies. This assumption aligns well with two-phase experiments that
528 grow individual plants in soils with different conditioning histories, and as such, patch occupancy
529 models can be readily parameterized with biomass measurements from pot experiments (e.g.,
530 by assuming establishment probability scales with the relative biomass performance). Alterna-
531 tively, patch occupancy models can also be parameterized with recruitment data from repeated
532 censuses, thereby incorporating microbial effects on multiple early life stages (e.g., seed survival,
533 germination, and seedling survival in Fig. 5; Krishnadas and Stump, 2021). Due to this connec-
534 tion with empirical data, patch occupancy models are commonly used in the PSF literature when
535 studies wish to extrapolate predictions based on pairwise biomass-based metrics to multi-species
536 communities (e.g., Mangan et al., 2010, Teste et al., 2017, Dudenhöffer et al., 2022).

537 The patch occupancy framework offers a pathway to effectively incorporate various temporal
538 aspects of plant–soil microbe interactions (Fig. 1; see also an example in Box 1). This is because
539 such models can treat different developmental stages of the soil microbial community as distinct
540 states so that the transitions between states reflect the conditioning and decay rates of soil microbes.
541 The explicit inclusion of microbial legacies in the form of an unoccupied but conditioned patch
542 state differs from previous feedback models, which usually assume tight coupling between plants
543 and microbes (Eppinga et al., 2018, Mack et al., 2019). For example, Ke et al. (2021) modified a
544 previous model (Fukami and Nakajima, 2013) by making microbial effects vary with the duration
545 of soil conditioning, which in turn influences the transient trajectory of community assembly. In
546 another example, Ke and Levine (2021) used a spatially implicit model to show that the strength of
547 stabilization driven by host-specific pathogens depends on how quickly the conditioning effects of
548 plants erode. The above models directly track the changes of microbial impact on plants through
549 time, and can thus be parameterized with the type of experiments mentioned in subsection III.3.
550 Alternatively, one can build simulation-based models that explicitly track the population size of
551 microbes at each local site, allowing the temporal development and decay of microbial effects to
552 emerge naturally (Schroeder et al., 2020). However, such models are harder to parameterize with
553 empirical data since they require detailed knowledge of microbial traits and population dynamics
554 (Jiang et al., 2020).

V.2 Models incorporating multiple demographic processes

In contrast to patch occupancy models, which usually assume that microbes only impact the establishment process, one can also formulate models that directly consider distinct microbial impacts on distinct plant demographic processes. Such an approach, which can be difficult to implement due to the extensive amount of work required to obtain all parameters, may be particularly fruitful in demographically complex systems. Demonstrating the power of this approach, a series of studies (Mordecai, 2013a,b, 2015, Uricchio et al., 2019) integrated models and empirical observations to investigate how pathogens affect competition between native perennials and invasive annual grasses. The plant demography components of these models begin with an approach often used for annual plants: they track the yearly population of each species' seeds, which persist in the soil seed bank from previous years or are produced by reproductive-stage individuals, and capture the effect of plant competition through density-dependent decreases in seed production (Fig. 2A; see also section II. and Box 2). The authors then incorporated perennial demography by additionally tracking the number of adult perennials, reflecting successful seed germination and recruitment, as well as adult survival from the previous year. This model structure can flexibly incorporate the effect of microbes by allowing them to modify various demographic transitions; in particular, the authors focused on a soil-borne pathogen that reduces seed persistence and germination (Mordecai, 2013a). With a plant competition experiment and manipulations of pathogen densities, Mordecai (2013b) parameterized a model with density-dependent microbial effects and concluded that pathogen spillover promotes the persistence of perennial bunchgrasses. Subsequent work further demonstrated the adaptability of this framework: Mordecai (2015) showed that the plant life stage attacked by pathogens (i.e., seedlings or dormant seeds) and environmental variation jointly determined the coexistence of competing annual plants. In another application, Uricchio et al. (2019) combined field observations and experiments to parameterize an even more realistic model, considering multiple annual and perennial species and incorporating two additional microbial effects (i.e., the impacts of foliar pathogens on seedling survival and adult perennial fecundity).

In addition to integrating multiple microbial effects, a demographically explicit model can help identify the most critical microbial effect via simulations. For instance, in the annual–perennial

584 plant model in Uricchio et al. (2019), foliar pathogens have little impact but seed pathogens can
585 have a more significant effect on perennial competitors in the system. Such a sensitivity analysis
586 is particularly useful when models include many mechanistic parameters for microbial dynamics
587 (e.g., Ke et al., 2015, Schroeder et al., 2020) and represents another reason why isolating microbial
588 effects on specific demographic transitions can be enlightening. Even for models that do not
589 explicitly incorporate microbial dynamics, identifying the bottleneck for population growth can
590 provide insights for future studies and guide more targeted experiments. Using an integral
591 projection model parameterized with long-term demographic data, Chu and Adler (2015) showed
592 that feedback loops during the recruitment stage contributed most to plant coexistence compared to
593 that during the growth and survival stages. The authors speculated this is due to the recruitment
594 stage involving many demographic transitions that are susceptible to soil pathogens (Chu and
595 Adler, 2015). In Box 2, with an annual–perennial plant model incorporating microbial effects
596 as qualitative switches in parameter values, we also demonstrate how sensitivity analysis can
597 help identify the relative importance of different microbial effects on the perennial plant. In
598 sum, formulating demographic models not only allows smooth integration of the temporal and
599 demographic dimensions of plant–soil microbe interactions but also provides an opportunity to
600 explore their consequences in multi-species communities.

601 **VI. Conclusion: moving forward with an empirical-theoretical feed-** 602 **back loop**

603 Since its introduction to community ecology, the study of plant–soil microbe interactions has long
604 been shaped by a tight link between empirical and theoretical approaches. By showing how
605 empirically tractable greenhouse experiments can yield data to calculate theory-derived metrics,
606 the approach from Bever et al. (1997) has motivated more than two decades of research to predict
607 the long-term consequences of soil microbes (Crawford et al., 2019). To date, new studies continue
608 to follow this integration, proposing new theories to capture different impacts of soil microbes as
609 well as new experimental designs to quantify them (e.g., Kandlikar et al., 2019, 2021, Yan et al.,
610 2022). Two key assumptions of this approach are that plant–soil microbe interactions follow a

611 simplified temporal trajectory, and that measuring microbial impact on plant biomass captures the
612 population dynamic consequences of soil microbes. While such abstractions have helped make
613 models generalizable, growing evidence has proven the relevance of the two knowledge gaps when
614 predicting the role of soil microbes in natural communities (Chung, 2023). Explicit consideration
615 of the temporal and demographic aspects not only leads to new research questions but also allows
616 researchers to draw conclusions grounded on relevant experimental settings. As such, we see
617 tremendous value in future efforts that aim to (1) develop theoretical models that can explicitly
618 incorporate the temporal and demographic components of plant–soil microbe interactions, and
619 (2) parameterize such models with corresponding observational data or experiments aimed at
620 quantifying these past-missing components.

621 New modeling frameworks should be developed in order to incorporate the aforementioned
622 temporal and demographic components. Here, we identify two paths moving forward. First,
623 patch occupancy models can be used to study the temporal dimensions of plant–soil microbe
624 interactions by tracking the transition between different soil microbial states, which impact the
625 subsequent establishment of plants in that patch. This framework also echoes recent theoretical
626 studies suggesting that competition for limited colonization sites generates more interpretable
627 frequency-based dynamics for multi-species communities than do extensions of the classic pairwise
628 feedback model (Miller et al., 2022). Second, instead of tracking species’ occupancy frequency, one
629 can also build demographic models that explicitly track plant population densities; this approach
630 offers the opportunity to easily incorporate microbial effects on multiple plant demographic stages.
631 We note that in practice, these modeling approaches are both flexible and can be used to answer
632 more than one research question (e.g., decay dynamics and time-dependent feedback can also
633 be built into a demographically explicit model; Senthilnathan and D’Andrea, 2023, Zou et al.,
634 2024). Ultimately, the choice depends on the research question and the focal plant–soil system.
635 For example, in systems with disturbances that may truncate soil conditioning at different timings
636 (Nagendra and Peterson, 2016), or those with low propagule availability such that conditioned soils
637 are not immediately recolonized, investigating the temporal dimension can provide great insights
638 into the role of soil microbes in nature; this can also be done by simulations of time-discrete
639 models (Zou et al., 2024) and individual-based models (Zee and Fukami, 2015). On the other hand,

640 when different soil microbes are known to impact different parts of the plant life cycle, integrating
641 multiple microbial effects into a single demographic model may be more important.

642 While patch occupancy models can be parameterized with either biomass measurements
643 (e.g., Mangan et al., 2010, Teste et al., 2017, Dudenhöffer et al., 2022) or census data (e.g., Stump
644 and Comita, 2018), we caution that the model itself is agnostic to the demographic details of plant–
645 soil microbe interactions and will encompass different microbial effects depending on the data used
646 for parameterization (Fig. 5). For instance, Stump and Comita (2018) parameterized their patch
647 occupancy model with CNDD patterns based on 5-year seedling survival (Comita et al., 2010),
648 which correspond to microbial effects on the survival of established older seedlings. On the other
649 hand, Krishnadas and Stump (2021) parameterized a similar model with CNDD patterns based on
650 the seed-to-seedling transition, thereby representing microbial effects on recruitment and earlier
651 life stages. Moreover, using different types of data to parameterize the model implies different
652 assumptions on how microbial effects operate. In particular, using performance measurements
653 from single-individual greenhouse experiments (e.g., Teste et al., 2017, Dudenhöffer et al., 2022)
654 to parameterize a patch occupancy model implies that the plant community is driven by how
655 soil microbes affect the density-independent growth rate of plant populations, whereas using
656 CNDD patterns from observational census incorporates how soil microbes and other non-microbial
657 mechanisms modify the nature of density dependence among plants.

658 Designing new experiments that provide the necessary information to parameterize the new
659 plant demographic models of plant–soil microbe interactions is another frontier of research. Some
660 models require experiments that are similar to current two-phase experiments. For instance, to
661 depict temporal development patterns, one can repeat an experiment along naturally occurring
662 variations in the duration of soil conditioning; to track multiple early life stage microbial effects, one
663 can directly plant ungerminated seeds into cultivated soils. However, some microbial effects cannot
664 be reliably estimated by classic two-phase experiments with a single-growing plant individual. For
665 example, if microbes are expected to affect not only plant intrinsic growth rate but also the nature of
666 density dependence among plants, then estimating microbial effects requires additional treatments
667 beyond the classic two-phase design. Recent studies linking plant–soil microbe interactions and
668 coexistence theory specifically highlight this scenario where soil microbes influence the model's

669 density dependence parameters (Kandlikar et al., 2019, Ke and Wan, 2020, Zou et al., 2024), which
670 require employing experiments that directly manipulate plant density and soil origin (Chung and
671 Rudgers, 2016, Cardinaux et al., 2018). An empirical–theoretical feedback loop is also central to the
672 design of such theory-driven experiments. For example, a proposed design based on the premise
673 that plant–plant interactions are competitive (Ke and Wan, 2020) was challenged by the observation
674 that facilitation is common, leading to a revised density gradient design with greater flexibility (Ke
675 and Wan, 2023). Again, the optimal approach depends on feasibility and which research question
676 can provide a fundamental understanding of the focal plant–soil system.

677 Recent census-based CNDD studies have introduced a promising approach to investigate
678 how microbe-mediated plant demography interacts with the three temporal aspects, namely, the
679 duration of soil conditioning, the life stage of responding plants, and the time delay between
680 consecutive colonizing plants. Current CNDD studies often calculate size-weighted abundance
681 when estimating conspecific densities, thereby implicitly considering soil conditioning time by
682 linking plant size to microbial effects. Additionally, microbial communities associated with plants
683 of different ages can be sequenced to examine the relationship between pathogen accumulation
684 and species’ CNDD strength (Chen et al., 2019). Long-term observational data should also allow
685 us to test whether conspecific effects change with the age/stage of the responding focal individual
686 (Bagchi et al., 2014, Zhu et al., 2015, 2018). For instance, Zhu et al. (2015) showed that the CNDD
687 effects attenuated as individuals mature from seedlings to adults. Finally, a recent study also
688 pioneered the inclusion of dead tree individuals into the abundance calculation (i.e., the effects of
689 decay; Magee et al., 2024). Insights from such CNDD studies can be used to parameterize patch
690 occupancy models with corresponding temporal aspects, offering new insights by integrating the
691 two overlooked components.

692 One of the remaining challenges is to move away from a plant-centered viewpoint towards
693 a better understanding of the dynamics and functionality of soil microbial communities (Jiang
694 et al., 2020). Theoretical models often assume simplified microbial dynamics (e.g., separation
695 of timescales) or treat soil microbes as a qualitative modifier of plant parameters. Incorporating
696 microbial community assembly processes, as outlined in section II, can help inform which processes
697 need to be prioritized when building mechanistic models of microbial community dynamics (e.g.,

698 Schroeder et al., 2020, see also Zou et al., 2024 for a discrete-time model with explicit consideration
699 of the temporal dynamics of soil microbes). Empirically, experiments that establish the causal
700 relationship between measured microbial dynamics and plant demographic responses can help
701 feed theory with realistically parameterized temporal patterns. To this end, a starting point is
702 to simultaneously measure shifts in both plant response and microbial community composition
703 within studies that vary the temporal components (e.g., Esch and Kobe, 2021, Ke et al., 2021,
704 Hannula et al., 2021, but see Carini et al., 2016 for technical challenges related to erroneously
705 detecting DNA from dead microbes in sequencing time series). Moreover, given the functional
706 plasticities and redundancies of microbial communities, improvements in identifying microbial
707 functionality beyond that based on taxonomic information are also needed. Explicit quantification
708 of microbial activity, such as measurements through multi-omics outputs, can allow for better
709 modeling of functional microbial dynamics. Future studies balancing both the plant and microbe
710 perspectives can further facilitate the empirical–theoretical feedback loop when studying the two
711 missing components of plant–soil microbe interactions.

712 In summary, we conclude that studying the temporal dimension and the multiple demo-
713 graphic consequences of plant–soil microbe interactions provides a better understanding of their
714 natural context. In addition to the maintenance of plant diversity, the two knowledge gaps can
715 also be important for other ecological processes (e.g., recovery following disturbance and gap
716 dynamics). The temporal dimensions highlighted here also underline the significance of phe-
717 nological mismatch among plants and soil microbes driven by climate change (Rudgers et al.,
718 2020; e.g., late-germinating plants may be more vulnerable to pathogens). Recognizing that soil
719 conditioning and plant response are temporally varying processes also provides insights into the
720 context-dependency of plant-soil microbe interactions: shifts in the abiotic environment can oc-
721 cur throughout a plant’s lifetime, and the timing of these shifts can alter the temporal trajectory
722 differently. Ultimately, knowledge of the system’s natural history should guide researchers to
723 recognize which aspects of the temporal and demographic components are important for the fo-
724 cal system and the research question. With the most critical aspect being identified, we believe
725 that parameterizing new demographic models provides an avenue to predict the long-term con-
726 sequences of plant–soil microbe interactions against a backdrop of real-world conditions in which

727 these interactions unfold.

Box 1: Implementing a patch occupancy model to study the temporal decay of microbial effects

Here, we demonstrate how the temporal decay of microbial effects can be studied with a multi-species patch occupancy model. We considered three different plant–soil microbe states (Box Fig. 1A): unconditioned soil (P_{00}), soils colonized and conditioned by plant i (P_{ii}), and uncolonized soils with a microbial legacy (P_{0i}). The transition among these different states can be described as follows (see also Ke and Levine, 2021 and Miller and Allesina, 2021):

$$\frac{dP_{00}}{dt} = \overbrace{\sum_{i=1}^N d_i P_{0i}}^{\text{decay of conditioning effect in empty patches}} - \overbrace{\sum_{i=1}^N r_i P_{ii} P_{00}}^{\text{plant establishment into empty and unconditioned patches}} \quad (1)$$

$$\frac{dP_{ii}}{dt} = \overbrace{r_i P_{ii} P_{00}}^{\text{plant establishment into empty and unconditioned patches}} + \overbrace{\sum_{j=1}^N r_i \sigma_{ij} P_{ii} P_{0j}}^{\text{plant establishment in empty but conditioned patches}} - \overbrace{m_i P_{ii}}^{\text{plant mortality}} \quad (2)$$

$$\frac{dP_{0i}}{dt} = \overbrace{m_i P_{ii}}^{\text{plant mortality}} - \overbrace{d_i P_{0i}}^{\text{decay of conditioning effect in empty patches}} - \overbrace{\sum_{j=1}^N r_j \sigma_{ji} P_{jj} P_{0i}}^{\text{plant establishment in empty but conditioned patches}} \quad (3)$$

Specifically, state transitions occur due to plant colonization/soil conditioning (r_i), plant mortality (m_i), and the decay of microbial effects (d_i , black arrows in Box Fig. 1A). Here, soil microbes affect the ability of plants to recolonize conditioned soils (red arrows in Box Fig. 1A). N represents the total number of species within the community.

To illustrate the consequences of variable decay rates of microbial effects, we simulated the microbial effects (σ_{ij}) for 16 plant species with data from Teste et al., 2017, which measured soil microbial effects on plant biomass accumulation. We randomly drew species' fecundity (r_i) from a uniform distribution between 0.2 to 0.25. This simulation illustrates how the decay rates of microbial effects determine the overall consequences of soil microbes on plant communities (Box Fig. ??B & C). Specifically, with this parameterization and when microbial effects persist after host death (i.e., low d_i ; left panels in Box Fig. 1B & C), plant–soil microbe interactions mostly result in the dominance of a single species, overwhelming

Box 1 (continued)

species' variation in fecundity. However, if the conditioned microbial effect decayed rapidly after the death of host plants (i.e., high d_i ; right panels in Box Fig. 1B & C), variation in species' fecundity allowed higher diversity in each simulation and more equal persistence probability across species. Therefore, predicting the consequences of plant–soil microbe interactions in nature also requires quantifying the decay rate of greenhouse-measured microbial effects.

730

Box 2: Implementing a demographic model to detect the most critical microbial effect

Here, we demonstrate how situating microbial effects within a demographic model of plant population dynamics can help integrate multiple microbial effects and identify the most critical one. We modified the model from Uricchio et al. (2019) to describe the competition between an annual plant (N_a) and a perennial plant with two stages, denoted as N_p and A_p for its seed and adult abundance, respectively:

$$N_a(t+1) = \underbrace{s_a (1 - g_a) N_a(t)}_{\text{survival of ungerminated seeds}} + \underbrace{N_a(t) \frac{g_a \lambda_a}{1 + \alpha_{ap} A_p(t) + \alpha_{aa} g_a N_a(t)}}_{\text{seed production}} \quad (1)$$

$$N_p(t+1) = \underbrace{s_p (1 - g_p) N_p(t)}_{\text{survival of ungerminated seeds}} + \underbrace{A_p(t) \frac{\lambda_p}{1 + \alpha_{pp} A_p(t) + \alpha_{pa} g_a N_a(t)}}_{\text{seed production by adult plants}} \quad (2)$$

$$A_p(t+1) = \underbrace{A_p(t) \xi}_{\text{survival of existing adults}} + \underbrace{N_p(t) \frac{g_p v}{1 + \beta_{p,A_p} A_p(t) + \beta_{p,N_p} g_p N_p(t) + \beta_{p,N_a} g_a N_a(t)}}_{\text{maturation of seeds into adult plants}} \quad (3)$$

The seed dynamics of both life history types are similar to that in the Beverton–Holt model, with a seed bank term influenced by germination (g_i , $i = a$ or p) and survival (s_i) as well as a seed production term (λ_i) that is discounted by competition (α_{ij}). The perennial plant differs from the annual in that its seed production (second term in equation 2) depends on the adult stage. The maturation of perennial seeds to adulthood (second term in equation 3) depends on the survival probability (v) and competition ($\beta_{p,j}$, $j = A_p$, N_p , and N_a) from individuals of all stages. Finally, perennial adults suffer mortality in a competition-independent manner such that the proportion surviving after each year is ξ .

For the perennial plant, there are five demographic parameters that can be affected by soil microbes (g_p , s_p , λ_p , v , and ξ). As demonstrated in section II., the first strength of a demographic model is that it can integrate multiple microbial effects. For example, if soil pathogens decreased all parameters of the perennial plant by 20%, the model suggests that it would nearly be outcompeted by the annual plant (i.e., from grey to blue dashed line). By only quantifying the impact of pathogens on the intrinsic fecundity (λ_p), as is commonly done in studies that grow individual plants in conditioned soils, we would have underestimated

Box 2 (continued)

the impacts of soil microbes in this system. The second strength of a demographic model is that it helps identify the most critical microbial effect. For example, sensitivity analysis (see Box figure legend for details) revealed that, compared to other demographic parameters, the impact of pathogens on adult survival probability (ξ) had the strongest impact on the perennial plant population.

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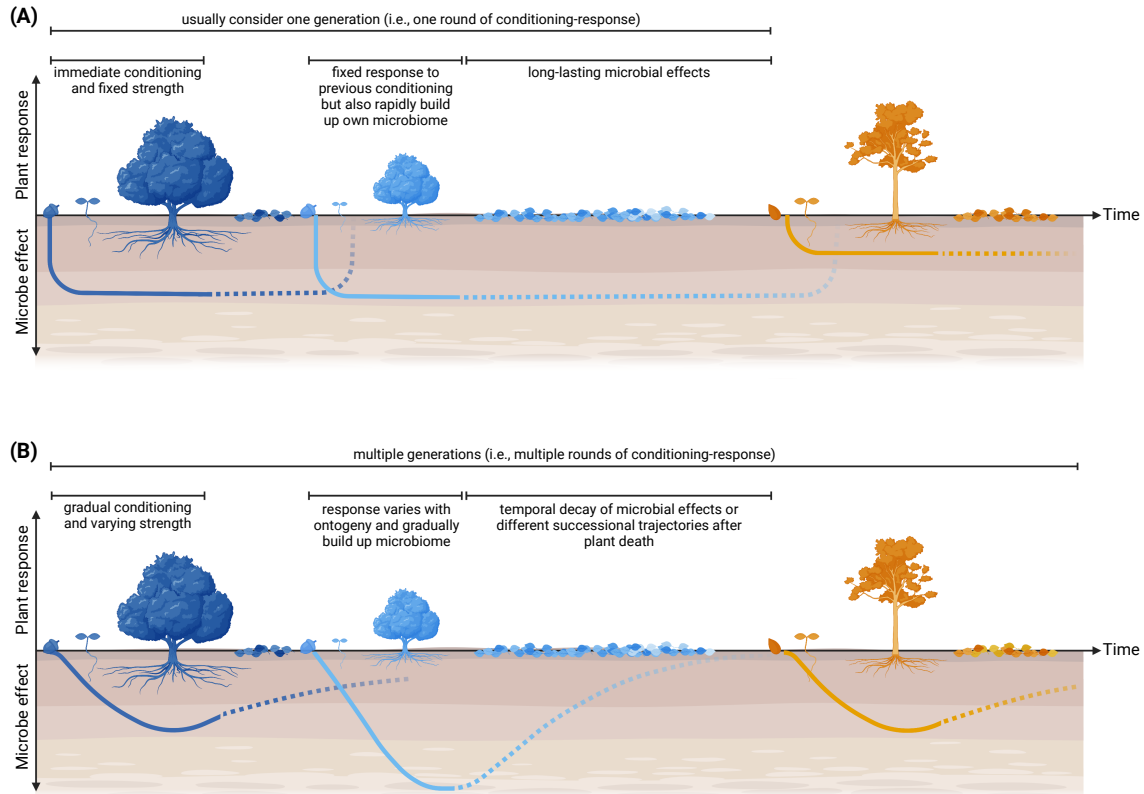


Figure 1 Temporal dimensions of plant–soil microbe interactions throughout the repeated process of plant establishment, growth, death, and recolonization by another individual. (A) The common assumptions of plant–soil microbe interactions implied by the design of classic experiments: microbial communities develop relatively quickly, with resulting microbial effects that are constant throughout different plant life stages and remain as long-lasting legacies after plant senescence to impact the next generation. (B) The dynamic plant–soil microbe interaction perspective highlighted in our review: microbial communities change continuously throughout the conditioning process, with impacts on plant performance that depend on both the duration of plant conditioning and response (subsection III.1). Moreover, microbial communities and their impacts on plant performance may diminish with time after the senescence of the previous conditioning individual (subsection III.2) or undergo different trajectories depending on the previous rounds of conditioning (mentioned as a future direction in subsection III.3).

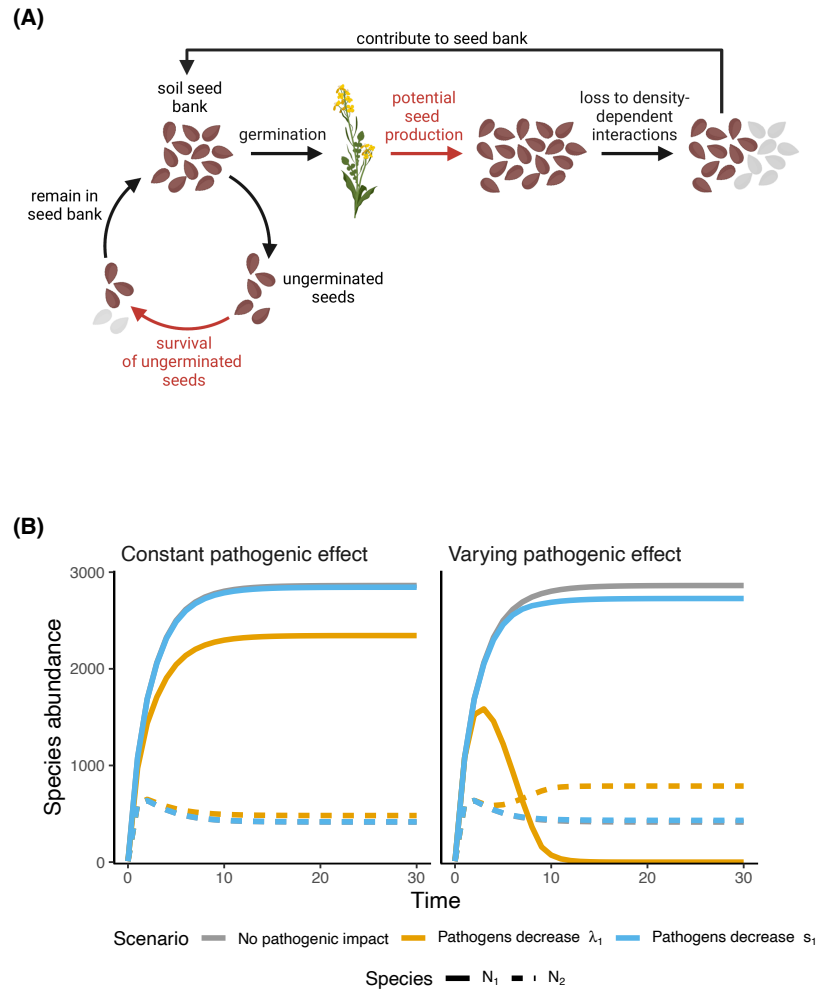


Figure 2 An example demonstrating how incorporating the temporal and demographic aspects of plant–soil microbe interactions can generate different competitive outcomes in the annual plant model. (A) A graphical representation of the Beverton–Holt annual plant model, which tracks the density of seeds prior to germination. Demographic processes influenced by soil microbes in this simulation are highlighted in red, including seed survival and the fecundity of germinated plants. (B) Abundance time series of N_1 (solid line) and N_2 (dashed line) under different microbial effect scenarios: no pathogenic effect (grey), pathogens decrease the seed survival of N_1 (s_1 ; blue), and pathogens decrease the fecundity of N_1 (λ_1 ; orange). The left panel assumes a 10% decrease in N_1 's demographic parameters, whereas the right panel assumes that the initial 10% decrease after one generation aggravates to a 80% decrease after eight generations (i.e., 10% decrease after every generation). Note that the blue lines often overlap the grey lines due to the minor impact of s_1 . Parameters are obtained from the species pair *Festuca microstachys* (N_1) versus *Hordeum murinum* (N_2) in Van Dyke et al. (2022): $g_1 = 0.752$, $g_2 = 0.667$, $s_1 = 0.134$, $s_2 = 0.045$, $\lambda_1 = 2129.950$, $\lambda_2 = 736.667$, $\alpha_{11} = 0.588$, $\alpha_{12} = 1.411$, $\alpha_{21} = 0.109$, and $\alpha_{22} = 0.948$.

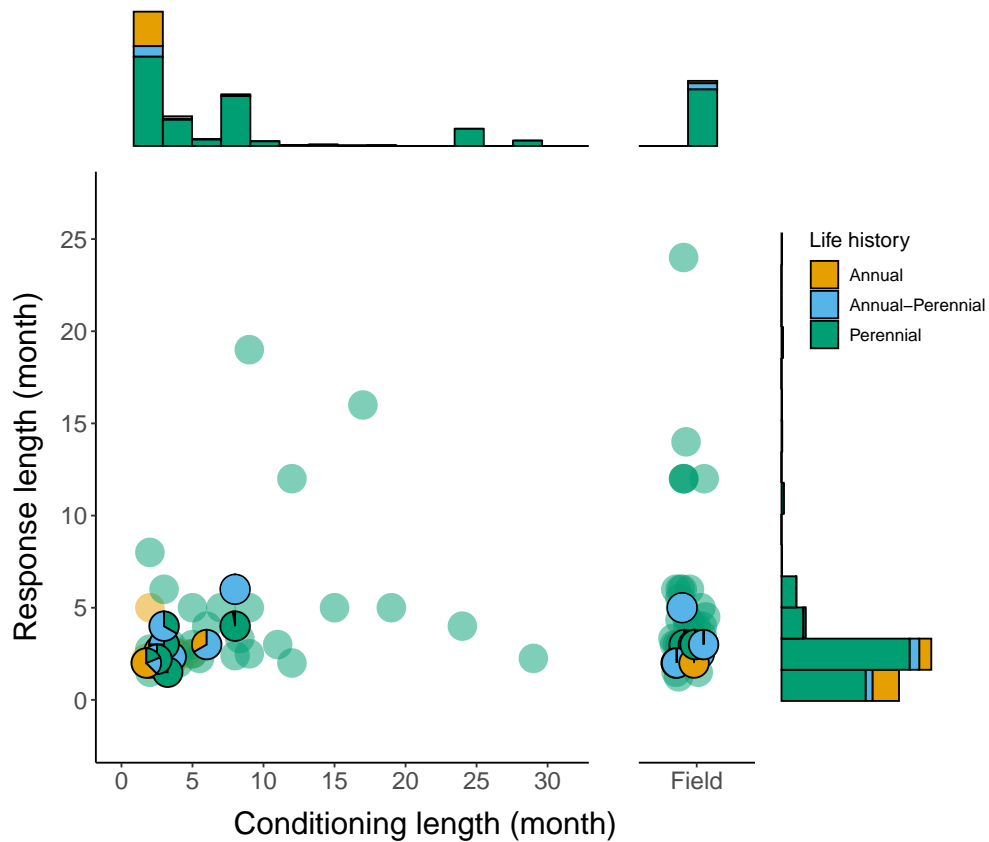


Figure 3 A summary of the experimental duration and life history information of the study species in the Crawford et al. (2019) and Yan et al. (2022) data sets. Since the two studies focused on the pairwise plant–soil feedback, we compiled information on plant life history and categorized each pairwise comparison as different “pair types”: annual (both plants are annuals; orange), perennial (both plants are perennials; green), or annual–perennial (match of an annual versus a perennial; blue). Highlighted points represent studies that evaluated plant–soil feedback between annual and perennial plants, with each pie chart representing the percentage of different pair types within the study (translucent points indicate studies that included only annual or only perennial species). The position of each pie chart indicates the duration of a study’s conditioning (x-axis; field-conditioned soil as a separate category) and response phase (y-axis). The upper and right stacked histograms depict the same information but are based on the number of experimental pairs across all studies. Note that one study with a conditioning length of 48 months and a response length of 32 months (Kulmatiski, 2019) was excluded from the figure to improve visualization (see supplementary data).

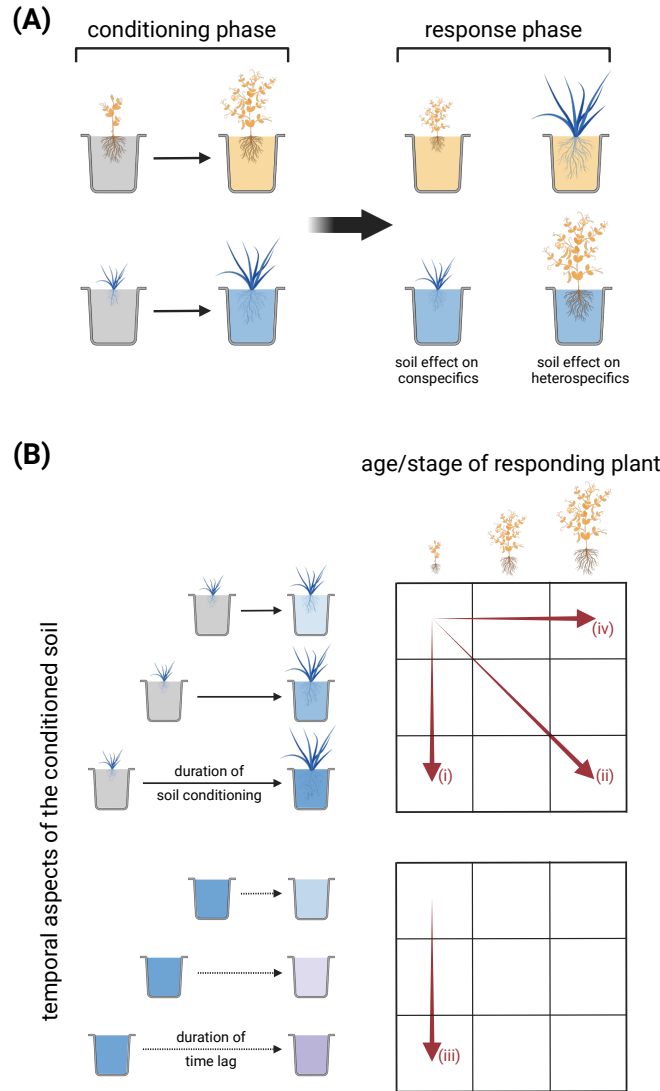


Figure 4 Experiments for studying plant–soil microbe interactions. (A) The classic two-phase experimental design, consisting of a conditioning phase during which plants modify the soil microbial community and a response phase during which plants respond to the soil modification. Depicted here in the response phase is the case of negative frequency-dependent feedback where conditioned soils favor the performance of heterospecifics over conspecifics. (B) Proposed experimental designs to study the various temporal dimensions in the main text (measuring the orange plant’s performance in soils conditioned by the blue plant as an example): (i) isolating changes in the soil microbial community by varying the duration of soil conditioning, (ii) sequential harvesting with both conditioning effect and plant age advancing simultaneously, (iii) isolating the decay process by incorporating a time lag after soil conditioning, and (iv) isolating changes in plant physiology by transplanting individuals of different age in the same conditioned soil.

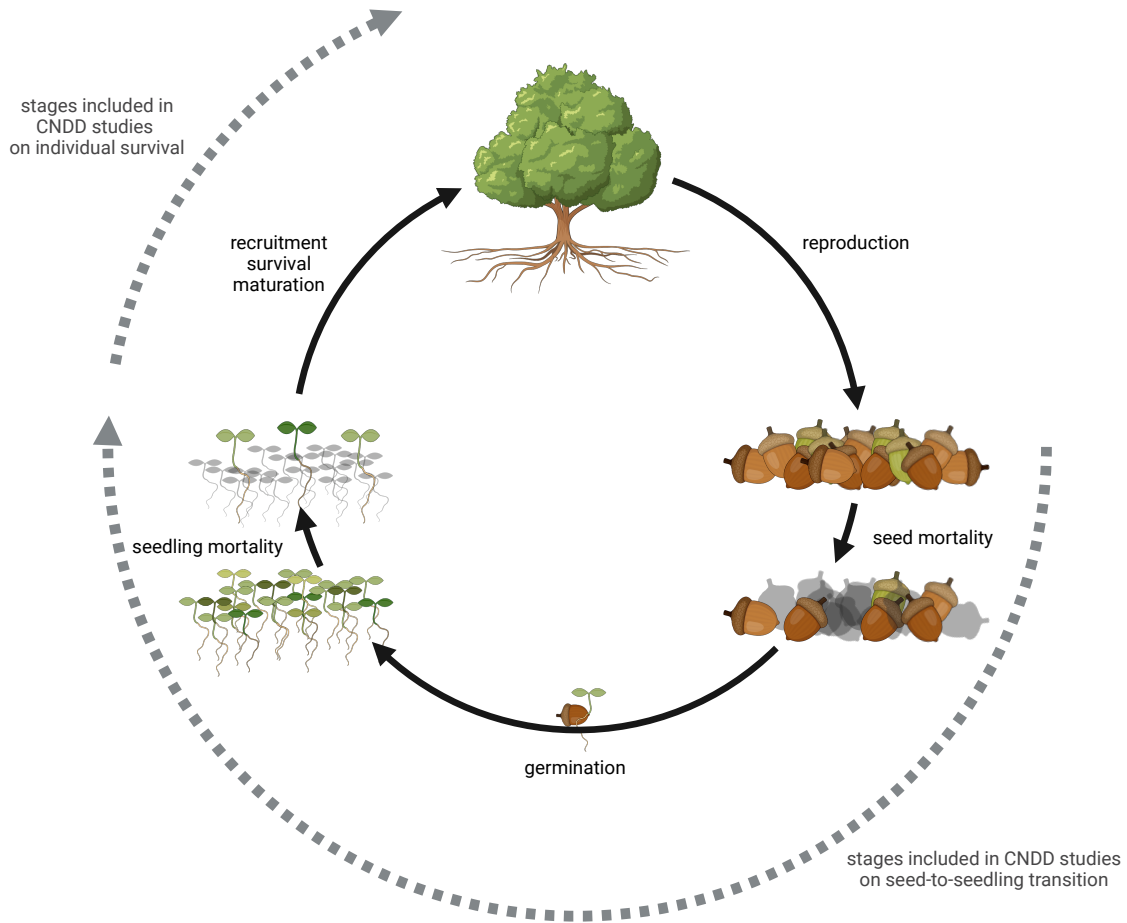
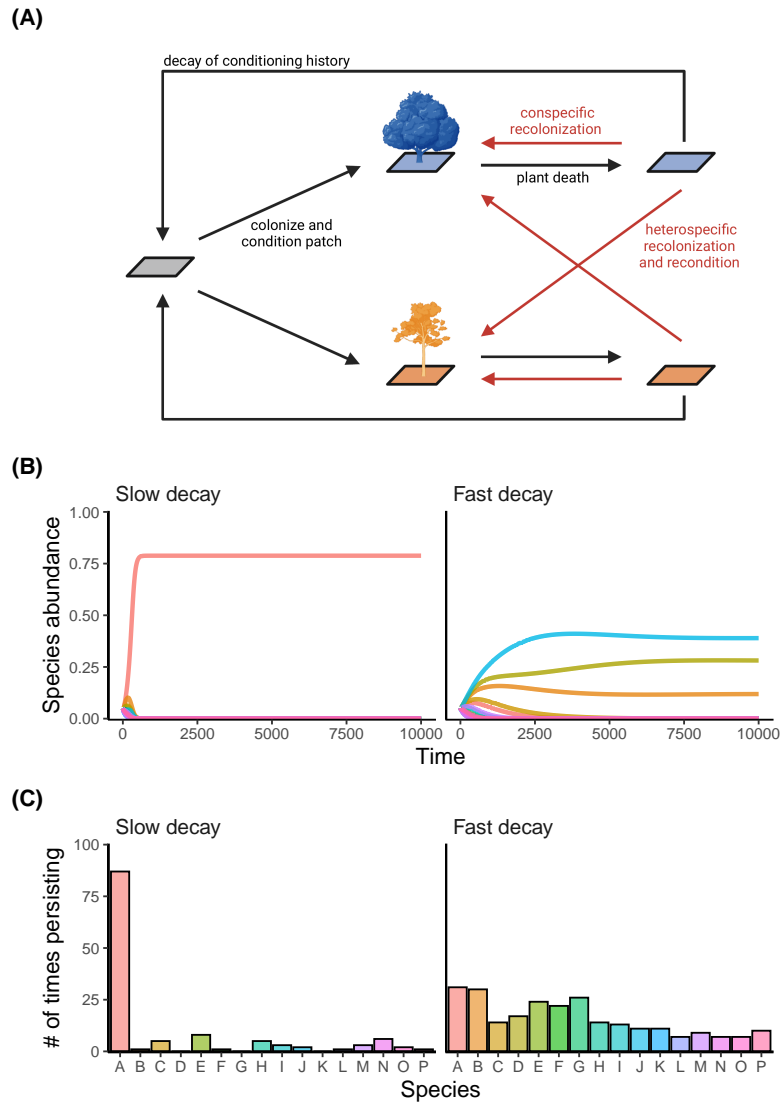
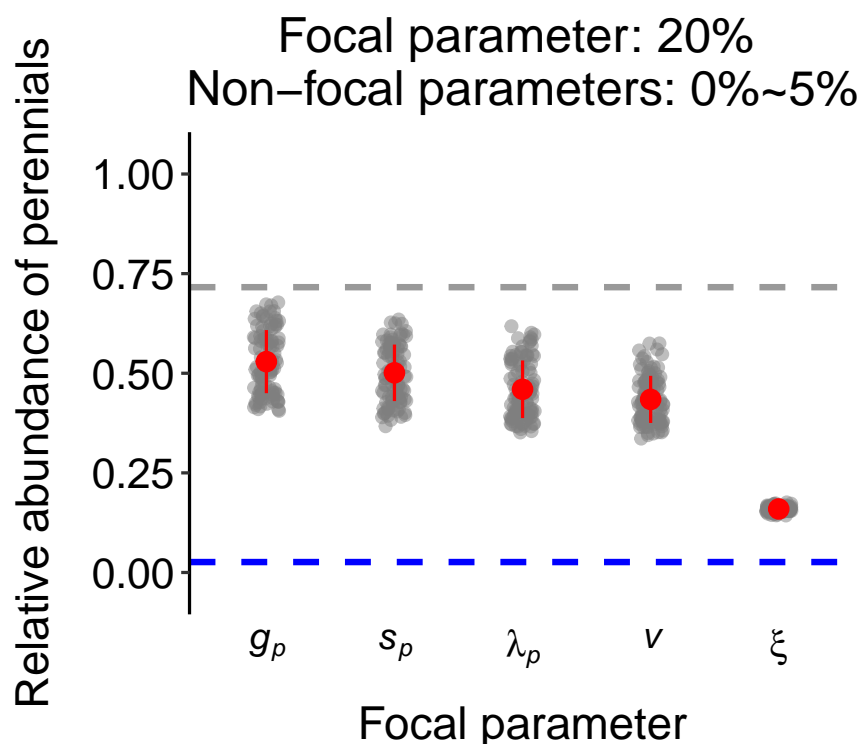


Figure 5 Conceptual diagram depicting multiple demographic consequences of soil microbes, with a particular focus on early plant life stages following most empirical studies. The inner circle (black arrows) indicates the distinct demographic processes that can be affected by soil microbes; in the main text, we highlight empirical evidence on seed mortality, germination, and early seedling survival. The outer circle (grey dashed arrows) indicates the life stages included in different studies on conspecific negative density dependence (CNDD).



Box Figure 1 An example demonstrating how the temporal decay of microbial effects can be studied with a patch occupancy model. (A) Transitions among different plant-soil microbe states occur due to plant colonization/conditioning, plant death, and the decay of microbial effects. Here, soil microbes affect the ability of plants to recolonize conditioned soil (red arrows). (B & C) Diversity of the plant community when microbial effects decay slowly ($d_i = 0.01$; left panels) or rapidly ($d_i = 0.99$; right panels). We simulated the dynamics of 16 plant species (depicted with different colors and letters). We ran 100 simulations; each time we randomly generated a new fecundity value for each species (i.e., $r_i \sim U(0.2, 0.25)$) while fixing the microbial effect parameters based on data from Teste et al. (2017). Panel (B) shows a representative time series of the relative abundance of different plant species (frequencies of empty patches are omitted). Panel (C) shows the number of times (out of 100 simulations) the focal species (x-axis; different species labeled with different capitalized letters) persisted in the final community. Mortality (m_i) is set to 0.05 for all plants and initial conditions are: $P_{00} = 0.2$, $P_{ii} = 0.05$ for $i = 1 \dots 16$, and $P_{0i} = 0.0$. See Box 1 for additional details.



Box Figure 2 Detecting the most critical microbial effect within an annual–perennial plant competition model (modified from Uricchio et al., 2019). Here, soil microbes can impact five demographic parameters of the perennial plant: seed germination rate (g_p), seed survival rate (s_p), intrinsic fecundity (λ_p), seedling survival rate (v) and adult survival rate (ξ). The grey dashed line represents the relative abundance of the perennial plant in the absence of any pathogenic effects from the microbes (i.e., unperturbed baseline parameters), while the dashed blue line shows the perennial’s relative abundance when the pathogen simultaneously causes a 20% reduction in all five parameters. To evaluate the demographic consequences of microbes primarily impacting one demographic process, we sequentially decreased the value of each parameter by 20%, while the other four non-focal parameters were randomly decreased by 0% to 5% (assuming weaker microbial impact). For each focal parameter, we repeated this process in 100 simulations (translucent grey points; red points and error bars represent the means and standard deviations) and ran each simulation for 200 generations. These simulations reveal that soil pathogens that primarily reduce adult survival (ξ) have substantially stronger demographic consequences than pathogens that primarily affect other demographic processes. See Box 2 for model description. The baseline parameters are obtained from the species pair *Elymus glaucus* (our perennial) versus *Bromus diandrus* (our annual) in Uricchio et al. (2019) – perennial plant parameter: $g_p = 0.125$, $s_p = 0.515$, $\lambda_p = 282.127$, $\xi = 0.920$, $v = 0.292$; annual plant parameters: $g_a = 0.168$, $s_a = 0.443$, $\lambda_a = 47.594$; competition reduction on seed production: $\alpha_{aa} = 0.066$, $\alpha_{ap} = 0.143$, $\alpha_{pp} = 0.018$, $\alpha_{pa} = 0.104$; competition reduction on perennial survival: $\beta_{p,N_p} = 0.086$, $\beta_{p,A_p} = 0.063$, $\beta_{p,N_a} = 0.002$.

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744 **Author Contributions**

745 P.-J. Ke, G.S. Kandlikar, and S.X. Ou conceived the study and took the lead in writing the first draft.
746 All authors contributed critically to developing the ideas and finalizing the manuscript.

747 **Data Availability**

748 The dataset used in Figure 3 and code used to generate model simulations are available on GitHub
749 (<https://github.com/pojuke/DemographicReviewPSF>) and will be made available on Zenodo
750 with a DOI upon publication. Figures 1, 2A, 5, and Box Figure 1A are created with BioRender.com.

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