

1 Native perennial and non-native annual grasses shape pathogen community composition and  
2 disease severity in a California grassland

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11     **Abstract**

12     1. The densities of highly competent plant hosts (i.e., those that are susceptible to and  
13       successfully transmit a pathogen) may shape pathogen community composition and  
14       disease severity, altering disease risk and impacts. Life history and evolutionary history  
15       influence host competence: longer-lived species tend to be better defended than shorter-  
16       lived species and pathogens adapt to infect species with which they have longer  
17       evolutionary histories. It is unclear, however, how the densities of species that differ in  
18       competence due to life and evolutionary histories affect plant pathogen community  
19       composition and disease severity.

20     2. We examined foliar fungal pathogens of two host groups in a California grassland: native  
21       perennial and non-native annual grasses. We first characterized pathogen community  
22       composition and disease severity of the two host groups to approximate differences in  
23       competence. We then used observational and manipulated gradients of native perennial  
24       and non-native annual grass densities to assess the effects of each host group on pathogen  
25       community composition and disease severity in 1-m<sup>2</sup> plots.

26     3. Native perennial and non-native annual grasses hosted distinct pathogen communities but  
27       shared generalist pathogens. Native perennial grasses experienced 26% higher disease  
28       severity than non-native annuals. Only the observational gradient of native perennial  
29       grass density affected disease severity; there were no other significant relationships  
30       between host group density and either disease severity or pathogen community  
31       composition.

32     4. *Synthesis.* The life and evolutionary histories of grasses likely influence their competence  
33       for different pathogen species, exemplified by distinct pathogen communities and

34 differences in disease severity. However, there was limited evidence that the density of  
35 either host group affected pathogen community composition or disease severity.

36 Therefore, competence for different pathogens likely shapes pathogen community  
37 composition and disease severity but may not interact with host density to alter disease  
38 risk and impacts at small scales.

39 **KEYWORDS**

40 plant-pathogen interactions, disease severity, pathogen community, host competence, life  
41 history, non-native species, grassland, fungi

42

43 **1 | INTRODUCTION**

44 Plant community composition can affect infectious disease risk and impacts (Mundt,  
45 2002; Rohr et al., 2020). The competence (i.e., susceptibility to and ability to transmit a  
46 pathogen; Stewart Merrill & Johnson, 2020) and density of hosts can affect pathogen persistence  
47 and incidence (Burdon & Chilvers, 1982; Fenton, Streicker, Petchey, & Pedersen, 2015).

48 Therefore, communities with higher densities of competent hosts are expected to experience  
49 greater disease risk (Joseph, Mihaljevic, Orlofske, & Paull, 2013; Young, Parker, Gilbert, Sofia  
50 Guerra, & Nunn, 2017). Because the relationship between community composition and disease  
51 can inform biodiversity conservation (Rohr et al., 2020), empirical studies of natural  
52 communities tend to focus on species richness more than host density (i.e., hosts per unit area;  
53 Wojdak, Edman, Wyderko, Zemmer, & Belden, 2014) or abundance (e.g., percent cover of plant  
54 hosts; Mitchell, Tilman, & Groth, 2002; Parker et al., 2015; Schmidt et al., 2020). It is therefore  
55 unclear how the densities of hosts that differ in competence drive disease risk.

56 Disease incidence (i.e., the proportion of hosts with symptoms in a given sampling  
57 period; Nutter, Esker, & Netto, 2006) and severity (i.e., the intensity of symptoms per sampling  
58 unit, such as a leaf or individual; Nutter et al., 2006) are indicators of disease risk (Rohr et al.,  
59 2020). Typically, multiple pathogens circulate within host communities, driving disease  
60 incidence and severity (Halliday, Umbanhowar, & Mitchell, 2017; Vasco, Wearing, & Rohani,  
61 2007). Variation among hosts in competence for different pathogens, which can arise through  
62 variation in traits and evolutionary histories with pathogens (Barrett, Kniskern, Bodenhausen,  
63 Zhang, & Bergelson, 2009; Joseph et al., 2013; Parker & Gilbert, 2004), can promote diversity in  
64 pathogen communities (Johnson et al., 2016). Therefore, variation in life history and  
65 evolutionary history may alter disease risk through pathogen community composition.

66 Shorter-lived species, such as annual plants, are expected to be less well-defended against  
67 pathogens and experience greater disease severity than longer-lived species because they allocate  
68 more resources to reproduction than survival (Cronin, Welsh, Dekkers, Abercrombie, &  
69 Mitchell, 2010; Joseph et al., 2013; Miller, White, & Boots, 2007). Plant species with longer  
70 evolutionary histories with pathogens in a given location may be more susceptible to attack by  
71 specialists that have overcome specific plant defenses (Parker & Gilbert, 2004; Telfer & Bown,  
72 2012). In addition, species introduced to a new geographic area are likely to leave their specialist  
73 pathogens behind, as predicted by the enemy release hypothesis (Keane & Crawley, 2002).  
74 However, non-native plants tend to be annual species (Sutherland, 2004) and can accumulate  
75 pathogens and disease symptoms comparable to native congeners within centuries (Hawkes,  
76 2007; Mitchell, Blumenthal, Jarošík, Puckett, & Pyšek, 2010), suggesting that long-established  
77 non-native plants may have overlapping pathogen communities with native species.

78        In general, higher densities of plant assemblages result in more contacts between  
79    susceptible host tissue and pathogen propagules (Burdon & Chilvers, 1982) and increase the  
80    negative effects of infection (Lively, Johnson, Delph, & Clay, 1995). Changes in the density of a  
81    single host type are more likely to affect specialist pathogens than generalist pathogens  
82    (Alexander & Holt, 1998), but specific plant traits may interact with plant density to mediate  
83    infection by generalist pathogens. For example, non-native annual grasses in California  
84    grasslands may increase pathogen transmission by filling in gaps between native perennial  
85    bunchgrasses (Parker, Seabloom, & Schimel, 2012) and native perennial grasses may grow later  
86    into the growing season than non-native annuals (Chiariello, 1989), providing additional  
87    opportunities for transmission (Thrall, Biere, & Antonovics, 1993). Thus, pathogen communities  
88    may shift, and disease severity may increase with increasing density of either non-native annuals  
89    or native perennials, but to a greater extent with increasing density of the more competent group.

90        Here we assess how the densities of native perennial and non-native annual grasses affect  
91    foliar fungal pathogen community composition and disease severity in a California grassland.  
92    California grasslands are dominated by non-native annual grasses, which differ in life history and  
93    local residence time from native perennial bunchgrasses (Heady, 1977). Non-native annual  
94    grasses have been established in California for more than a century (Heady, 1977) and, with  
95    native perennials, serve as hosts for a diversity of foliar fungal pathogens (Spear & Mordecai,  
96    2018) that are transmitted through density-dependent mechanisms (McCartney, Fitt, & West,  
97    2006). We collected data from ten studies within the grassland to answer the question: 1. *How do*  
98    *(a) pathogen community composition and (b) disease severity differ between native perennial*  
99    *and non-native annual grass hosts?* Pathogen community composition and disease severity  
100   depend on, among other factors, host competence and can indicate propensity for transmission

101 (Barrett et al., 2009). We hypothesized that native perennials would host more specialized  
102 pathogens due to longer evolutionary history with local pathogens, that non-native annuals  
103 would experience higher disease severity due to lower allocation to defenses, and that the two  
104 groups would host overlapping pathogen communities due to the long residence time of non-  
105 native annuals (>100 generations). We then evaluated the effects of host density on disease risk  
106 in an observational study and a manipulated experiment, answering the question: 2. *How do*  
107 *native perennial and non-native annual grass densities affect (a) pathogen community*  
108 *composition and (b) disease severity?* We hypothesized that increasing densities of either native  
109 perennials or non-native annuals would shift pathogen communities and increase disease  
110 severity, and that the density of the more competent group (suggested by the results of *Question*  
111 *I*) would have a larger effect. We hypothesized that the relationship between host density and  
112 disease risk would be stronger in the manipulated experiment, where plots contained more  
113 extreme values of host density and had fewer plant species than the observational study.

114

## 115 **2 | MATERIALS AND METHODS**

### 116 **2.1 | Study system**

117 We evaluated the pathogen community composition and disease severity of native  
118 perennial and non-native annual grasses at Stanford University's Jasper Ridge Biological  
119 Preserve (JRBP) in San Mateo County, California, USA. California grasslands are dominated by  
120 non-native Mediterranean annual grasses that rapidly established during European settlement,  
121 replacing dominant perennial bunchgrass species, such as *Stipa pulchra* (Heady, 1977).  
122 Grasslands at JRBP occur on sedimentary-derived soil, which we focus on in this study, and  
123 serpentine soil (McNaughton, 1968). Plant growth at JRBP begins with the onset of precipitation

124 in late fall, progresses through cool, wet winters into spring, and ends in warm, dry summers  
125 (Chiariello, 1989). The cumulative precipitation in San Mateo county between September and  
126 April was 579 mm (2014-2015), 728 mm (2015-2016), and 1139 mm (2016-2017), ranging on  
127 both sides of the 100-year average of 683 mm (NOAA, 2020). Such temporal variation in  
128 precipitation is typical of California grasslands, can impact plant community composition  
129 (Fernandez-Going, Anacker, & Harrison, 2012), and may also affect plant-pathogen interactions  
130 (Thompson, Levin, & Rodriguez-Iturbe, 2013).

131 A study at JRPB in 2015 demonstrated that unique pathogen communities were  
132 associated with several grass species, but that generalist pathogens were shared among them  
133 (Spear & Mordecai, 2018). The data from that study are included here, along with data collected  
134 in the next two years. We assessed foliar fungal disease associated with four non-native annual  
135 grass species (*Avena barbata*, *Bromus diandrus*, *Bromus hordeaceus*, and in some cases, *Avena*  
136 *fatua*, Table 1) and two native perennial grass species (*S. pulchra* and *Elymus glaucus*). While  
137 other non-native annual grasses, including *Brachypodium distachyon*, *Bromus sterilis*, *Festuca*  
138 *myuros*, and *Gastridium phleoides*, were locally common (Table S1), we focused on the four  
139 *Avena* and *Bromus* species because they are widespread at JRPB, have spatially variable  
140 densities, and are the primary competitors of native grasses (McNaughton, 1968; Uricchio,  
141 Daws, Spear, & Mordecai, 2019). All of the non-native species except *B. sterilis* and *G.*  
142 *phleoides* are considered invasive in California (Cal-IPC, 2020).

## 143 2.2 | JRPB compilation

144 To evaluate the differences between foliar fungal pathogen communities (*Question 1a*)  
145 and disease severity (*Question 1b*) of native perennial and non-native annual grasses, we used  
146 plants located within ten compiled data from two previous sampling efforts studies at JRPB in

147 2015 and 2016 and collected additional data in 2017 (i.e., JRPB compilation, Fig. S1). The  
148 sampling efforts were established conducted to characterize variation in the host ranges  
149 and fitness impacts of pathogens (observational study and additional sampling across JRPB in  
150 2015; Spear & Mordecai, 2018) and to for multiple purposes beyond the questions addressed  
151 here, including measuring plant demographic responses to competition and pathogen infection  
152 (observational study, manipulated experiment, and germinant study in 2016; Uricchio et al.,  
153 2019)(observational study, manipulated experiment, and germinant study in 2016; Uricchio et al.,  
154 2019). In 2017, we repeated sampling in the observational and germinant studies and collected  
155 samples from plants grown in pots and growing medium and placed in areas around JRPB (i.e.,  
156 “sentinel plants”, Fig. S1). characterizing natural variation in disease severity and pathogen  
157 community composition (Spear & Mordecai, 2018), and assessing the effects of global change  
158 factors on grasslands (Shaw et al., 2002). The oTwo of the studies (observational study and  
159 manipulated experiment (described below) contained gradients of native perennial to non-native  
160 annual grasses and were therefore used to answer *Questions 2a and 2b* (sections 2.3 and 2.4).  
161 Depending on the study goals, plants were either planted at JRPB by researchers, grown in pots  
162 and growing medium (i.e., “sentinel plants”), or occurred at JRPB without known human  
163 involvement. The plants sampled received no experimental treatment besides, in some cases,  
164 manipulation of plant community composition.

165 To characterize the pathogen community composition of native perennial and non-native  
166 annual grasses (*Question 1a*), we collected one leaf with disease symptoms per plant from  
167 grasses in ten studies at JRPB between March and June in 2015, 2016, and 2017 each year (Table  
168 1). We isolated fungi from the lesions, assigned each an operational taxonomic unit (OTU), and  
169 estimated the species identity (section 2.5). We defined a community as the fungal isolates

170 associated with a grass species in a particular year and omitted communities with fewer than four  
171 isolates, leading to six communities associated with native perennials and ten communities  
172 associated with non-native annuals (Table S2).

173 To characterize the disease severity of native perennial and non-native annual grasses  
174 (*Question 1b*), we selected plants without a priori knowledge of their infection status. [Disease](#)  
175 [severity was assessed in a subset of the JRPB compilation locations from three studies at JRPB](#)  
176 ([Table 1](#)): four transects (T11-T14, Fig. S1) in March and April 2015, the observational study in  
177 March and April 2015 and May 2016, and the manipulated experiment in May 2016 ([Table 1](#)).

178 The assessments in March and April of 2015 used many of the same plants, so we analyzed these  
179 data separately. For each plant, we haphazardly selected up to six leaves, based on availability,  
180 and visually approximated the proportion of leaf surface area with lesions. Disease severity was  
181 measured as the proportion of leaf surface area with lesions, including of leaves lacking lesions,  
182 which, when averaged over all leaves of a plant, combines the proportion of leaves with lesions  
183 and the proportion of leaf surface area with lesions.

### 184 **2.3 | Observational study**

185 Together with the manipulated experiment (section 2.4), the observational study was  
186 designed to measure plant demographic responses to [competition and](#) pathogen infection (Spear  
187 & Mordecai, 2018; Uricchio et al., 2019). Both studies contained gradients of native perennial  
188 and non-native annual grass densities. Five plant species were included in both studies: seedlings  
189 of *A. barbata*, *B. diandrus*, *B. hordeaceus*, *E. glaucus*, and *S. pulchra* and adults of *E. glaucus*  
190 and *S. pulchra*. We included both seedlings and adults of perennial species because the  
191 demographic responses of both life stages contributed to the original study goals (Uricchio et al.,  
192 2019). In spring 2015, we established ten transects across visually-assessed gradients of

193 perennial grass-dominated to annual grass-dominated areas. Transects consisted of four to five  
194 1-m<sup>2</sup> plots (Fig. S1) and were sampled over two years. Following the first year, we supplemented  
195 transects lacking the five plant species to allow for better comparison with the manipulated  
196 experiment by adding approximately 20 seeds of each species and one adult of each perennial  
197 species into every other plot (i.e., plots 1, 3, and 5 of a transect with 5 plots). To characterize the  
198 density of native perennial and non-native annual grasses, we counted the number of individuals  
199 per species within subplots of 47 and 18 plots during April 2015 and late June/early July 2016,  
200 respectively, and scaled the counts up to 1-m<sup>2</sup> (Table S1). We did not include forb density in our  
201 analyses even though forbs were present in the plots because foliar fungal pathogens often  
202 exhibit a phylogenetic signal (Gilbert & Webb, 2007; Parker et al., 2015), so forbs are less likely  
203 to share pathogens with the sampled grasses than are other grass species.

204 To evaluate the effects of native perennial and non-native annual grass densities on  
205 pathogen community composition (*Question 2a*), we collected one leaf with disease symptoms  
206 per plant from grasses in 31 plots in 2015 and six plots in 2016 (Table 1). We isolated and  
207 identified fungi from the lesions (section 2.5) and evaluated changes in isolation frequencies of  
208 the most common OTUs over the host group density gradients (section 2.6.3).

209 To evaluate the effects of native perennial and non-native annual grass densities on  
210 disease severity (*Question 2b*), we conducted disease severity assessments of grasses in 46 plots  
211 in March 2015, 25 plots in April 2015, and 18 plots in 2016 following the methods described for  
212 the JRBP compilation (section 2.2). We evaluated changes in disease severity over the host  
213 group density gradients (section 2.6.4).

214 **2.4 | Manipulated experiment**

215 In fall 2015, we established 210 1-m<sup>2</sup> plots in a 35 m x 35 m area of JRBP where weed  
216 matting had been placed in the preceding spring to suppress background plant recruitment (Fig.  
217 S2; Uricchio et al., 2019). Within the 1-m<sup>2</sup> plots, we manipulated the densities of the five plant  
218 species described in section 2.3 to 10%, 20%, 40%, 80%, or 100% of the density of each in  
219 monoculture by sowing seeds of each species or transplanting adult perennial species. In  
220 addition, 30 2 x 2 m plots were cleared and planted with one seed of each species and one adult  
221 of each perennial species. In January 2016, we added “focal” individuals to the 1-m<sup>2</sup> plots by  
222 planting ten seeds of each species and one adult of each perennial species. We also reseeded 18  
223 plots with 75%–100% of their original added seed weight to account for low germination. Two-  
224 thirds of the plots received either fungicide application or liquid fungal inoculum and one-third  
225 received an equivalent volume of water (ambient). However, we only used the ambient plots in  
226 this analysis (70 1-m<sup>2</sup> plots and 10 4-m<sup>2</sup> plots, Fig. S2). During June 2016, we counted up to 50  
227 individual grasses in each plot, identified them to species, and scaled the densities to 1-m<sup>2</sup> (Table  
228 S1). We weeded non-planted species throughout the growing season, but some survived and we  
229 included their densities in our analyses.

230 To evaluate the effects native perennial and non-native annual grass densities on  
231 pathogen community composition (*Question 2a*), we collected one leaf with disease symptoms  
232 per plant from grasses in 28 plots (Table 1). Because destructive sampling could interfere with  
233 assessing plant competition in low density plots (one of the goals of the experiment; Uricchio et  
234 al., 2019)~~and because we expected the largest effect of background plants to occur at higher~~  
235 ~~densities~~, we only sampled from plots planted at 80% and 100% density. These two planting  
236 treatments still produced a range of realized native perennial and non-native annual densities  
237 (Fig. S3B, D) because of variation in survival of intentional and unintentional plants. We isolated

238 and identified fungi from the lesions (section 2.5) and evaluated changes in isolation frequencies  
239 of the most common OTUs over the host group density gradients (section 2.6.3).

240 To evaluate the effects of native perennial and non-native annual grass densities on  
241 disease severity (*Question 2b*), we assessed grasses across all of the ambient plots (Table 1)  
242 following the methods described for the JRBP compilation (section 2.2). We evaluated changes  
243 in disease severity on native perennial and non-native annual grasses over the host group density  
244 gradients (section 2.6.4).

245 **2.5 | Identifying foliar fungi**

246 We isolated fungi associated with foliar lesions and estimated the species identity to  
247 address questions pertaining to pathogen community composition (*Questions 1a* and *2a*). As  
248 described by Spear and Mordecai (2018), we excised 2 mm x 2 mm segments of symptomatic  
249 tissue from the edge of foliar lesions and surface-sterilized (sequential immersion for 60 s each  
250 in 70% ethanol and 10% household bleach) and plated each tissue piece on 2% malt extract agar  
251 (MEA) with the antibacterial agent chloramphenicol. For each tissue piece, morphologically  
252 distinct hyphae (i.e., morphotypes) were isolated into pure culture on 2% MEA plates. The  
253 Mordecai lab maintains reference strains (California Department of Food and Agriculture permit  
254 3160). For each fungal isolate, we extracted genomic DNA and amplified the internal transcribed  
255 spacer (ITS) regions 1 and 2, the 5.8S rRNA gene, and part of the rRNA LSU as detailed in  
256 Spear and Mordecai (2018). However, in 2017, we modified our protocol to produce longer  
257 consensus reads. Specifically, we paired the forward primer ITS1-F (Gardes & Bruns, 1993) with  
258 the reverse primer LR3 (Vilgalys & Hester, 1990), rather than ITS4-B (Gardes & Bruns, 1993).

259 We processed the Sanger sequencing reads from MCLAB (San Francisco, California,  
260 USA) with Geneious 7.1.9 (Kearse et al., 2012). We trimmed and automatically assembled reads

261 when possible; when not possible, we manually assembled reads or selected the longest trimmed  
262 individual read over 100 bp. We clustered all consensus sequences into OTUs based on 97%  
263 sequence similarity using USEARCH 10.0.240 (Edgar, 2010). If different morphotypes from the  
264 same tissue piece were clustered into the same OTU, we assumed they represented the same  
265 isolate. We estimated the taxonomic placement of the ITS OTUs with the UNITE database  
266 01.12.2017 (Nilsson et al., 2019) and assigned taxonomy in mothur 1.40.5 (Schloss et al., 2009)  
267 using the naïve Bayesian classifier (Wang, Garrity, Tiedje, & Cole, 2007) with a bootstrapping  
268 confidence score of at least 80% for species name and at least 60% for any other taxonomic rank.

## 269 **2.6 | Statistical analyses**

270 Statistical analyses were completed in R version 3.5.2 (R Core Team, 2018) using vegan  
271 (Oksanen et al., 2019), rusda (Krah et al., 2018), glmmTMB (Brooks et al., 2017), MuMIN  
272 (Bartoń, 2019), and tidyverse (Wickham, 2017) packages.

### 273 **2.6.1 | *Question 1a: Pathogen community differences between host groups***

274 We evaluated dissimilarities among pathogen communities (section 2.2) with a  
275 permutational multivariate analysis of variance (PERMANOVA) using the Chao method, which  
276 accounts for unobserved species and is robust to differences in sample sizes (Chao, Chazdon, &  
277 Shen, 2005). We used a community matrix (each community as a row, each OTU as a column,  
278 isolate abundances as entries) as the response variable and the “grass species”, “year”, and “host  
279 group” as predictor variables. We visualized results with non-metric multidimensional scaling  
280 (NMDS), also using the Chao method.

281 We estimated the host ranges of pathogens associated with each host group to evaluate  
282 whether escape of non-native annual grasses from specialist pathogens could explain differences  
283 in pathogen community composition (Keane & Crawley, 2002). We used two methods to

284 estimate host range: (1) we searched the U.S. National Fungus Collections Database (hereafter,  
285 “database”; Farr & Rossman, 2019) for host species associated with the estimated fungal species  
286 (Schmidt et al., 2020) and (2) we compiled the host species from which each OTU was isolated  
287 across ten studies at JRBP (section 2.2). Host species sampled (sample sizes in parentheses)  
288 included *A. barbata* (210), *A. fatua* (12), *B. diandrus* (120), *B. distachyon* (4), *B. hordeaceus*  
289 (85), *E. glaucus* (242), *Festuca perennis* (a non-native perennial, 21), *Phalaris aquatica* (a non-  
290 native perennial, 19), and *S. pulchra* (436). To test whether pathogens associated with native  
291 perennial and non-native annuals differed in their host ranges, we performed Welch two sample  
292 t-tests for each of the two host range sources. By using each fungal isolate as a replicate, species  
293 or OTUs that were isolated more frequently contributed more to the average host range. Note  
294 that the database may provide more information, and potentially larger host range estimates, for  
295 fungi of crops and economically important plants, fungi intercepted at ports of entry, common  
296 fungi, and invasive or emerging fungal pathogens (Farr & Rossman, 2019).

297 **2.6.2 | Question 1b: Disease severity differences between host groups**

298 To evaluate the differences in disease severity between native perennial and non-native  
299 annual grasses, we fit a generalized linear mixed effect model with a logit-link beta error  
300 distribution to the proportion of leaf surface area with lesions (section 2.2). Because our data  
301 contained many zeros, which cannot be included in a beta regression, we transformed disease  
302 severity using the equation  $t = (s \times (n - 1) + 0.5) / n$ , where  $t$  is the transformed value,  $s$  is the  
303 original value, and  $n$  is the size of the dataset (Douma & Weedon, 2019). The predictor variable  
304 was “the host group” and the random effect intercepts were “plant ID” nested within “plot”  
305 nested within “study” and crossed with “year”. We removed study from the random effects

306 (variance  $< 2 \times 10^{-22}$ ) for model convergence; the random effect “plot” still accounted for spatial  
307 heterogeneity.

308 **2.6.3 | Question 2a: Effects of host density on pathogen communities**

309 To evaluate the effects of native perennial and non-native annual density on pathogen  
310 community composition, we analyzed the isolation frequencies of the most common OTUs. To  
311 select the most common OTUs, we ranked all of the OTUs from [ten-the JRPB studies](#)  
312 [compilation](#) (section 2.2) by the number of isolates obtained in each year (i.e., abundance). We  
313 evaluated the differences in abundance between consecutive ranks and found relatively large  
314 differences between the fifth and sixth most common OTUs in 2015 and 2016 and between the  
315 fourth and fifth most common OTUs in 2017 (Fig. S43). Therefore, we selected the top five,  
316 five, and four most common OTUs in 2015, 2016, and 2017, respectively, which resulted in  
317 seven focal OTUs. The fungal species associated with these OTUs were *Alternaria infectoria*,  
318 *Parastagonospora avenae*, *Pyrenophora chaetomioides*, *Pyrenophora lolii*, *Pyrenophora tritici-*  
319 *repentis*, a [n unidentified](#) *Pyrenophora* species [identified only to genus level \(“Pyrenophora](#)  
320 [sp.”\)](#), and *Ramularia proteae*. Note that we refer to the OTUs by their estimated species names  
321 in the results, but these same species names may be associated with less common OTUs as well.

322 We fit generalized linear mixed effect models with logit-link binomial error distributions  
323 to the presence/absence of each focal OTU for each isolate collected from the observational  
324 study and manipulated experiment. The predictor variables were [the “host group”](#) (from which  
325 the isolate was collected) and plot-level densities of “native perennial grasses”, “non-native  
326 annual grasses”, and, when present, grasses that were either unidentified or not included in either  
327 host group (“other grasses”, Table S1). The fixed effects also included interactions between  
328 “host group” and each of the grass density measurements. Random effect intercepts were “plot”

329 crossed with “year” for the observational study and “plot” for the manipulated experiment  
330 (which had only one year of data). Exceptions to the general model formulation were made to aid  
331 in model convergence (Methods S1). We performed model selection by fitting models with all  
332 subsets of the fixed effects. The Akaike information criterion with a correction for small sample  
333 sizes (AICc) was calculated for each model and we extracted the subset of the models for which  
334 the cumulative sum of the normalized model likelihoods was greater than or equal to 0.95 (i.e.,  
335 the 95% confidence set of models). We report coefficient estimates from the average of the 95%  
336 confidence set.

#### 337 **2.6.4 | Question 2b: Effects of host density on disease severity**

338 To evaluate the effects of native perennial and non-native annual grass densities on the  
339 disease severity of each host group, we fit generalized linear mixed effect models with logit-link  
340 beta error distributions to the scaled proportion of leaf surface area with lesions (section 2.6.2).  
341 The fixed effects were the same as those described for the pathogen isolate models (section  
342 2.6.3). The random effect intercepts were “plant ID” nested within “plot” and crossed with  
343 “year” for the observational study and “plant ID” nested within “plot” for the manipulated  
344 experiment. We did not perform model selection as sub-models could not converge during model  
345 averaging.

346

### 347 **3 | RESULTS**

#### 348 **3.1 | Question 1a: Pathogen community differences between host groups**

349 We identified 83 unique OTUs from the 961 foliar fungal isolates collected from six  
350 grass species across JRBP (Fig. 1A). Forty-one OTUs were isolated from only native perennial  
351 grasses, 18 were isolated from only non-native annual grasses, and 24 were isolated from both

352 host groups. The host groups explained 25% of the variance in pathogen community composition  
353 (Table 2) and the pathogen communities associated with the two groups were distinct (Fig. 1B).  
354 However, the 24 OTUs isolated from both host groups made up 78% and 96% of the isolates  
355 from native perennial grasses and non-native annual grasses, respectively, leading to overlap  
356 between the pathogen communities associated with the two host groups (Fig. 1A). Fungal  
357 species names (29 total) were estimated for 282 native perennial grass isolates (53%) and 266  
358 non-native annual grass isolates (62%). Based on the database, the estimated fungal species  
359 isolated from non-native annual grasses had, on average, smaller host ranges than those isolated  
360 from native perennial grasses (Fig. 1C,  $t = 4.53$ ,  $df = 480$ ,  $P < 0.001$ ). However, within JRBP,  
361 the OTUs isolated from non-native annual grasses had, on average, larger host ranges than those  
362 isolated from native perennial grasses (Fig. 1C,  $t = -7.97$ ,  $df = 944$ ,  $P < 0.001$ ).

### 363 **3.2 | Question 1b: Disease severity differences between host groups**

364 Based on assessments collected from three studies at JRBP, native perennial grasses had  
365 26% higher disease severity than non-native annual grasses ( $P < 0.001$ , Table S3). However,  
366 disease severity was generally low: an average of 1.5% and 1.1% of leaf surface area was  
367 covered with lesions for native perennials and non-native annuals, respectively. These patterns  
368 were maintained when data collected in April 2015 from the observational study were substituted  
369 for data collected in March 2015 (Table S3).

### 370 **3.3 | Question 2a: Effects of host density on pathogen communities**

371 The seven most common OTUs from the foliar fungal isolates collected at JRBP (i.e., the  
372 focal OTUs) comprised 66% and 77% of the isolates from native perennial and non-native  
373 annual grasses, respectively, across the density gradients (Table 3). In both the observational  
374 study and manipulated experiment, the grass communities included either high densities of one

375 host group and low densities of the other or low densities of both (Fig. S4Fig. S3A–B). The  
376 densities in the manipulated experiment exceeded those in the observational study. The majority  
377 of the plots had more non-native annuals than native perennial grasses (Fig. S4Fig. S3C–D).

378       None of the focal OTUs significantly increased in relative abundance with native  
379 perennial or non-native annual grass density (Tables S4–S5). We calculated the predicted change  
380 in relative abundance of each pathogen on each host group with the addition of 50 native  
381 perennial grasses  $\text{m}^{-2}$  (Fig. 2A–B) or 5000 non-native annual grasses  $\text{m}^{-2}$  (Fig. 2C–D) to bare  
382 plots—reflecting the difference in naturally occurring densities of these species groups. Such  
383 increases in density exceed those recorded in the observational study (Fig. S4Fig. S3A), but they  
384 still had small predicted impacts on the relative abundances of most pathogens (Fig. 2). Although  
385 not statistically significant, *P. lolii* relative abundance decreased with 50 additional native  
386 perennial grasses (Fig. 2A–B), the relative abundance of *the unidentified Pyrenopthora species*  
387 *sp.* increased with 5000 additional non-native annual grasses (Fig. 2C–D, Fig. S5), and *P.*  
388 *chaetomoides* relative abundance on non-native annuals decreased with 5000 additional non-  
389 native annual grasses in the manipulated experiment (Fig. 2D).

390 **3.4 | Question 2b: Effects of host density on disease severity**

391       Disease severity was generally low across both host groups and grass density ranges (Fig.  
392 3) and did not significantly change with non-native annual grass density (Tables S6–S7). Native  
393 perennial grass density significantly increased disease severity in the observational study (Table  
394 S6), particularly on native perennial hosts (Fig. 3A), but this effect was lost later in the season  
395 (Fig. S6A). Disease severity was higher on native perennials than non-native annuals across  
396 grass densities (Tables S6–S7).

397

398 **4 | DISCUSSION**

399 To evaluate the effects of host competence and density on disease risk, we characterized  
400 pathogen communities and disease severity of native perennial and non-native annual grasses in  
401 a California grassland. Consistent with two of our hypotheses, the host groups shared generalist  
402 pathogens and native perennials hosted more specialized pathogens based on data collected from  
403 JRBP (*Question 1a*). However, non-native annuals hosted more specialized pathogens based on  
404 the U.S. National Fungus Collections Database (*Question 1a*). Both host groups experienced low  
405 disease severity, but native perennials had higher disease severity than non-native annuals—the  
406 opposite of what we had expected (*Question 1b*). Despite distinct pathogen community  
407 compositions between the host groups and differences in disease severity, we did not find  
408 substantial effects of host group density on pathogen community composition (*Question 2a*) or  
409 disease severity (*Question 2b*). Our findings suggest that native perennial and non-native annual  
410 grasses differ in competence, shaping their own pathogen communities, but that their densities  
411 do not amplify their pathogen communities, or foliar fungal disease in general, at least at the 1-  
412 m<sup>2</sup> plot scale and over the time span of our study.

413 **4.1 | *Question 1a: Pathogen community differences between host groups***

414 Plant species vary in susceptibility to different pathogens (Barrett et al., 2009), in part  
415 due to life history (Cronin et al., 2010) and evolutionary history (Parker & Gilbert, 2004).  
416 Accordingly, native perennial and non-native annual grasses had distinct foliar fungal pathogen  
417 communities. Plant–pathogen interactions can also depend on environmental conditions (Barrett  
418 et al., 2009). Sampling year explained 42% of variation in pathogen community composition,  
419 suggesting the influence of temporally variable factors such as precipitation (Thompson et al.,  
420 2013) and temperature (Liu et al., 2019). Our study included two (*Questions 1b, 2a, 2b*) to three

421 (Question 1a) years of data from a single grassland, but longer time series could help link  
422 climate variation to pathogen community composition.

423 Hosts are frequently infected by multiple pathogens and many pathogens can circulate  
424 among different hosts within the same community (Halliday et al., 2017; Schmidt et al., 2020).

425 Our study is unique, however, in seeking to understand how hosts that differ in life and  
426 evolutionary histories shape aboveground pathogen community composition (but see Seabloom,  
427 Borer, Lacroix, Mitchell, & Power, 2013). A pathogen community perspective demonstrated that  
428 high relative susceptibility of one group to one pathogen (e.g., native perennial grasses to *P.*  
429 *tritici-repentis*) can be balanced by high relative susceptibility of another group to another  
430 pathogen (e.g., non-native annual grasses to *P. chaetomioides*). This insight is likely to be  
431 general given that variation in evolutionary history also shapes soil microbial community  
432 composition (Kourtev, Ehrenfeld, & Häggblom, 2002; Wolfe, Rodgers, Stinson, & Pringle,  
433 2008) and cautions against conclusions about disease risk that focus on a single pathogen (Lloyd-  
434 Smith, 2013).

435 The enemy release hypothesis posits that native plants will experience greater disease  
436 pressure than non-native plants because the latter will lose specialist enemies during transport to  
437 a new region and resident specialist enemies will be slow to attack non-native plants (Keane &  
438 Crawley, 2002). We isolated more unique OTUs from native perennials than non-native annuals,  
439 which supports this hypothesis, but the average host range of pathogens associated with non-  
440 native annuals was more specialized than that of pathogens associated with native perennials  
441 based on the database. The latter result should be interpreted with caution, however, because  
442 many pathogens did not have host range information available in the database, some estimates of  
443 host range were smaller than those characterized at JRB (e.g., *R. proteae*), and we found the

444 opposite relationship from nine host species at JRPB. Nonetheless, non-native annual grasses  
445 may host more specialized pathogens because the grass species have been in JRPB or nearby  
446 counties since 1893 or earlier (JRPB, 2020), allowing more than 120 annual plant generations for  
447 resident pathogens to adapt to the novel hosts (Carroll et al., 2005; Hawkes, 2007) and for  
448 repeated introductions of pathogens from their native geographic ranges to occur (Dutech et al.,  
449 2012). Some of the identified pathogens are globally-distributed (Aboukhaddour, Cloutier,  
450 Lamari, & Strelkov, 2011; Stukenbrock, Banke, & McDonald, 2006), suggesting that repeated  
451 introductions may be plausible.

452 **4.2 | Question 1b: Disease severity differences between host groups**

453 Native perennial grasses experienced higher disease severity than non-native annual  
454 grasses. While this finding contradicts our expectation that non-native annuals would have  
455 higher disease severity because of life history, it is consistent with multiple studies  
456 demonstrating higher disease severity on native than non-native plants (Chun, van Kleunen, &  
457 Dawson, 2010; Han, Dendy, Garrett, Fang, & Smith, 2008; Hawkes, Douglas, & Fitter, 2010; but  
458 see Parker & Gilbert, 2007). Native perennials may be more exposed to transmission and/or  
459 more susceptible to infection than non-native annuals. Exposure may be partially explained by  
460 the long-lived life-history of native perennials and their role as long-term pathogen reservoirs  
461 (Thrall et al., 1993). Indeed, the difference in disease severity between native perennials and  
462 non-native annuals was greater in the observational study than in the manipulated experiment,  
463 where plant communities had been recently assembled. In addition, non-native annual grasses  
464 may shed leaves with fungal lesions more frequently than native perennials, creating the  
465 appearance of lower disease severity (Vloutoglou & Kalogerakis, 2000). In general, disease

466 severity was low, suggesting that both host groups have low competence for foliar fungal  
467 pathogens.

468 **4.3 | Question 2a: Effects of host density on pathogen communities**

469 Changes in density of native perennial and non-native annual grasses had limited effects  
470 on the relative abundance of foliar fungal pathogens. Therefore, even though the two host groups  
471 had different pathogen communities (*Question 1a*), they may not amplify the transmission of  
472 pathogens with which they are frequently infected. For example, *P. chaetomioides* was isolated  
473 frequently from the two *Avena* species in the non-native annual group but was predicted to  
474 decrease in relative abundance on non-native annuals with increasing density of non-native  
475 annuals. Changes in plant community composition within the host group, such as an increase in  
476 *Bromus* spp. and a decrease in *Avena* spp., along the density gradient or generally low disease  
477 severity and limited capacity for transmission may have contributed to this pattern.

478 Our results indicate that shifts in the densities of hosts that have similar life history  
479 strategies and local residence times do not necessarily shape the assembly of pathogen  
480 communities. While interpretations of biodiversity–disease risk relationships often invoke a  
481 strong role for host density (e.g., Young et al., 2017), plant pathogen communities may be more  
482 influenced by other factors, such as microbial interactions. For example, priority effects can  
483 influence the assembly of yeast communities in flower nectar (Peay, Belisle, & Fukami, 2012)  
484 and foliar fungal communities on grasses (Halliday et al., 2017). One limitation to evaluating  
485 disease risk by particular pathogens in our study is that we lack data on the absence of infection.  
486 In addition, transmission events may occur at a scale greater than study plots, causing the plot-  
487 level density of grasses to be an inaccurate estimate of transmission pressure.

488 **4.4 | Question 2b: Effects of host density on disease severity**

489 Disease severity increased with increasing native perennial grass density in the  
490 observational study, but not with increasing non-native annual grass density or in the  
491 manipulated experiment. Not only was the manipulated experiment more recently established,  
492 but the experimental designed differed in multiple ways that could affect pathogen transmission:  
493 the total area of the experiment was smaller, there were open corridors between the plots instead  
494 of continuous grassland, and plant community composition varied randomly in space instead of  
495 gradually shifting between the two host groups. Deviations of our results from strong positive  
496 relationships between plant abundance and disease severity (Mitchell et al., 2002; Parker et al.,  
497 2015) may be explained by low average disease severity and high plant diversity. High host  
498 diversity can hinder foliar fungal pathogen adaptation to specific host defenses (Mundt, 2002) or  
499 otherwise prevent specialized pathogens from becoming common (i.e., the dilution effect; Rohr  
500 et al., 2020), making pathogens less capable of exploiting locally-abundant hosts, and in turn less  
501 sensitive to changes in the density of any particular host group. Indeed, host abundance in  
502 diverse old fields did not affect disease severity caused by aboveground pathogens (Schmidt et  
503 al., 2020). In addition, density effects may be transient, as exemplified by dampened density–  
504 disease severity relationships later in the growing season.

505

## 506 5 | CONCLUSIONS

507 This study of foliar fungal pathogen communities and disease severity on native perennial  
508 and non-native annual grasses suggests that differences in life history or local residence time  
509 may contribute to disease risk through differences in competence, but not through changes in  
510 density. We could not parse out the independent effects of life history and local residence time,  
511 but previous studies of plant diseases suggest that both life history (Cronin et al., 2010) and

512 evolutionary history (Parker & Gilbert, 2004) are strong drivers of competence. Our results are  
513 likely to be generally relevant, however, because non-native plants are likely to be annuals  
514 (Sutherland, 2004). These findings have implications for understanding the impacts of invasive  
515 species. For example, when species initially invade a community, they can affect total host  
516 density, altering the proportion of hosts infected (Searle et al., 2016). The invasive species we  
517 evaluated, however, are well-established, suggesting that the expected impacts of invasive  
518 species on disease risk may be greater earlier in invasions. Our study demonstrates that host  
519 community composition can affect pathogen community composition and disease severity  
520 through variation in competence among hosts.

521

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535

536 **Authors' contributions**

537 EAM and ERS designed the research, ERS and SCD conducted the field work and laboratory  
538 work, AEK conducted the analyses and wrote the first draft of the manuscript, all authors  
539 contributed to manuscript revisions and approved the final version.

540

541 **Data availability**

542 The data and code will be available on the Github repository  
543 <https://github.com/ae kendig/invasion-pathogen-communities> and archived with Zenodo.

544

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758

759

760 **Tables**

761 **Table 1.** Data types, sources, years, and sample sizes used to address each question. All data  
 762 sources included two native perennial species (*E. glaucus* and *S. pulchra*) and three non-native  
 763 annual species (*A. barbata*, *B. diandrus*, and *B. hordeaceus*). Some also included the non-native  
 764 annual species *A. fatua* (indicated with †). Sample sizes in parentheses represent an additional  
 765 sampling period in the same year (analyzed separately).

Question	type	Data source	Year	Native	Non-native
				perennials	annuals
1a	isolates	<a href="#">JRB-P compilation</a> <a href="#">obs. and additional</a> <sup>†</sup> <a href="#">(10 studies)</a>	2015	91	75
		<a href="#">obs., man., and additional</a>	2016	261	242
		<a href="#">obs. and additional</a>	2017	182	110
1b	severity	<a href="#">JRB-P compilation (3 studies)</a> <a href="#">obs. and additional</a>	2015	101 (71)	292 (129)
		<a href="#">obs. and man.</a>	2016	338	172
		<a href="#">observational study</a> <a href="#">obs.†</a>	2015	69	55
2a	isolates	<a href="#">observational study</a> <a href="#">obs.†</a>	2016	22	17
		<a href="#">manipulated experiment</a> <a href="#">man.</a>	2016	135	76
		<a href="#">observational study</a> <a href="#">obs.†</a>	2015	101 (56)	292 (79)
2b	severity	<a href="#">observational study</a> <a href="#">obs.†</a>	2016	69	11
		<a href="#">manipulated experiment</a> <a href="#">man.</a>	2016	269	161

766 Notes: obs. = observational study, man. = manipulated experiment, additional = additional

767 sampling (see Fig. S1 for details)



769 **Table 2.** PERMANOVA describing the effects of host group (native perennial versus non-native  
770 annual), grass species, and sampling year on pathogen community composition ( $n = 961$   
771 isolates).

Variable	df	Sums of sqs.	Mean sqs.	F	R <sup>2</sup>	P
Host group	1	0.516	0.516	23.506	0.250	<b>0.001</b>
Grass species	4	0.510	0.127	5.801	0.247	<b>0.004</b>
Year	2	0.862	0.431	19.606	0.417	<b>0.001</b>
Residuals	8	0.176	0.022	NA	0.085	NA
Total	15	2.064	NA	NA	1	NA

772 df = degrees of freedom, sqs. = squares, NA = not applicable; P-values indicating statistical  
773 significance ( $P < 0.05$ ) are in bold.

774

775 **Table 3.** Pathogen species assigned to the focal OTUs, their host ranges based on the number of  
 776 host species found in the database and identified at JRB (out of nine species), and their  
 777 abundances (the number of isolates, and proportion in parentheses) from each host group  
 778 collected across the observational and manipulated density gradients.

Pathogen	Database host range	JRB host range	Native perennial abundance	Non-native annual abundance
<i>Alternaria infectoria</i>	50	8	27 (0.12)	35 (0.24)
<i>Parastagonospora avenae</i>	54	5	32 (0.14)	4 (0.03)
<i>Pyrenophora chaetomioides</i>	7	7	0 (0)	19 (0.13)
<i>Pyrenophora lolii</i>	11	7	12 (0.05)	19 (0.13)
<i>Pyrenophora tritici-repentis</i>	63	2	23 (0.1)	0 (0)
<i>Pyrenophora</i> sp.	NA	6	44 (0.19)	31 (0.21)
<i>Ramularia proteae</i>	1	7	11 (0.05)	6 (0.04)

779

## Figure legends

781 **Figure 1.** Pathogen communities associated with native perennial and non-native annual grasses.  
782 (A) Composition of fungal pathogen isolates for each grass species. Each OTU is represented by  
783 a different color (including varying shades of brown) and the legend is provided for the seven  
784 focal OTUs: *Alternaria infectoria* (*A. inf.*), *Parastagonospora avenae* (*P. ave.*), *Pyrenophora*  
785 *chaetomoides* (*P. cha.*), *Pyrenophora lolii* (*P. lol.*), *Pyrenophora tritici-repentis* (*P. tri.*),  
786 *Pyrenophora* sp. (*Pyr. sp.*), and *Ramularia proteae* (*R. pro.*). The number of isolates per grass  
787 species is to the right of the bars. (B) Non-metric multidimensional scaling (NMDS) plot of  
788 pathogen communities associated with the two host groups. A community is defined as all of the  
789 foliar fungal isolates from one grass species in a year. Ellipses represent 95% confidence regions  
790 for the host group centroids (means). (C) The average number of host species in the database  
791 (top panel) and the JRBP compilation (bottom panel) for fungal pathogens isolated from each  
792 host group (mean  $\pm$  1SE). Averages comprise all fungal isolates with estimated species names  
793 and available data ( $n = 548$ , top panel) or all OTUs ( $n = 961$ , bottom panel).

794 **Figure 2.** The average predicted effect ( $\pm 1\text{SE}$ ) of adding (A–B) 50 native perennial grass  
795 individuals  $\text{m}^{-2}$  or (C–D) 5000 non-native annual grass individuals  $\text{m}^{-2}$  to bare plots on the  
796 relative abundance of each of the seven focal OTUs on each host group (x-axes) based on  
797 regressions fit to the (A and C) observational ( $n = 163$  isolates) and (B and D) manipulated ( $n =$   
798 211 isolates) studies (Tables S4–S5). Pathogen abbreviations are in Fig. 1.

799 **Figure 3.** The effect of (A–B) native perennial and (C–D) non-native annual grass density on  
800 scaled disease severity of native perennial and non-native annual hosts in the (A and C)  
801 observational study ( $n = 1847$  leaves) and (B and D) manipulated experiment ( $n = 1177$  leaves).

802 The average scaled disease severity is plotted at each density value (points). Lines and shaded  
803 regions represent linear regression fits (mean  $\pm$  1SE, Tables S6–S7).